

An Intelligent Approach of Faults Detection and Location Methods for Power Transmission Line

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Abstract - This paper presents an innovative approach for the simultaneous detection and localization of electric faults in transmission lines through machine learning (ML) techniques. By harnessing supervised learning algorithms, the system is trained on a comprehensive dataset comprising normal and fault scenarios. Extracting relevant features from critical parameters such as voltage, current, and phase angle, the ML model is equipped to discern between fault and non-fault states. Additionally, a localization algorithm is incorporated to pinpoint the exact location of the identified faults. Real-time monitoring facilitates rapid response, minimizing downtime and enhancing the overall reliability of the power grid. The proposed ML-based framework not only advances fault detection accuracy but also provides a precise spatial assessment, contributing to the optimization of maintenance efforts and the resilience of the transmission infrastructure.

Key Words: Decision tree, Electric Faults, Transmission line, Fault Detection, Feature Extraction, Reliability.

1. INTRODUCTION

In this modern world, steady supply of electric power is becoming very important nowadays. Hence, electricity is transmitted for generation end to consumer end. This is done using transmission line across both ends. The reliable and efficient operation of

transmission lines is paramount for maintaining the stability of modern power grids. Electric faults in these lines can lead to disruptions, downtime, and potential damage to equipment, necessitating swift and accurate detection and localization mechanisms. This paper introduces a pioneering approach to address this challenge by integrating machine learning (ML) techniques into the domain of fault detection and localization in transmission lines.

Traditional methods for fault detection often face limitations in terms of speed and precision. ML, with its capacity to analyze complex patterns and learn from diverse datasets, offers a promising solution. By training supervised learning algorithms on a rich dataset encompassing normal and fault conditions, our proposed system aims to not only detect the presence of faults but also precisely locate them along the transmission lines.

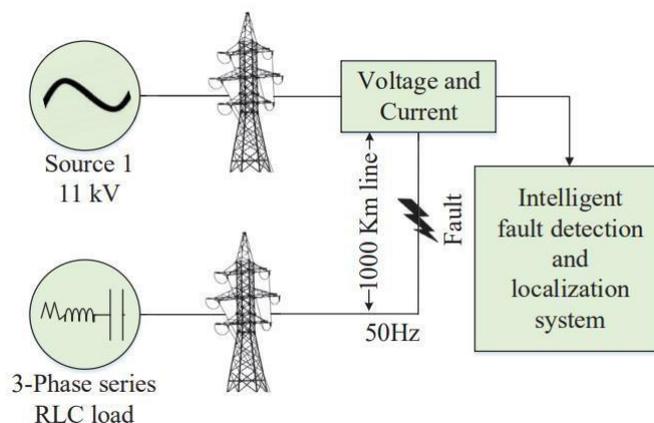


Fig 1.1 Fault analysis model

In Fig 1.1 is a basic diