Deep Learning-based Fault Diagnosis in Transmission Lines via Long Short Term Memory Networks

by

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Abstract

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In electrical power systems, transmission lines are responsible for transferring power across the grid. However, faults in these lines are abnormal conditions that can destabilize the transmission system if sustained longer. To diagnose the faults, IEC61850 based digital substations provide the sampled value measurements in the substation. In addition to existing model-based techniques to diagnose the fault, machine learning techniques are explored in the literature. In this thesis, we present a novel Long Short Term Memory (LSTM) based fault classifier using current and voltage measurements as the input. Compared with deep learning algorithms proposed in the literature i.e. RNN and SVM, the proposed classifier provide improved performance in the classification of faults, tested on data obtained from a PSRC D6 benchmark testbed. The performance of the classifier is explained with the evaluation metrics i.e. test accuracy, precision, recall, F1 score and confusion matrix to show the classification performance.

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Chapter 1

Introduction

This chapter provides the introduction of the work with a brief summary of the problem, proposed solution and methodologies used along with key contributions and an overview of the thesis.

1.1 Motivation

The power grid is evolving with a vision of a smart grid with the bidirectional flow of energy and data. In a smart grid, the goal of a stable and reliable operation of the grid is important with increasing generations and demand along with time. The transmission system in the smart grid acts as the inter-connection from the various generations including renewable energy resources to the consumers. The protection of the transmission system is important for the stable operation of the smart grid.

However, due to natural disasters, extreme weather as well as human-made interventions, abnormal conditions i.e. faults in the transmission system arise. In order to overcome the negative impact of faults on the dynamics and stability of this infrastructure, the role of the protection system of the power grid is important and it needs continuous improvements. In the protection system of transmission lines, fault diagnosis i.e. fault detection, its classification and the location of the faults is done with the help of various protective relays. However for the post-fault diagnosis tool using the recorded events, have been developed using model-based as well as data-driven approaches. The goal of fault diagnosis in the off-line implementation is to analyze the fault in terms of its type, location and reasoning due to system disturbances. There have been data driven methods explored to provide this fault diagnosis task for the transmission line in the digital substations.

Ranging from classical algorithms to modern techniques, there are methods available for detecting, classifying the fault for the transmission line protection system. The fault detection is done in transmission lines via over-current relay, distance relay and differential relay with unique characteristics of each relay. The fault classification is classically done via sequence component distance relays to classify the fault in the system by using positive, negative and zero sequence components. Especially the fault classification is done via sequence component based relays however due to inclusion of distributed energy generations, the effectiveness of sequence component based approaches is declining. This has led to use of signal processing techniques i.e. with wavelet transforms, S-transform and fuzzy logic based techniques to solve the fault classification problem with improvement in analyzing the current and voltage signals. Recent data-analytic techniques, in particular sequence learning models, are considered promising techniques for the fault detection and classification tasks in the transmission line.

The motivation behind the use of sequence models are two folds. First, LSTM networks are at the best to extract the features from the temporal data in sequential manner. Second, Unlik RNNs, it overcomes the vanishing gradient problem in the learning from sequential data. The potential of transformer model was another candidate approach, however it doesn't provide the learning in sequential manner as required in power system measurement data.

With help Long Short Term Memory (LSTM) networks, the temporal information from the sequential data can be learnt and classified for various abnormal behaviours including faults. The fault detection and classification task are achieved with input current and voltage measurement data available in the substation. In this thesis, the approach of sequence learning models is applied to solve the fault classification problem.

The intended end-user of this LSTM based fault diagnosis tool are the manufacturers of the digital substation devices, which are used to diagnosis the fault in off-line implementation in the IEC 61850 based substations. Since in the online fault classification, these machine learning models are not in compliance with time-requirement of real-time protection system. The goal is to use these data-driven tool for the off-line use for post-fault analysis for the fault events in the substation to build a classifier based on history of recorded measurement data.

1.2 Contributions

This thesis focuses on the task of fault detection and classification in the digital substation connecting transmission line. It proposes a LSTM based fault classifier which classifies type of faults by learning from the available history of data in the substation.

The novelty of this work is based on firstly, the use of adaptive LSTM based architecture for feature extraction and secondly, development of softmax classifier for the multi-class classification of three kinds of faults and a normal class, which is the extension and improvement in the binary classification explored in the literature for fault detection and classification.

With focus on developing deep learning based fault classification technique, the contributions of this thesis are three-folds:

- The thesis provides an improved fault detection and classification methodology using sequential models, especially with Long Short Term Memory (LSTM) networks.
- With experiments conducted for its performance on simulated current and voltage data shows the potential of its implementation in the post-fault analysis devices for fault classification using deep learning.
- The goal of multi-class classification with three kinds of faults and a normal class were identified from the test dataset along with the improved performance com-

pared to existing models used for binary classifications.

- The comparative study indicates the better performance of the classification task by the proposed classifier in comparison of recent deep learning techniques for this task.

1.3 Overview

Chapter 2 provides the motivation of the deep learning-based fault detection and classification with an approach to the problem formulation. The reasoning for choosing a machine learning-based hypothesis and its impact is highlighted.

In Chapter 3, the required background of concepts of fault detection and classification is covered. Literature surveys of classical and machine learning techniques used in this subfield of power system protection are highlighted with the need for sequential learning-based techniques.

Chapter 4 gives a background of sequential learning networks i.e. RNN and LSTMs and proposes the LSTM network-based classifier with its architecture.

Chapter 5 focuses on a testbed of power transmission line and approach for the solution with sections of dataset generation, model training methodologies.

In Chapter 6, the results of performance evaluation of the classifier model are provided with performance metrics and a comparative discussion with alternative models is done.

We conclude the thesis in Chapter 7 with directions for future work in this field of research.

Chapter 2

Problem Formulation

This chapter states the existing approaches for the fault detection and classification task of transmission lines. Along with the challenges and limitations of the diverse techniques used, it provides advantages of machine learning techniques assisting in detection and classification. A brief introduction of a viable solution, i.e. Long Short Term Memory (LSTMs) network-based fault classifier is presented at the end.

2.1 Importance of Fault Diagnosis

In power systems, transmission lines are three-phase connections between various substations which transfers power from generating stations, to the distribution system at high voltage levels. In a transmission line system, a fault can be defined as contact between conductors or with the ground. In the three-phased transmission line, these faults are classified in Single Line to Ground (LG), Double Line to Ground (LLG) and Three Lines to Ground (LLLG) among others.

In power system, a complex and critical infrastructure, the change in measurement data i.e. voltage and current signals, is frequently experienced. Along with several disturbances, the various system faults in power systems are caused by number of reasons [3], out of which around 85% of them are contributed by faults in the transmission system

[4]. The faults in the power systems are unavoidable considering their physical nature e.g. in overhead transmission lines and in underground cables [5]. These faults can cause substantial economic damage in addition to personal and equipment loss [6]. These implications in the complex transmission line network, have highlighted the need to diagnosis the fault in a fast and timely manner.

The fault detection is the procedure to detect the abnormal condition of the transmission line based on the data obtained by CT and VT protective relays and the status of circuit breakers of the protective zone. The goal of fault classification is to categorize the fault by its type i.e. which phase of the system is at fault and its nature.

One of the prominent techniques widely used in power systems is Symmetric Component-based relays for fault classification. This technique is completely dependent on the estimation of the fundamental component of current and voltage signal during the fault. In addition to the Symmetric Component Distance Relay [7], the advancement of data-analytics and machine learning prompted increasing research in the depth and breadth of task of fault diagnosis techniques via decisions made with the help of history of data in the system and learning out of it.

2.2 Data-Driven Fault Diagnosis in Transmission Line

The fault diagnosis in the transmission system is defined as identifying the fault, classifying its nature and identifying the location in the transmission system. The goal of fault diagnosis in the transmission system is to detect the fault in the line, classify the type of fault, and localize the fault for the restoration of the line. The protection system of transmission lines is used to monitor health of the lines and isolate the line in case of the fault. The protection systems include primarily circuit breakers to isolate the line, CT and VT for measurement of current and voltage signals, merging units, and protective relays.

Fault diagnosis can be divided into model-based and history data based. Model-based techniques perform fault analysis by describing a system (or process) through quantitative

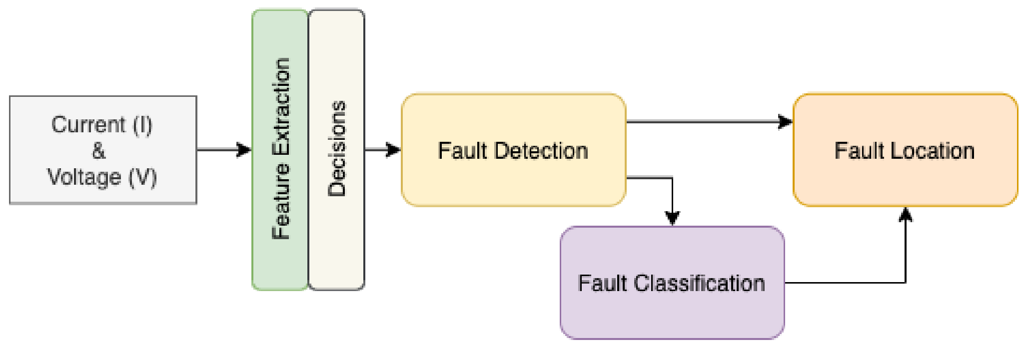


Figure 2.1: Stages of fault diagnosis in transmission system

or qualitative models. Data history-based techniques rely on empirical measurements of the process and develop a mapping between inputs and desired outputs, without performing any prior mathematical estimation. In power systems, model-based techniques find few applications because of their computational intensity and sensitivity to parametric changes, which results in slow and inconsistent diagnosis [8].

In model-based methods for fault diagnosis, a suitable mathematical model describing the system is required. This description, or prior knowledge, is fundamentally derived from the underlying physics of the system behaviour and can be both quantitative and qualitative. Considering the model based fault diagnosis in transmission lines, there are several types of protective relays which are based on the model based methods used for fault detection. For example, the commonly-used protective relay for the fault classification is sequence component based protective relays

On the other hand, sufficient historical process data is required for process history-based (or pattern recognition) methods. Intuitively, this task is described by a set of measurement data, which can be mathematically expressed as a function between measurements and decision. There is no need of an estimated mathematical description of the underlying physical process [8]. For example, in transmission line protection, the classification of the fault can also be done via analyzing the history of the data and abnormal conditions in the data.

In recent years, the methods of fault diagnosis, i.e., fault detection, classification, and location of transmission lines have been extensively explored using data-analytic techniques [9] [10]. With the focus on smart grid, the importance of intelligent health monitoring of transmission systems and fault diagnosis led to the development of statistical and machine learning based methods concerning the detection and classification of types of fault in power systems[11].

2.3 Scope of Fault Diagnosis Tool

With help of history of data measurements e.g. current and voltage signals, the goal of the fault diagnosis tool use a LSTM network based sequential model architecture for the detection and classification of fault in the transmission line of the power systems.

In comparison to various stages of fault diagnosis in the transmission system, our work is limited to the first two tasks whereas the classification task is inclusive of the detection task i.e. as the fault is detected in the system, it output the type of the fault detected directly. Additionally, the detection task could also be differentiated in the architecture of the work which is exclusive to classification task.

As shown in the 2.2, the objectives of the fault diagnosis tool used in our work is to use the deep learning based diagnosis tool to classify the input measurement in normal class or the fault class where fault class is designed to output three types of fault i.e. Single Line to Ground (SLG), Double Line to Ground (DLG) and Triple Line to Ground(TLG).

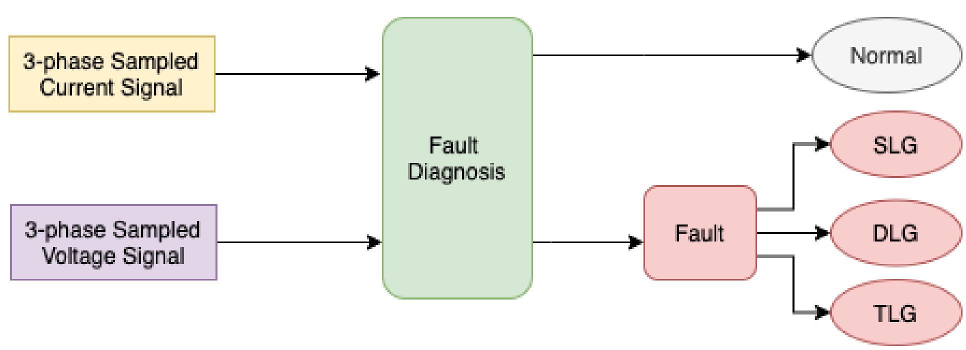


Figure 2.2: Illustration of Fault Diagnosis tool with its objectives

2.3.1 Assumptions

To achieve the goal of fault classifier using sequential models, we make following assumptions to progress towards the solution of detection and classification task in transmission line protection.

- It is assumed that the input data i.e. current and voltage are available from the event recording system in the substation for the particular transmission line.
- The classifier is used for fault diagnosis where it can detect the fault, classify the fault for the post-fault analysis. It is proposed for off-line implementation. The goal of online implementation is also a possibility however it will require high computing and faster processing time.
- In the evaluation of the classifier, while producing the generated data from the testbed system, it is assumed that all transmission line physical parameters are constant and any abnormalities except the faults are neglected.

2.3.2 Overview of the Problem

In this thesis, the goal is to develop a fault classifier for the fault diagnosis in the protection system of the transmission line, using LSTM networks as feature extractor and Softmax layer as decision layer where it utilizes the temporal nature of historical measurement data and extract the feature for the improved classification of faults.

The objective of the problem statement is to achieve the classification performance of post-fault diagnosis from a data driven approach rather a model based approach. The use of sequential models especially LSTM networks are considered potential candidates to learn the temporal information sequentially from the sampled current and voltage data available from CT and VTs in digital substation via IEC61850 based standard communication infrastructure.

Based on the formulation of the problem, the goal of the next chapters is to explain the existing model based methods for the fault classification, data-driven methods from classical signal processing methods to artificial neural network methods. Furthermore, the vanilla RNN layer and LSTM layer network will be explained along with the proposed classifier architecture where it can exploit the temporal information of input signals via LSTMs and produce potential results in classification task of the fault diagnosis. In the classification task, the detection of fault is implied in this goal as the classification of the input sample as normal condition and one of three kinds of fault conditions of the transmission line will be considered.

Chapter 3

Background & Previous Work

This chapter focuses on providing background concepts in protective relay principles, fault detection and classification along with an literature survey of previous work in this field. Firstly, the classical approaches of fault classification are explained briefly and later, machine learning and deep learning based techniques are explained.

3.1 Protective Relay Principles

3.1.1 Protection System

A protection system in power system protects the grid from detrimental effects of a sustained fault. A fault is an abnormal system condition (in most cases, it's a short circuit). If a faulted power system component (e.g. in our case, a transmission line) is not removed from the system quickly, it may lead to instability in the power system or higher disintegration of the system by other protective devices. Thus, a protection system must isolate the power from this faulted element from the rest of the system as soon as possible.

The protective system consists of subsystems which help to remove the fault. As illustrated in 3.1, the circuit breaker (CB) isolates the faulted circuit by interrupting the current at or near current zero. The measuring transducers (current and voltage

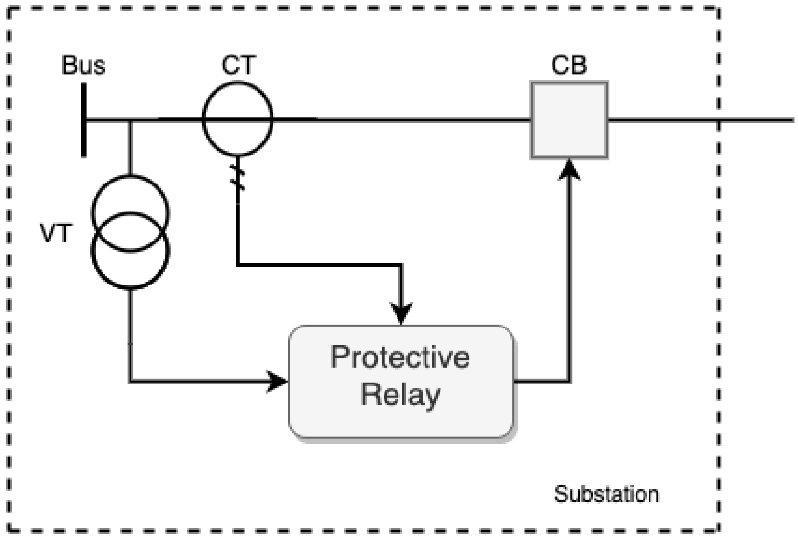


Figure 3.1: Overview of sub-systems of protection system

transformers) makes another major sub-system of protection system. CTs and VTs are required to measure current and voltage signals by reducing the high magnitude of current and voltage from primary circuit to low values in secondary circuit. The secondary circuit values of CT and VT are standardized to 1 Amp or 5 Amp and 67 volts phase-to-neutral respectively [12]. Thus, the relay observes scaled down versions of currents and voltages that exist in power systems.

The most important sub-system of protection system is the protective relay. This device takes inputs (voltage signal, current signal or contact status) in such a way that it outputs a trip signal to CB when input conditions correspond to the faults the relay is designed for. The relay has two requirements i.e. it is dependable and it is secure. Dependability means that the relay will always operate for fault conditions, it is designed to operate. Security means that the relay will not operate for other power disturbances.

3.1.2 Protection of transmission lines

In the protection system of transmission lines, the classical fault detection is done in several relays, in order to avoid common failure modes among different protection systems. However, all the relays can be classified as:

- Pick-up Relays: These relays respond to magnitude of input quantity. For example, an over-current relay which responses if the magnitude (generally rms value) of input current is above a set threshold, I_p.
- Directional Relays: These relays respond to phase angle between two AC inputs. For example, a common directional relay compares the phase angle of current and voltage signal. Another way is to compare the phase angle of one current to another current signal.
- Ratio Relays: These relays respond to the ratio of two input signals expressed as phasors. Since the ratio of two phasors is a complex number, the relay can be designed to respond to the magnitude of the complex number or the complex number itself. For example, the common ratio relays are impedance or distance relays.
- Differential Relays: These relays respond to the magnitude of the algebraic sum of two or more inputs. In the common form, the relays respond to the algebraic sum of currents entering a zone of protection.
- Pilot Relays: These relays are based on utilizing the communication infrastructure between two remote substations. For example, the decision of local relay is communicated to other terminals of the transmission line.

3.2 Classical Fault Analysis

Fault classification is important for fast and reliable operation of protective relaying in transmission lines. Classically the faults in transmission lines can be categorized in two types: series (open circuit) fault or shunt (closed circuit) fault. Open circuit faults create abnormal change in phase voltage values whereas short circuit faults can be identified by abnormal phase current value. Short circuit faults are divided into two types, i.e. asymmetrical faults, and symmetrical faults. Asymmetrical faults are line to ground (LG), line to line (LL), and double line to ground (LLG), and symmetrical faults are

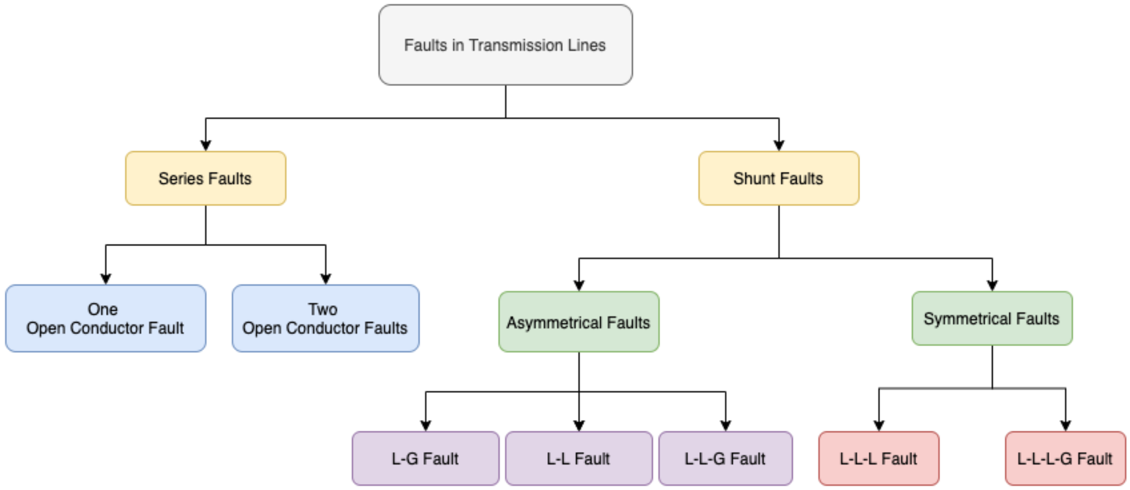


Figure 3.2: Classification of faults in transmission lines

triple line (LLL) and triple line to ground (LLLG) faults, as shown in 3.2.

The severity and frequency of these faults are briefly explained to understand the need to identify and classify these faults accordingly. The most frequently occurring fault is LG fault though it's not the most severe fault. The next most frequent and severe faults are LL and LLG. The most severe faults for the stability of power system are LLL and LLLG faults, if occurred and not identified timely, these faults can collapse the system. So the protection system needs to detect the fault and classify the nature of the fault and location of the fault within less time to avoid the major adversarial impact on the system.

3.2.1 Classical Model-based Approaches

In Model based approaches for the task of fault detection and classification in the transmission line, the commonly used approaches are as follows:

Symmetric Component Protective Relays

In three-phase network of power systems, the measurement signals are obtained from CTs and VTs at the protective relay location for example one end of a transmission line. Under steady state and balanced network conditions, phase voltages are of equal magnitude and spaced equally in 120° apart. This is true for the phase currents as well considering the balanced line.

However when short circuit or open circuit fault occurs or system is unbalanced, in that situation the network analysis is difficult. Hence, the sequence component based modelling is done to solve the unbalanced network in steady state conditions. The phasors are used to represent the ac waveform of the current and voltage measurement signals. Furthermore, the equivalent sequence components represents the three unbalanced phasors as follows:

$$\begin{aligned} X_{0a} &= \frac{1}{3}(X_a + X_b + X_c) \\ X_{1a} &= \frac{1}{3}(X_a + \alpha X_b + \alpha^2 X_c) \\ X_{2a} &= \frac{1}{3}(X_a + \alpha^2 X_b + \alpha X_c) \end{aligned}$$

where operand α represent a phase shift of $\angle 120°$. X_{0A}, X_{1a}, X_{2a} are the zero sequence, positive sequence and negative sequence respectively for the X_a signal. It can be writeen in compact form where A is sequence component transformation matrix.

$$\begin{bmatrix} X_0 \\ X_1 \\ X_2 \end{bmatrix} = \frac{1}{3} \begin{bmatrix} 1 & 1 & 1 \\ 1 & \alpha & \alpha^2 \\ 1 & \alpha^2 & \alpha \end{bmatrix} \begin{bmatrix} X_a \\ X_b \\ X_c \end{bmatrix} = \begin{bmatrix} A \end{bmatrix} \begin{bmatrix} X_a \\ X_b \\ X_c \end{bmatrix}$$

Using the sequence components, the equivalent sequence network can be represented where sequence voltages and sequence currents are used instead of three phase quantities. Further, the impedance for each sequence can be decoupled resulting in better diagnosis of fault if occurs in each phase, using boundary conditions in the equivalent networks.

However, the sources of sequence component are the system imbalance, error in instrument transformers and filter transients. With inclusion of distributed generations and power electronics based devices for AC/DC conversions, it provides the challenges in the design of the fault identification, classification of type logics using the sequence components [13].

To understand how fault detection and classification tasks are achieved via data-driven methodologies in transmission lines, various classical techniques, signal processing and analytical approaches are available with its advantages and disadvantages. To easily understand, the available literature of fault classification is categorized in two categories, prominent approaches (Section 3.2.1) and hybrid approaches (Section 3.2.3)[14].

3.2.2 Classical Data-Driven Approaches

These popular approaches are well-known techniques from signal conditioning point of view, which are used in fault classification algorithms of digital relays. To further understand the basis of these approaches, it is categorized in three types:

Wavelet based Approaches

These approaches are based on the fundamental concept of wavelet transformation (WT) in signal processing to obtain fundamental components in fault transients which are difficult to obtain using other methods including Fourier transforms. The idea is to choose a wavelet function as “mother wavelet” carefully and afterward execute moved and enlarged adaptations of this wavelet. Wavelets can be picked with recurrence and time attributes when contrasted with Fourier procedures. With time and frequency data, WT can split signals into different frequency bands with the help of multi resolution analysis (MRA). It is used in detecting faults and to estimate the phasors of the current and voltage signals, which are important signals for the protection of transmission lines.

For example, an approach using wavelet entropy principle was used for fault analysis in transmission line where the distributed parameter model was used to simulate the line in the electromagnetic transients program (EMTP) [15]. Using mexican hat and coif let as mother wavelet, an algorithm was implemented for classifying the fault and computing the fault distance within half cycle after the fault initiation [16]. Moreover, the fault transients are utilized to get its wavelet coefficient energies and coefficient decomposition to develop fault analysis [17].

Discrete Wavelet Transform (DWT) is also researched extensively for classification of faults in transmission systems. In, [18] a DWT based fault classification was presented for three-terminal transmission lines. The maximum detail coefficient, energy of signal and energy change per phase current was calculated using DWT and classifying transmission line faults. Whereas in [19], a wavelet based current signature analysis method is used to classify the nature of the fault.

Fuzzy Logic based Approaches

Fuzzy logic technique has also been explored in fault classification problems since the 1990s. Fuzzy logic is a hypothesis which involves uncertainty in input information to achieve the output. To achieve classification of faults utilizing fuzzy set methodology, [20] calculated symmetric components in presence of harmonic components and exponential decay of R-L model. With consideration of travelling waves, fuzzy logic method is used to estimate frequency, fault voltage at one end of line, and to calculate the fault location by calculating travel time by the wave [21]. Similarly in [22], fault classification for single and double-circuit transmission lines is improved where fuzzy logic methodology could find symmetrical and asymmetrical faults. A comparative study of fuzzy rule based technique with s-transform and wavelet transform was made showing the effectiveness of s-transform [23].

Artificial Neural Network (ANN) based Approaches

Earliest work on fault analysis of relaying systems in transmission lines using neural networks is in 1995 [24] where signal conditioning and multi-layer perceptron (MLP) model is used to classify the faults. Another neural network based technique for fault classification and location is explored in [25] where voltage and current signals are used as inputs. Moreover, only current signals were also used to investigate hidden features which led to identify faults and classify the faults in [26] and in [27] where only current signals were also used for fault classification in the double circuit overhead line. Other works have demonstrated fault analysis of six-phase transmission lines using ANN considering the increasing infrastructure of high-phase order transmission systems in the present day scenario.

Using ANN, an adaptive protection scheme for doubly fed transmission lines demonstrate the line-to-ground (L-G) faults in forward and reverse scenario [28]. This methodology uses fundamental component of voltage and current signals measured at one end and provides fault direction after one cycle from inception of the fault. Considering the architectural improvement in neural networks, a comparative study of fault analysis is done with three feed-forward neural networks i.e. cascaded correlation feed forward network, radial basis function (RBF) and back propagation network(BPN), for a double circuit transmission line [29].

However, in most of the works, conventional feed-forward dense neural networks were used to classify the fault in various scenarios and recurrent neural networks and Long Short Term Memory based classification are limited.

3.2.3 Hybrid Approaches

In hybrid approaches, the integration of two or more techniques (i.e. wavelet transform, fuzzy logic or ANN) are used to achieve the goal of identification, classification of the faults in transmission line. The goal of the most of the work was to overcome drawbacks of one approach while utilizing strengths of another.

A combination of fuzzy-logic and neural network which is called adaptive neuro-fuzzy inference system (ANFIS) is utilized in [30], where sequence components and line currents were used to detect phase faults and phase to earth faults. Another approach with a fuzzy neural network is used for distance relaying [31]. Applications of ANFIS are explored in detail for fault analysis in transmission lines using measurement data at one end [32], using multiple ANFIS networks for long transmission lines [33], and for series compensated transmission systems using WT and ANFIS [34].

With a combination of wavelet transform and neural networks, the focus of most of the work was getting features from WT and classifying it using neural networks. A fault classification problem was defined, where wavelet coefficients are fed to the MLP network [35]. A comparative study of Fourier and WT methods with NN is done where DWT is considered best for phase-to-ground fault whereas DFT is better in others [36]. Using wavelet entropy and neural network, a fault classification technique showed only three levels of decomposition of voltage signal was enough, to classify symmetrical and asymmetrical faults at varied locations [37]. In [38], probabilistic neural network and WT based fault classification of multi-terminal series compensated lines is shown with robustness.

Another hybrid techniques are a combination of wavelet transform and fuzzy-logic where WT is used to decompose the voltage and current signals, which are fed to a fuzzy-logic system to classify the fault. For example, in [39], fault classification technique is developed using fuzzy inference system where only three line currents were used to identify faults and it is extended to locate the faults [40]. Using DWT and fuzzy logic, a fault classification technique is developed [41] where db4 mother wavelet is used, in Thailand power transmission system.

3.3 Machine Learning based Fault Detection and Classification

In previous studies of fault detection of power system faults, several artificial intelligence based techniques have been proposed including expert systems [42] [43], rough sets [44] [45], Bayesian Networks [46], petri-nets [47] and neural networks [48], [49]. Classically, the classification task is achieved via support vector machines and decision trees. Classification via featue extraction has been implemented via stacked autoencoders in the literature as well.

Support Vector Machine based Approaches

One of the most used methodologies for fault classification in machine learning domain is support vector machine (SVM) for binary classes, fault or no-fault. Originating from statistical learning theory, SVM is a computational learning method for separating function in classification and estimation in regression problems. SVM based methods for fault classification in transmission lines are explored as well where SVM acts as a classifier once features are extracted.

Usefulness of SVM has been proved in [50] where the sensor faults were classified by three SVM kernels and in [51] where transformer winding faults were classified with better performance than past data-driven methods. In [52], data-driven line trip prediction is proposed with SVM as a fault detector for a substation configuration.

A multi-class SVM based fault classification method [53] is developed where wavelet decomposition of post-fault currents are used as input to SVM with one-verses-all and one-verses-one kernels are used. Generalization of SVM with limited test-data was demonstrated as an optimized classifier. A different method for location of faults is used using fuzzy logic and SVM [54] in which comparative study shows better performance of SVM from MLP perceptron model. In [55], a technique for real-time fault analysis was developed using SVM where phase angles among line currents were used as input. However, it is completely dependent on the ability of separable input points with selection of nonlinear kernels. Wavelet technique for feature extraction and SVM for classification is used as well [56]. A technique for fault classification in thyristor controlled series compensated line using SVM is presented where one SVM is trained for fault with firing angles as input while another for section identification in the line [57].

Decision Tree based Approaches

Decision tree is a transparent and easy to follow technique, where a tree structure is used for conditional decision making at each node. For fault classification task in power transmission system, decision tree based methods are developed as well. For example, using a decision tree, a fault detector is developed which can determine the fault inception time using a travelling wave in a double circuit transmission line [58]. In another method, a fault detector for a thyristor controlled series compensated line with unified power flow controller is developed which uses zero-sequence voltage and current to construct the optimal decision tree.

Stacked Auto-encoders (SAE)

In the research work of power system fault diagnosis, auto-encoders are also researched for classification. For example, in [59], authors used stacked auto-encoders for classifying reclosing failure and success faults. Moreover, stacked sparse auto-encoders are used for detecting faults in rotating machinery.

The neural networks have been researched extensively in recent years for fault prediction [60] and classification via radial basis functions [61]. However, there is large temporal information in the transmission line system which contributes to fault detection, and those features can't be extracted perfectly with classical feed-forward neural networks. [52] Recurrent Neural Networks and its extension Long Short Term Memory networks focus on temporal information in learning in time-sequence data like current and voltage signals. Due to this, these recurrent neural networks and long short term memory networks are called, sequential models which are discussed in next section.

3.3.1 Sequential Model Approaches

Sequential learning models i.e. recurrent neural networks and its extensions are widely useful due to its effectiveness on learning from time-series data and predictions. These models are shown to have capability to capture hidden features in data-centric applications e.g. in voice conversion [62] [62], natural language processing [63]. These models also have shown better performance while dealing with faults in sequential data of fields other than power systems [64] [65].

However, the simple RNN networks have the problem of gradient vanishing because as the information flows from the first node to the last node, the gradient diminishes. Additionally, RNNs can't have long-term dependencies in temporal sequences as we increase hidden input windows. To address this, Long Short Term Memory (LSTM) Networks [66], an improved extension of RNNs is used to solve the long-term dependencies and vanishing gradient problem. LSTMs work better in extracting the features from long temporal sequences due to its architecture of gate neural networks. For example, in [67], LSTM network was proposed to accomplish detection and identification of faults using available measurement signals. It was shown that the LSTM network was better than convolutional networks. Moreover, in [68], an LSTM model is proposed to achieve forecasting of traffic and compared results demonstrated the better performance by LSTM network based model.

3.3.2 Literature Gap: Extending potential of sequential models in classification task

Existing work in machine learning based fault classification ranged from utilizing classical techniques e.g. SVM, decision trees as well as sequence models i.e. RNN and LSTMs. Utilizing the both kinds of algorithms, in [69], authors used SVM classifier and LSTM based classifier to detect faults in using voltage variation in pre-fault and post-fault prediction. Similar work [52] has used LSTM networks for feature extraction of current, voltage, active power signals using LSTM network for predicting the binary class i.e. fault, no-fault classification from measurement data. In this work, the LSTMs were used to extract the features to train the binary classifier. However, the goal of fault classification (with multiple classes) task was not achieved using the sequential models i.e. RNNs or LSTM networks.

In general, LSTMs are better in providing detection and classification objectives in long temporal measurement data. However data-driven fault detection, classification is still in the beginning stages. Considering the IEC 61850 based communication infrastructure in substations, availability of high sampled historical event data, prompt the researchers to work on better algorithms and architecture of deep learning based classifiers with improvement in accuracy of classification in digital substations.

Additionally, the performance of the classifier model can be improved via modification in the architecture of LSTM networks for the feature extraction, later the Dense layers and softmax based classification layers can achieve the goal of classification. Adaptive architectures which can be potential solutions for implementation of off-line and online fault classification in the digital substations. The feature extraction of the features and temporal information in detection and classification of the fault is the primary function of machine learning models, however most of the methods with high performance i.e. with LSTM networks have used conventional architecture for the features of current and voltage signals.

As discussed, the LSTM networks for fault classification with goal of classifying the type of faults isn't explored in the existing literature. Hence, the need to achieve the task of the multi-class classification and improve the architecture of LSTM networks as well as fault classification for a transmission line is a need of research with deep learning techniques especially the potential network of LSTMs for feature extraction with adaptive nature in different phases of input measurement data.

In the upcoming chapter, we propose the sequence learning models i.e. RNN and LSTMs and the mathematical background to achieve the improved architecture of fault classifiers for the transmission system.

Chapter 4

Proposed Sequence Learning based Fault Classifier

In this chapter, we propose the approach of deep learning based Fault classifier and provide a mathematical background of sequential learning models i.e. recurrent neural networks (RNNs) and Long Short Term Memory Networks (LSTMs). Additionally, further details about the classifier model is provided to help understand the solution for fault detection and classification.

4.1 Fault Classification using Deep Learning

As seen in Chapter 2 and 3, the fault classification using machine learning models have been explored from classical support vector machines to deep sequential models like recurrent neural networks. With the goal of detecting the fault within a few cycles of fault inception [], the performance of the sequential models have shown the potential of usage in digital relays in modern substation.

The RNNs and LSTMs networks have been used dominantly to extract temporal features from the time-sequence data i.e. current and voltage signals and these temporal features in the hidden layers are used to detect, classify and locate the fault. There was little exploration in the use of different architecture and hyper-parameters for the improved performance rather sequence models were used as a primal approach.

In the upcoming section, we provide the foundation of sequential models for classification and in Section 4.4, the proposed classifier is proposed with architectural advantages in temporal signals of the power system.

4.2 Sequential Learning Models for Classification

In this section, a brief overview of sequential models is presented with focus on detailed working of recurrent neural networks and long short term memory networks. For both models, the purpose of selection as well as mathematical description is provided.

4.2.1 Recurrent Neural Networks

A recurrent neural network (RNN) is a class of neural networks which utilizes the temporal information of input data and learns the temporal information through hidden node connections over time steps. The unrolled architecture of RNN forms a directed graph as shown in 4.1, sharing parameters across time-steps.

Since traditional feed-forward neural networks can't learn the sequential information from the time series input data. This issue is resolved by recurrent neural networks due to continuation of information in its loops. The Recurrent neural networks are formed by recurrence in its structure over time sequences. As shown in figure 4.1, a node of RNN network A, gets the input x_t and outputs the value h_t as hidden node output. A recurring loop allows the network to pass information from one time step to the next one within its directed cycle network if shown as an unrolled RNN node.

The value of hidden node, h_t can be written as,

$$h_t = f(h_{t-1}, x_t; \theta) \tag{4.1}$$

where h_{t-1} is the previous hidden state, x_t is the input at time step t, and θ are the

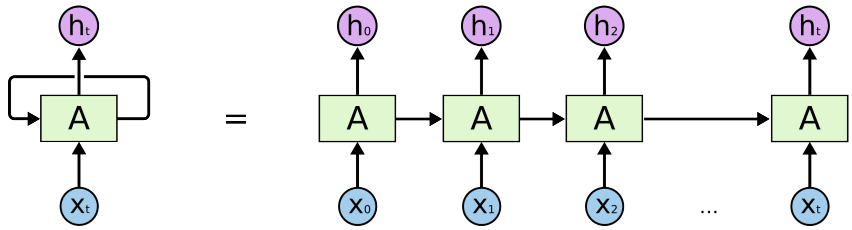


Figure 4.1: An illustration of RNN with unrolled network [1]

parameters of function f.

Vanilla RNN in basic form with shared hidden node information as shown in figure 4.2 can be expressed as

$$s_t = Wh_{t-1} + Ux_t + b_h \tag{4.2}$$

$$h_t = tanh(s_t) \tag{4.3}$$

$$a_t = Vh_t + b_o \tag{4.4}$$

where U are input weights, W are the hidden weights and s_t is sum with weights of input and hidden information. h_t is the value of the hidden node at time t after passing through the tanh activation function. a_t is the output value of RNN at time step t.

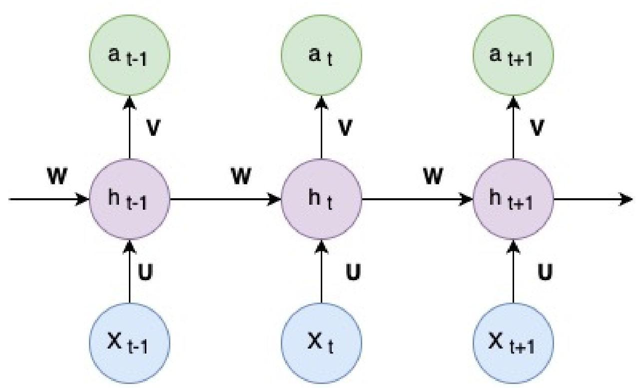


Figure 4.2: Working of RNN network

As we see, the hidden node of RNN not only receives the input data at time step t but also the value of previous hidden node at $t - 1$, thus RNN network can remember the information from the previous time-step and include it in calculating value in current time-step. This feature is the reason for better performance for RNN network in tasks with temporal information.

Regarding the output of RNN network and training the network with supervised learning, a backpropagation algorithm is used after checking the loss at each time-step. The big challenge while training the RNN network is the problem of vanishing gradients. This problem arises when the information of previous nodes decreases significantly as we move across time steps. This challenge of long-term temporal information dependencies lead to extension of RNN networks with a way to control the temporal information from one time-step to another.

4.2.2 Long Short Term Memory (LSTM) Networks

Coming up as a solution to the problem of long-term dependencies and learning from the sequential data, LSTM networks are popular with the advantage of keeping temporal information for a long time using a memory cell in its node. Instead of having just one neural node with non-linear function as we saw in RNN, LSTM has multiple gate layers with the purpose of forgetting information from memory, storing new information in memory and outputting the information as the information moves across time-step.

The LSTM node at time-step t takes three inputs, x_t is the input data at current time-step, h_{t-1} is the output of the hidden layer at previous time-step and C_{t-1} is the memory cell from the previous hidden layer. The node outputs its memory cell C_t and output of the node, h_t. Hence, a LSTM node at time-step t takes these inputs and generates output while updating its memory. To have an understanding of internal information flow while updating memory in LSTMs, we can look at the following gate layers, as shown in figure 4.3:

1. **Forget Gate Layer:** This gate focuses on information to be forgotten while coming from C_{t-1}. The gate layer takes input as input data, output of previous layer and bias b_f and outputs values between 0 to 1 using a sigmoid activation function. The forget gate value f_t and input memory cell value is updated by element-wise

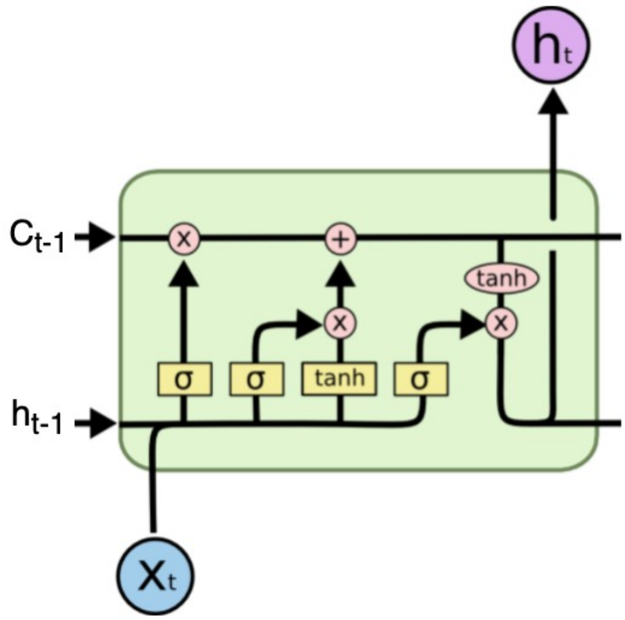


Figure 4.3: An illustration of LSTM network with four neural gate layers [1]

multiplication at input valve, ⊗ in the top-left of the diagram.

$$f_t = \sigma(W_f.[h_{t-1}, x_t] + b_f \tag{4.5}$$

2. **Input Gate Layer:** This is first of two layers which decides what new information will be stored in cell state, C_t. Since it decides how much influence current node memory should have in the memory cell, it is also called memory input gate layer. The value of sigmoid activation (between 0 and 1) controls how much current cell memory will be given to the memory cell.

$$i_t = \sigma(W_i.[h_{t-1}, x_t] + b_i \tag{4.6}$$

3. **Memory Gate Layer:** As the second layer, it generates the candidate values of memory of the current node at time-step t. Memory is generated using inputs as input data, previous hidden layer output, and outputs candidate value of memory

as after passing through $tanh$ activation function.

$$\tilde{C}_t = tanh(W_c.[h_{t-1}, x_t]) + b_c \tag{4.7}$$

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t \tag{4.8}$$

4. **Output Gate Layer:** Acting as the last gate layer, output gate layer decides about output of information to h_t, which is decided by memory cell C_t, previous hidden layer output h_{t-1} and input data x_t. After running the sigmoid function over the output gate layer, and tanh function over the memory cell, the output valve controls the output value of the current LSTM node.

$$O_t = \sigma(W_o.[h_{t-1}, x_t] + b_o) \tag{4.9}$$

$$h_t = O_t * tanh(C_t) \tag{4.10}$$

The advantage of LSTM network for long-term dependencies and overcoming vanishing gradient problems comes from the memory cell and the control of memory update on the memory cell. As the memory gate layer and output layer based sigmoid functions take value as 0, the update on memory is stopped and the value memory cell remains constant resulting no effect on output of LSTM node at time step t. Thus while training via back-propagation algorithms, the gradients can traverse back across time-step without going to zero or exploding to ∞. Because of this advantage of having a long short term memory cell, the LSTM networks have the ability to learn long-term dependencies from temporal input data and perform better than vanilla RNN networks.

4.3 Classification Task

For fault detection and especially identifying the nature of faults in the transmission system, classification into categorizes is the key step. To understand the binary classifier and then multi-class classification task, logistic classifier and softmax classifiers are explained, which are included in the proposed classifier.

4.3.1 Logistic Regression Classifier

The goal of logistic regression classifiers is to learn a decision boundary for the binary classes from the training data, (x_i, y_i) where $i \in [1..N]$ and $y_i \in \{0, 1\}$ using a logistic function.

Given the N training data, the hypothesis function can be expressed as,

$$h_\theta(x) = \frac{1}{1 + \exp(-\theta^T x)} \tag{4.11}$$

where θ are the weight parameters of the classifier to be learnt from training data. The hypothesis function provides the probabilities of the classes,

$$P(y = 1|x; \theta) = h_\theta(x)$$

$$P(y = 0|x; \theta) = 1 - h_\theta(x)$$

Hence, using maximum likelihood estimate, the cost function for the logistic classifier can be written as shown in eq. 4.12. Thereafter, a gradient descent algorithm or any optimization algorithm can be used to minimize the loss function.

$$J(\theta) = -\frac{1}{N} \sum_{i=1}^{N} (y_i \log h_\theta(x_i) + (1 - y_i) \log(1 - h_\theta(x_i))) \tag{4.12}$$

4.3.2 Softmax Classifier

Softmax classifier is the generalization of Logistic Regression classifier with the goal of categorizing multiple classes, using softmax function. Softmax function is an activation function which converts numeric output of the last layer of the Dense neural network i.e. logits into normalized probabilities for each class so that each vector adds to one. The last layer of Dense network uses softmax function as the activation function for this purpose in our multi-class fault classification.

Given N training data points (x_i, y_i) where $i \in [1..N]$ and $y_i \in \{0, 1, ..K\}$, after processing through the layers, the input vector of z of size K can be expressed via the softmax function,

$$\sigma(z)_i = \frac{e^{z_i}}{\sum_{j=1}^{K} e^{z_j}} \text{ for } i = 1, \dots, K \text{ and } \mathbf{z} = (z_1, \dots, z_K) \in R^K$$

It can also be interpreted as the output probability for the i^{th} class, given the input vector z as input to the softmax layer.

Given the mapping from input x_i to output y_i, using a mapping function $y_i = f_i(x_i; \theta)$ the softmax classifier uses cross-entropy loss as shown in eq. 4.13 to optimize the weights in the training.

$$J_i = -\sum_{i=1}^{K} t_i \log(\sigma(y)_i) \tag{4.13}$$

Here, t_i are ground-truth labels and y_i are estimated labels via softmax classifier.

4.4 Proposed LSTM based Detector and Classifier

4.4.1 Architecture Design Approach

Using the LSTM networks, the fault detector and classifier is proposed for the transmission line protection system using current and voltage signals from the one end of the line, in substation. For the design and architectural preferences for the proposed Fault Classifier, the following questions were proposed to get the required architecture of classifier model using LSTMs network:

- What are the top performing classification models in the existing literature for the time-series data in the literature?
- How do we improve the architecture of models used for sequential data of two

different nature of features?

- What are the needs for the classifier models for better performance?

- How can the architecture be extended for the additional features in consideration?

Given the time-series data, the top performing models explored and shown in the literature are LSTM based classifiers primarily using RNNs but later using LSTM layers.

To create a LSTM model for feature extraction for the sequential data, utilizing different LSTM networks for each type of feature is a better idea for the temporal dependencies in particular nature of feature as well as investigating the parameters of the network. Hence, LSTM networks for each phase of currents and voltages are utilized.

For the goal of better performance of fault classification model, the extracted features of the temporal data should be classified with minimal, however effective layers of deep learning model to obtain the categorical probabilities for each test sample. Hence, only a single Dense layer is utilized in the proposed classifier.

For our goal, a multi-class classification is done for obtaining the fault type where a softmax function is used for normalized probabilities for each class. To incorporate this in the model, the last layer of the Dense neural network has activation function as softmax, naming the layer as Softmax layer.

Lastly, to make the architecture robust for the addition of the new features in the classifier, a new network for the new type of feature e.g. sampled reactive power or data from phasor measurement units (PMU) etc can be incorporated in this classifier model.

With the above questions in the focus, the Classifier model architecture was chosen with a separate LSTM network for each feature i.e. three phase currents (I_a, I_b, I_c) and three phase voltages (V_a, V_b, V_c) in the substation.

4.4.2 Handling Overfitting in Classifier

In the proposed classifier, the overfitting is one of the issues considering the characteristics of the fault classification and its imbalanced data in the power system. In normal operation of transmission lines, current and voltage signals propose imbalanced dataset for classification as occurrence of fault is rare. Hence, the training of the classifier with imbalanced dataset may result in overfitting problems while training. To avoid the overfitting the classifier is equipped with a dropout layer in the classification part of the architecture. Another option is batch-normalization layer after Dense layer. The solutions of overfitting problem are discussed as follows:

Dropout

The basic idea of dropout [70] is to randomly drop neural units (along with their connections) from the Dense layer during training. To ensure its methodology, the neurons are neglected with probability P while the forward pass of the training and backward pass of backpropagation with random nodes in each pass. Hence, training the network with dropout can be considered as training multiple networks averaging the output. Thus, it provides better regularized performance in validation set and later in test-set.

Batch Normalization

Batch normalization is a technique to improve the training of the classifier by reducing internal covariance shift among layers of deep neural networks [71] by normalizing each layer of the network. As normalizing each layer adjust the distribution features of the data to mean and standard deviation as 0 and 1 respectively. Thus, the training and test data distribution is reduced to normalized distribution in each layer, reducing the problem of overfitting as well as improving the learning rates and training time. Hence, batch-normalization layer is important to improve the performance of the classifier by reducing overfitting.

4.4.3 Description of Fault Classifier

Utilizing the LSTM networks for capturing temporal features from input signals, classifier sub-network for multi-class classification and dropout for better generalization performance, the Fault classifier is designed as shown in 4.4. Based on data obtained from CTs and VTs of the particular line in substation, the proposed classifier captures the temporal features from each phase of the current and voltage, the size of the hidden layer is kept proportional to the window size of the input data.

After the LSTM layer, a merge layer for fusion of features from current and voltages is added. To consider information from each phase, the fusion (merging) of layers is kept as concatenating.

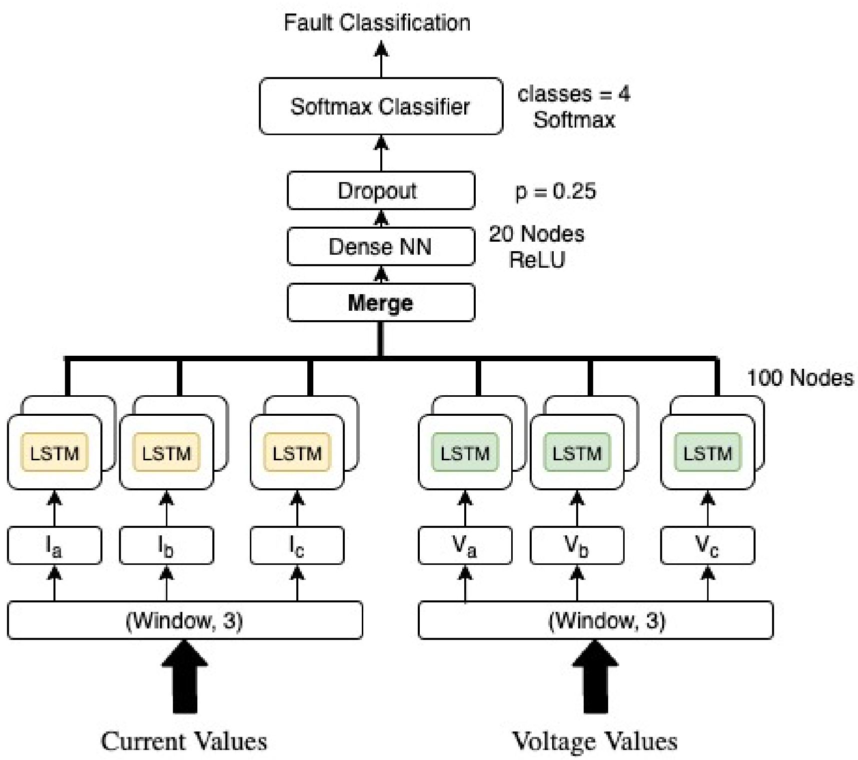


Figure 4.4: Architecture of Proposed Fault Classifier with LSTM networks

After getting information in a concatenated vector, a deep learning Dense layer is used to obtain absolute values for each class, for particular samples. To obtain the generalization over the test-set, batch normalisation and dropout layers are used in the classifier model as well. Finally, the classification is achieved with a softmax layer is added at the end for obtaining the normalized probability for each class in the given input sample.

In the next chapter, the training workflow of the proposed classifier will be discussed and methodologies of data generation on benchmark testbed used will be described.

Chapter 5

Testbed for Classifier Training

This chapter introduces the benchmark testbed used for data generation and training methodologies of classifier models.

5.1 Transmission Line Testbed

To illustrate the transmission line protection system and fault classification using proposed classifier, a standard test system i.e. IEEE Power System Relaying Committee (PSRC) D6 benchmark system [2][72][73] is used as shown in figure 5.1. As part of a 500kV transmission system, this test system consists of four transmission lines L1-L4 and four identical 400 MVA generators G1-G4 as power sources. The remaining power grid is modelled as a 230 kV infinite bus, S1, representing the remaining network. All circuit breakers except CB10 are closed as shown in figure. The generated power by G1-G4 flows to S1 via the transmission lines. The line L1 is considered for fault classification using data recorded from measuring instruments i.e. current transformers CT1 and voltage transformers VT1 installed at Line L1 at substation A.

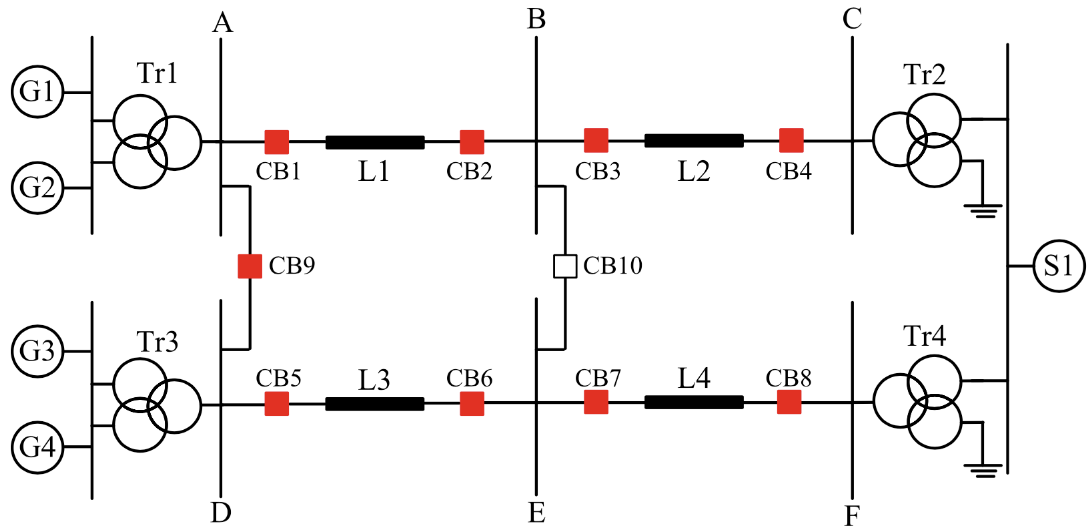


Figure 5.1: Illustration of IEEE PSRC D6 Test System [2]

5.2 Dataset Generation

For the training and performance testing of classifier, fault dataset was generated from the PSRC D6 benchmark test system simulated in OPAL-RT HyperSIM simulator.For this classifier, we consider A-G (Single Line to Ground) fault, A-B-G (Double Line to Ground) fault, A-B-C-G (Triple line to Ground) fault with all combinations of fault occurring in the line L1 with different generations. The minimum generation limit is 300 MW and maximum generation limits is 400 MW for all the generators. The generation is changed in step size of 10 MW for each new simulation.

To generate the data, several simulations were performed for 200 milliseconds with fault occurring at t = 100 ms at multiple locations to create variance in the dataset of the classifier. In the simulator the data are sampled at sampling frequency of 4800 samples per second i.e. 80 samples per cycle with compliance of Sampled Values (SV) specifications of IEC 61850-9-2 in digital substations [74]. Hence, the each simulation obtained 920 samples of three phase current and voltages measurements. The simulated data are exported from CT and VT of Line 1 as COMTRADE format.

In figure 5.2, a sample of current measurement data, where sample values are normal-

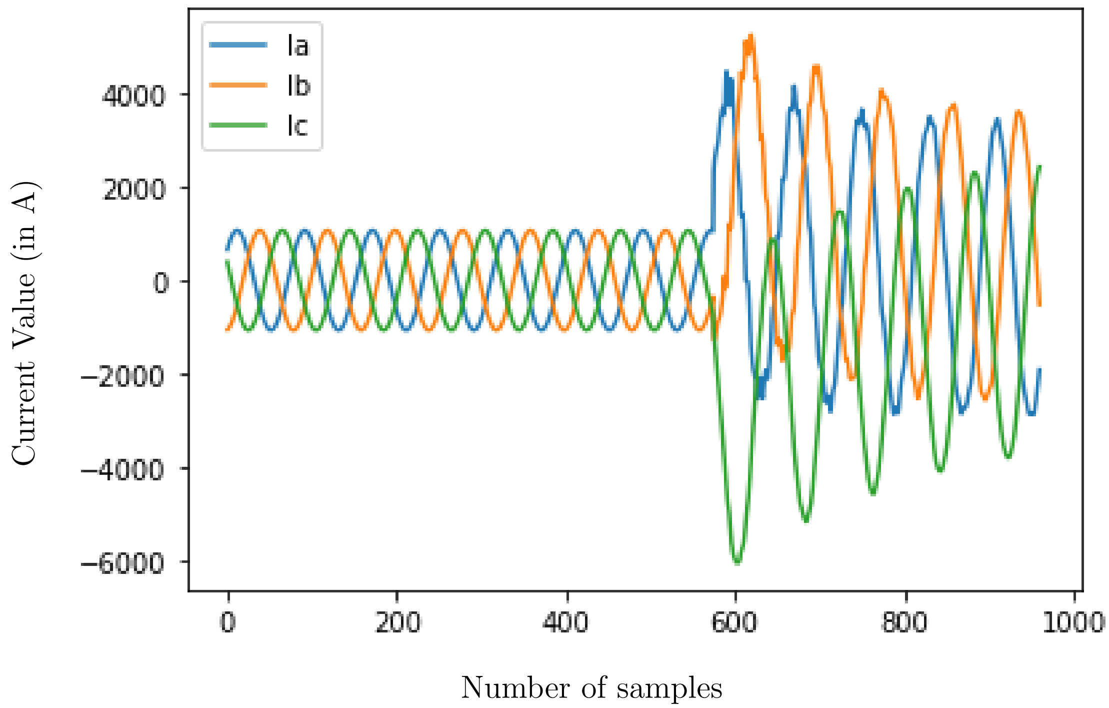


Figure 5.2: A sample of data with three phase fault

ized from COMTRADE format to true RMS value of current are shown with a sliding window generating each window as a sample to be fed to the classifier model. Further, each window will be labelled to get the dataset for each class.

5.3 Training Methodologies for Proposed Classifier

The training methodologies starting from data preprocessing to regularization comparison is shown in this section to accomplish the task detection and classification of faults.

5.3.1 Data Pre-Processing

To train the proposed classifier, the simulated data samples are processed for RMS values of current and voltages followed by normalization. From the given bias and factor values in configuration, the COMTRADE data is formatted to true values of current and voltages obtained from CT and VT respectively.

To obtain the normalized data for the efficient training of the classifier with higher convergence rate, all the samples are scaled to mean 0 and standard deviation of 1 using

$$x_{scaled} = \frac{x - x_{min}}{x_{max} - x_{min}}$$

where x_{scaled} is normalized data in mean 0 and standard deviation 1 from unprocessed data x.

Data Windows Generation

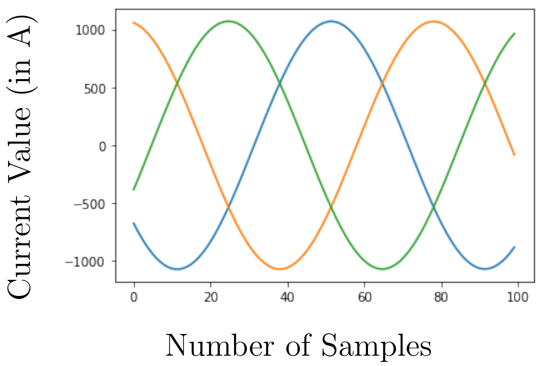
To train the classifier with a parameter of input size of data i.e. number of samples fed to the classifier, the simulated samples are converted to windows of fixed *window_size* with a *step_size* where windows are slid with a number of *step_size* samples. This window size parameters changes the amount of samples fed to the classifier and its computation time at test-time. The larger the window size, the longer it takes to output the predicted class of samples. In our training process, window size is varied as a hyperparameter and later kept at 100 samples i.e. around 20 ms cycle with step size of 50 samples i.e. around 10 ms of step size.

Labelling of Dataset

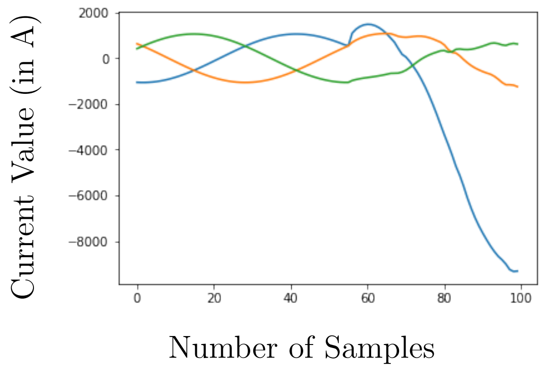
The labelling of the training dataset is important for training the proposed supervised learning based classifier. From the simulated data for the different kinds of faults, In our case, the labelling is done for four classes: Normal, A-G Fault, A-B-G Fault, A-B-C-G Fault. Firstly, each simulation data was turned into running windows with a window size and a step size so that each window represent one of the four classes. Each running window is labelled normal if all the samples are in no-fault scenario else to fault class (A-G, A-B-G, or A-B-C-G) if any of the samples in the window are from fault. This labelling is done using Python script over the dataset.

5.3.2 Training of the Classifier

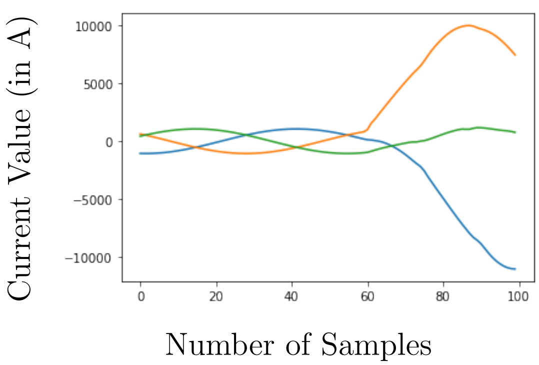
With focus on extraction of temporal information, from training data, the proposed LSTM based classifier is trained to classify the four classes from measurement current



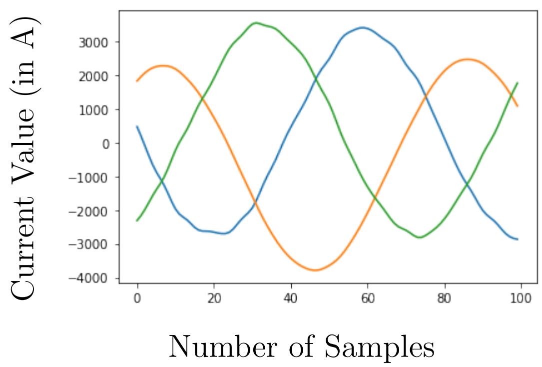
(a) Normal Sample



(b) SLG Fault



(c) DLG Fault



(d) TLG Fault

Figure 5.3: Illustration of Sample windows with classes

and voltage data. In this section, the methodology for the training of the classifier is written.

Summary of Classifier Architecture

The summary of the architecture of the classifier is provided in Table 5.2 where parameters (weights and biases) of each layer will be trained to predict the class of the test samples.

Data Split

For the training classifier, the available normalized data is split into training set, validation set and test set. Among the available windows of data, where each window is a labelled data point, the data are split into 80% data for training and validation and 20% as test data. Further, the training and validation set are split into 80% and 20%

Category	Label Index
Normal	0
A-G Fault	1
A-B-G Fault	2
A-B-C-G Fault	3

Table 5.1: Labelling of Samples

Layer	Output Shape	Parameters
LSTM Nodes	(None, 100)	41,600
Dense Hidden	(None, 20)	2020
Dense Output	(None, 4)	84
Total params:	43,704	

Table 5.2: Summary of LSTM Model

respectively. Hence, the split of data into training, validation, test is in 64%, 16% and 20% respectively.

Training Set	Validation Set	Test Set	Total Samples
922	230	288	1440

Table 5.3: Distribution of Samples for Training

The distribution of the data samples in terms of the classes associated with it, are balanced dataset considering the fault or normal dataset as each sample is generated by a window of 100 samples run through the 921 data point sample.

Handling imbalanced dataset

If the dataset is unbalanced in the real world training methodologies, the associated problem of having larger normal data and small number of fault data points can be removed by following methodologies:

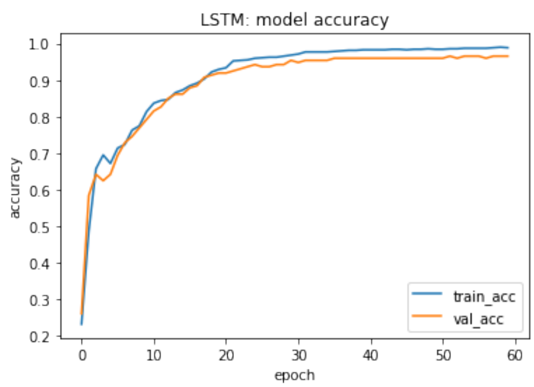
- Generating new dataset with resampling process (where normal class will be undersampled but fault classes will be oversampled) resulting in the updated and balanced dataset with respect to the class labels.
- Another way to avoiding the data imalance problem is via creating weighted error

loss where the number of data points per class are considered in the total error in classification task.

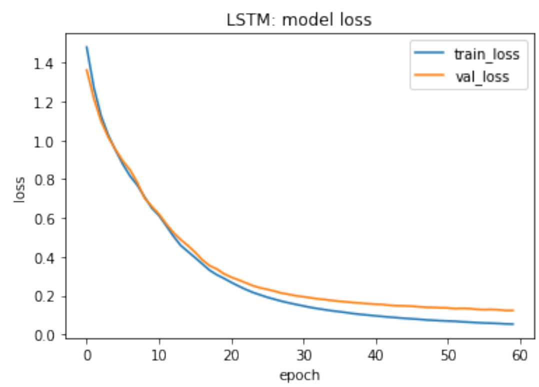
Training

After the data split into the training, validation and test sets, the classifier model is trained on training data with batch size of 50 for a duration of 60 epochs. The ADAM optimizer is used for the training of the classifier with categorical labels.

The plot for the accuracy and loss during training are shown in figure 5.4a and 5.4b below.



(a) Training and Validation Accuracy



(b) Training and Validation Loss

Figure 5.4: Accuracy and Loss Plots for the training process of classifier

The performance of the proposed classifier model on the test dataset is evaluated in the next chapter with the several performance metrices. The comparative experiments are also discussed to see the improvement of proposed classifier model in comparison with available machine learning models.

Chapter 6

Results and Discussion

In this chapter, results of the classifier model are presented with effectiveness in classification of faults. A comparative study of alternative available machine learning based is done to evaluate the test time performance.

6.1 Performance Evaluation of Fault Classification

The goal of the proposed classifier is to predict the type of the fault in the transmission line accurately using the window on the test samples. To illustrate the training and the test performance methodology of the classifier, a flow diagram is described in figure 6.1.

During Test performance, the sampled testing data are input from ADC of CT and VT and normalized and sampled into windows. Each test sample is sampled in a window sample of the window size for the classifier in the test training phase. As the trained model is loaded in the computer relay, it can classify the type of fault or normal condition of the input test samples. It repeats over the windows of the input test sample data.

To evaluate the performance of the classifier in correctly predicting the class of fault, the performance metrics are chosen as shown below.

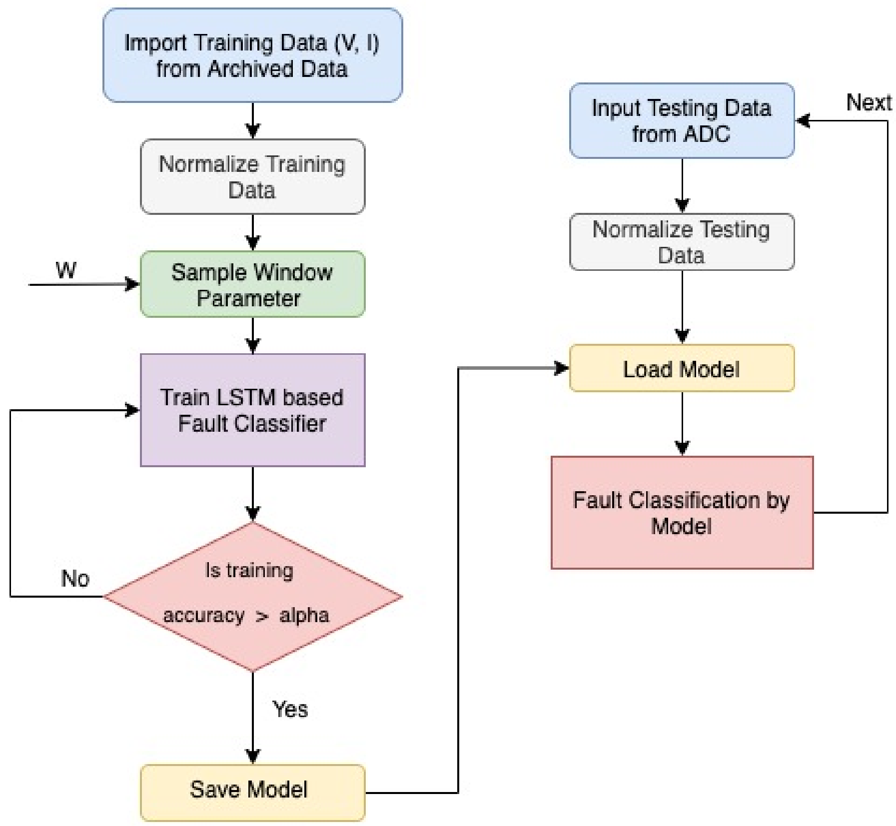


Figure 6.1: Training and Testing methodologies for the fault classifier

6.1.1 Performance Metrics

Accuracy

Generally for the performance of the model, the accuracy of the prediction can be considered one of the metrics. It is dependent on the number of test samples as well.

With the window size W and Step Size T of the input data format, the classifier was trained, validated and tested with data proportion split. The performance is shown in Table 6.5

$$\text{Test Accuracy} = \frac{\text{No. of correctly classified samples}}{\text{Total no. of test samples}}$$

Metrics	W = 100, T = 50	W = 100, T = 10
Training Accuracy	99.71 %	99.67 %
Validation Accuracy	97.69 %	98.92 %
Test Accuracy	98.61 %	99.42 %

Table 6.1: Accuracy of classifier over training, validation and test sets

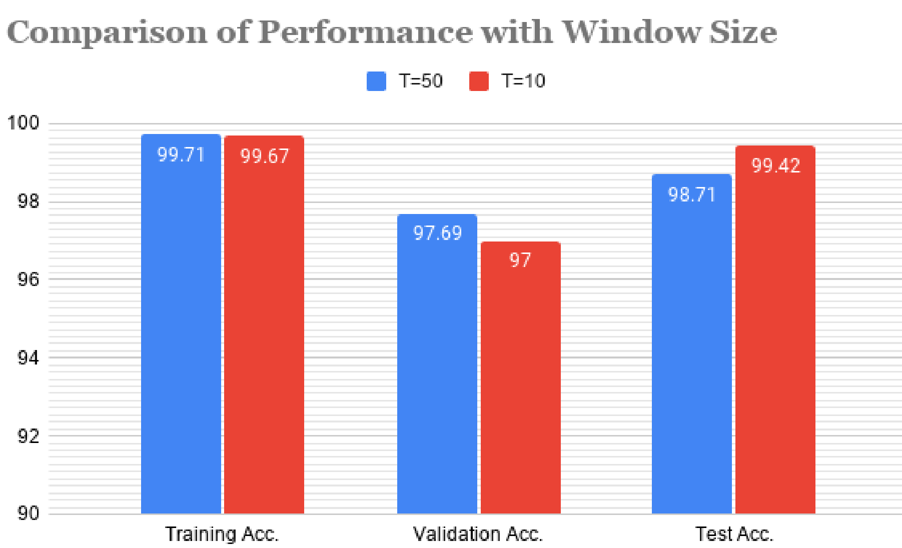


Figure 6.2: Comparison of performance in training, validation and test sets with varied Window Size

Precision, Recall and F1 Score

To evaluate the classifiers on how well it does on imbalanced data with True Positive (TP), False Positive (FP), True Negative (TN) and False Negative (FN). The metrics used are Precision

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

i.e. metric to know how many classified categories, are true categories of samples. In case of multi-class classification, the precision is calculated with the sum of true positives across all classes divided by the sum of true positives and false positives across all classes.

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

i.e. metric to know how many true categories were classified. Similarly for multi-class classification, the TP and FN are across all classes. F1 score is a combined metric with harmonic mean of precision and recall.

$$F1Score = \frac{2(Precision * Recall)}{Precision + Recall}$$

Metrics (Avg.)	LSTM Classifier (T=50)	LSTM Classifier (T=10)
Precision	0.971	0.994
Recall	0.98	0.990
F1 score	0.9756	0.9919

Table 6.2: Performance of categorization

Confusion Matrix

To show the accuracy of the classification with the classes, the confusion matrix is plotted with predicted class in the vertical axis and actual class in the horizontal axis. This heatmap matrix shows the number of correctly classified sample windows in the particular fault class or normal class.

As we can see the imbalance of the classes in the confusion matrix, please note that it is due to samples generated with normal class as equal to other fault classes due to samples used using the window size and step size on each recorded sample from the test-bed.

It also shows the mis-classifications of test samples from true class to wrong predicted class. For example, 4 normal samples were classified to Three-Line-to-Ground (TLG) class. The mis-classfied samples are illustrated with True class and predicted class. This might be due to failure to get the correct features. The likely reason is the similarity in the both class samples once the fault is in recovering with stability looking alike the normal samples with minor difference in the magnitude. The disadvantage of deep learning based classifier is to explainability of the reason behind its decision in concrete way.

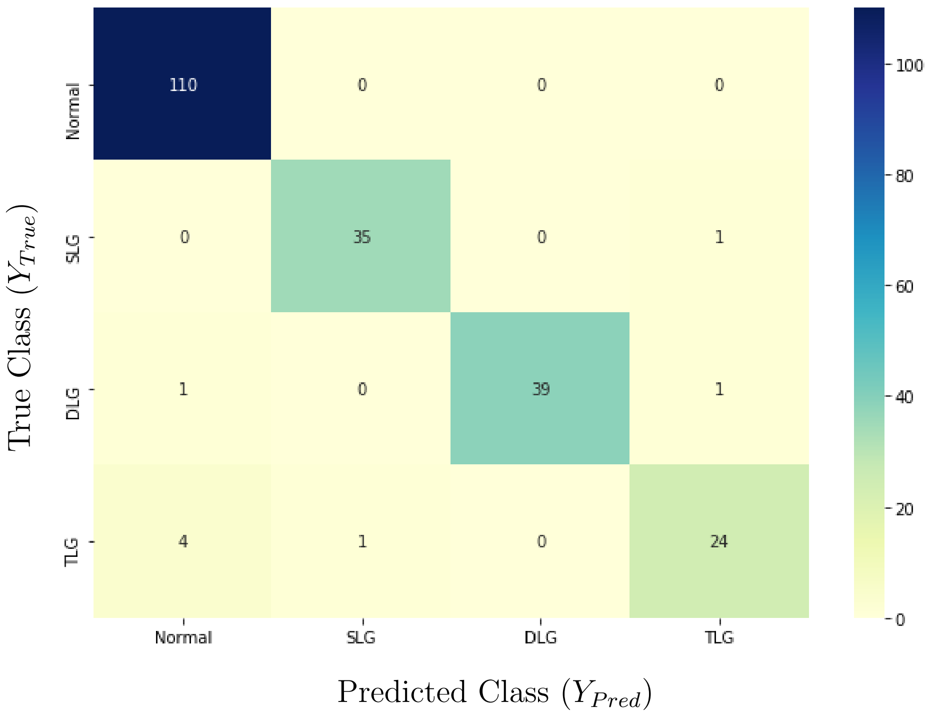
6.1.2 Comparison with existing models for fault classification

To compare the performance of the proposed LSTM based fault classifier with existing alternative machine learning techniques, the following state-of-the-art models are considered as available in the literature.

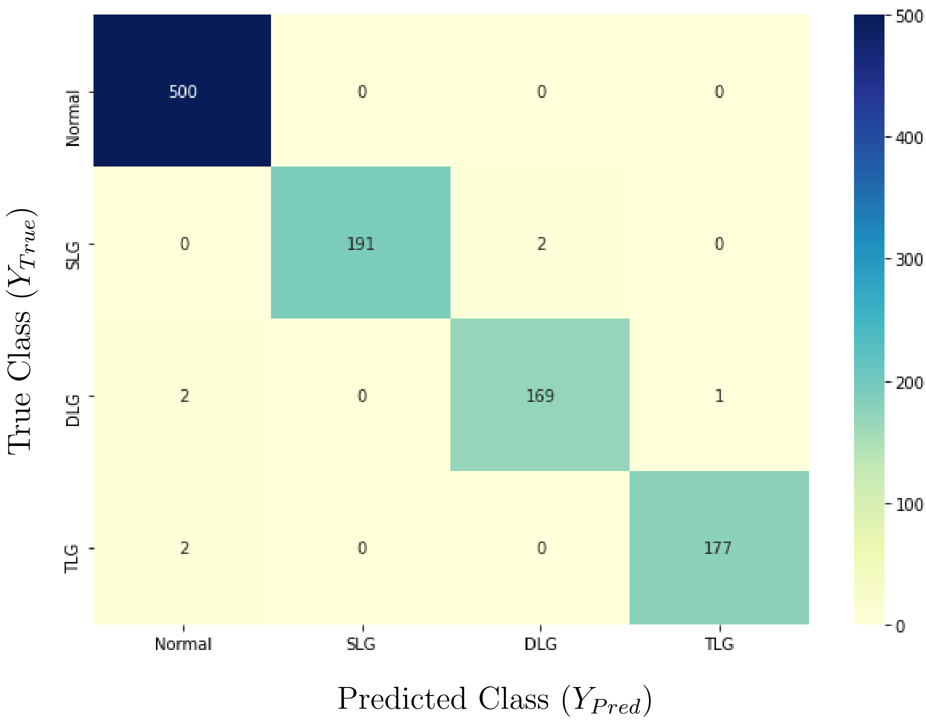
The comparative experiments were done with the same window size (100 samples) and step size (10 samples) of data fed to each model. The training, validation and test sets were also kept uniform to evaluate the performance of each classifier model in the

SVM based Classifier

As we have seen in Chapter 3, Support Vector Machine (SVM) based fault classification has been explored in the literature for fault detection and classification [75]. SVM is used to create a decision boundary of binary or multi-class classification. For the goal of classification of various faults, a SVM based multi-class classifier is implemented via the same data distribution of training, validation, and test sets as used in the LSTM classifier. The SVM for multi-class classifier is designed with one vs one (ovo) decision shape technique where six features are transformed into 2D space and classified for the four classes of fault.

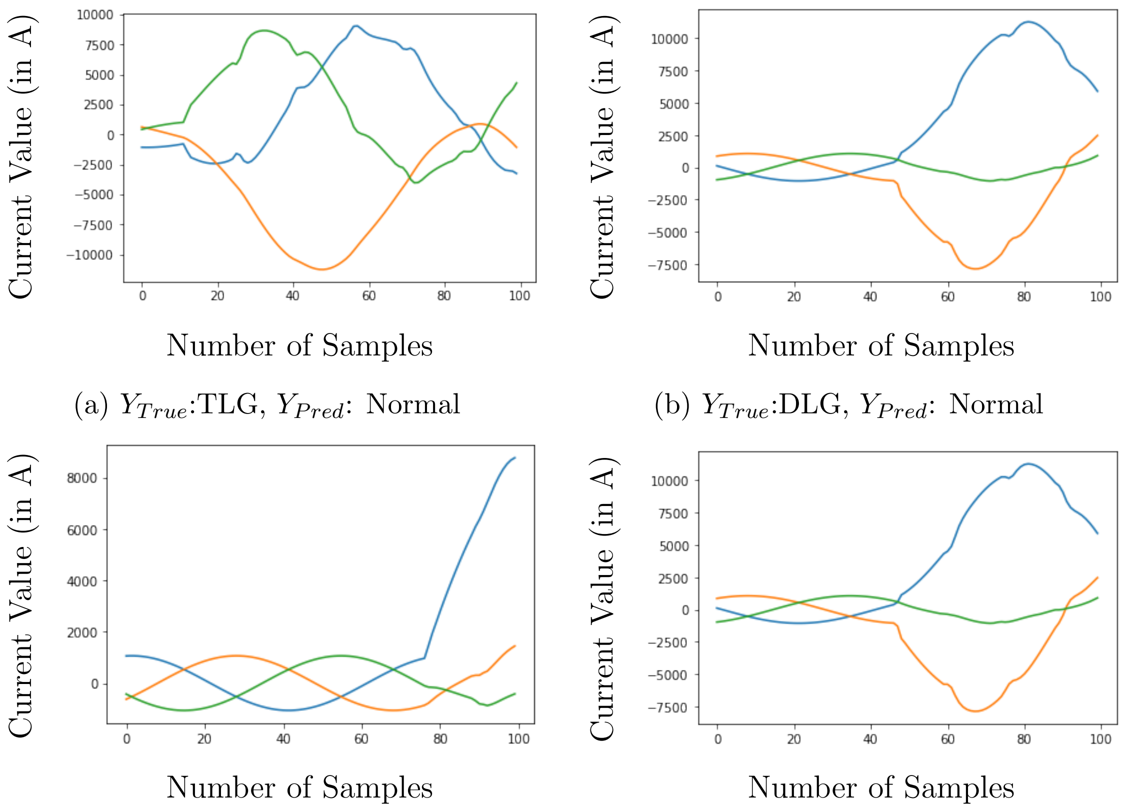


(a) With W=100 and T=10 (216 samples)



(b) With W=100 and T=10 (1044 samples)

Figure 6.3: Confusion Matrix with the True and Predicted Classes



(a) Y_{True}:TLG, Y_{Pred}: Normal

(b) Y_{True}:DLG, Y_{Pred}: Normal

(c) Y_{True}:SLG, Y_{Pred}: DLG

(d) Y_{True}:DLG, Y_{Pred}: TLG

Figure 6.4: Illustration of Misclassified Samples by Classifier

The comparative study shows the improvement in the classification accuracy during validation as well as test time accuracy on the same distribution as shown in the table 6.5 as well as in figure 6.5.

RNN based Classifier

As various vanilla RNN networks are explored in literature as state of the art methods for the fault detection and classification in power system protections, we have compared the RNN network based classifier model with the proposed LSTM based classifier model.

With the same performance metrics, the RNN model is trained with the same distribution of datasets (training, validation and test sets).

The architecture of RNN based classifier is shown with the simpleRNN nodes used in the layer for the feature extraction as shown in 6.4.

Metrics	SVM Classifier
Training Accuracy	97.38 %
Validation Accuracy	98.25 %
Test Accuracy	97.65 %

Table 6.3: Performance of SVM Classifier on same distribution of datasets

Layer	Output Shape	Parameters
RNN Nodes	(None, 100)	10700
Dense Hidden	(None, 20)	2020
Dense Output	(None, 4)	84
Total params:		12,804

Table 6.4: Summary of RNN Model

Comparative Performance of LSTM Classifier

In comparison with the existing models for the fault classification i.e. SVM for multi-class classification, RNN for feature extraction and classification, the proposed classifier using LSTM performs better in the test-time performance as seen from the comparative study results as shown in table 6.5 and in figure 6.5.

Metrics	SVM Classifier	RNN Classifier	LSTM Classifier
Training Accuracy	97.38 %	99.58 %	99.71 %
Validation Accuracy	98.25 %	98.42 %	99.69 %
Test Accuracy	97.65 %	98.42 %	99.53 %

Table 6.5: Accuracy of classifier over training, validation and test sets

6.2 Discussion

In this section, we will discuss the results of experiments with varied experiments during training the classifier as well as impact of classification performance on the protection of the transmission line.

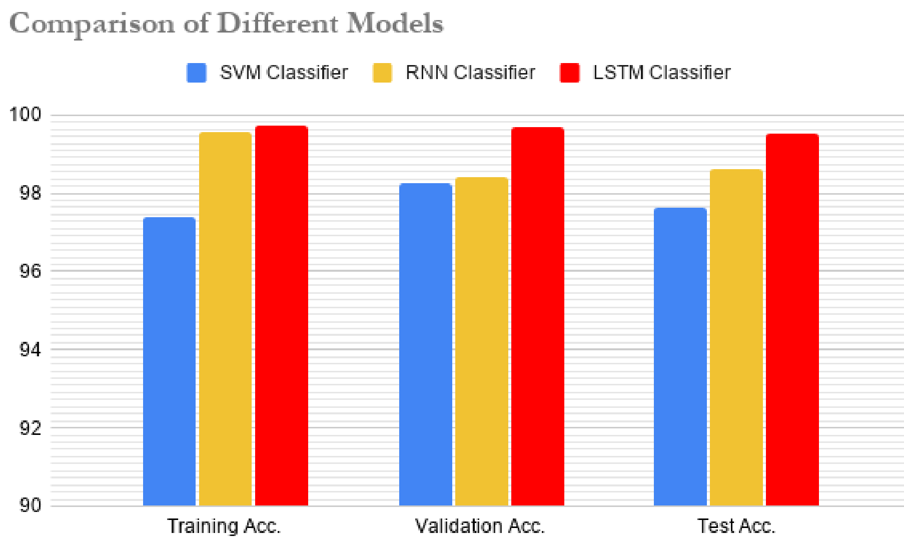


Figure 6.5: Comparison of performance of proposed model with existing models

6.2.1 Implementation of proposed classifier

As per the experiments conducted for the training of the fault classifier and test-time performance suggests the best methodologies for the implementation of the fault classifier in the transmission line protection of a substation. The following experiments suggests the methodologies for the best approach:

- **Window Size of Input data:** The window size has a significant impact on the performance of the classifier. As per the performance of the classifier with different window size of the input measurement data, the test-time performance indicates that the Window Size $W = 100$ with step-size $T = 10$ has better performance than the $T = 50$. This might be because of small step-size of a window results in more window samples for training and hence, the identification of a specific fault is faster than having smaller samples of the window size. However, as the window size is reduced from $W = 100$ to $W = 50$, the performance of the classifier degrades again.

- **Regularization of the Classifier:** Addition of batch normalization and dropout layers helps in the regularization of the classifier during the training and better test-time performance on the test set data.

- Performance of fault classifier on the multi-class classification indicates its potential to classify the additional fault types in the transmission line as those labelled data are included in the training of the classifier.

- With help of available recorded data of the fault events, the classifier can be trained for specific transmission line offline and the saved model can be loaded in the relay algorithm for the classification of the fault as illustrated in figure 6.1.

The potential of the proposed classifier and its performance suggests the classification of the transmission line can be achieved with the available history of previous fault events. The LSTM based classifier can be easily extended to the various kinds of the faults in the transmission line if those labelled dataset can be obtained. Similarly, the potential of a classifier suggests its performance in the distribution systems as well if it's trained on the recorded fault event datasets to classify the different kinds of faults with available data.

6.2.2 Improved Performance of Proposed Classifier

Extending the performance of the fault classification task via sequence learning models utilizing the temporal information, suggested the potential of LSTM based classifiers in comparison to existing RNN models as well as classical ML techniques i.e. Support Vector Machines for multi-class classification.

Even with the same distribution of datasets, the improved test-time performance is credited to the extended functionality of the LSTM model to control memory while learning the training dataset of temporal information, as explained in the Chapter 4. The increased controlling weights in a LSTM cell improves the performance however it is also increasing the number of parameters to be trained in the classifier.

The proposed architecture to learn the feature of each phase of current and voltage signals, promises the implementation of this classifier for the purpose of fault diagnosis (in off-line mode) in substation where the accuracy as well as classification metrics are promising. Additionally, with longer training with past history datasets, the classifier can achieve even better test accuracy and classification accuracy making it a candidate solution for the real-time fault detection/classification in the protection system of transmission line, provided the pragmatic assumption of high computing devices in the substation of the future.

Chapter 7

Conclusion and Future Work

This chapter concludes the thesis with the summary of work done in the above chapters. Additionally, it provides the direction of the work in the future in regards to the proposed classifier and its robustness analysis.

7.1 Conclusion

With focus on developing a fault classifier for the protection system of a transmission line using machine learning techniques, the temporal information of the current and voltage signal are utilized to build a LSTM based classifier. The previous work in fault detection and classification is explained in the Chapter 2 and Chapter 3, where the importance of research work with machine learning based techniques especially sequence learning models i.e. RNNs and LSTMs are highlighted.

The proposed classifier brought the improvements in performance in the fault classification task from the measurement signals obtained from the bench-marking testbed of the transmission system.

In conclusion, the following work is presented in this work.

- In Chapter 4, the background on LSTM models with its effectiveness in feature extraction from the temporal features of the measurement signals from CT and VTs and improvement of the architecture is illustrated.

- In chapter 5, the PSRC D6 benchmarking testbed is explained where the proposed classifier is tested with the current and voltage measurement data of the transmission system. The input data pre-processing and training methodologies are explained with the setting up of the experiments.

- Results obtained in Chapter 6, for the classification task of the fault diagnosis is explained with firstly, with comparison of window size, step size as well as impact of regularization controllers on its test-time performance. Secondly, the proposed LSTM based classifier has shown improved performance in comparison with existing state of the art techniques e.g. RNN and SVM based classifiers trained on the same data.

The proposed fault diagnosis and the LSTM based proposed classifier suggests the effectiveness of its usage in the IEC61850 based automated substations where with abundance of the sampled measurement data suggests the machine learning techniques with temporal information extractions are feasible and effective in the test-time performances.

7.2 Future Work

As the fault classifier is used in the test-time performance in the substation for the transmission line protection, there is a need to evaluate the robustness of the classifier with various scenarios. Therefore, the future work includes:

- Robustness analysis of the classifier from the various conditions in the transmission system as well as attack-defence paradigms.

- With the vulnerabilities of the IEC61850 based communication infrastructure in the substations, the security evaluation of the Sampled Values (SV) measurements using IEC 62351 standards needs to be evaluated to ensure the injected input data are secure.

- Since machine learning based fault classifier, similar to other existing fault detection and classification approaches, are completely dependent on the measurement data from CTs and VTs, the adversarial data attacks to classifier input can utilize this vulnerability for the mis-classification of the classifier during normal and fault scenarios.

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These future work directions can be pursued to check the robustness of the classifier model with respect to training data, input test data attacks on the classifier performance.

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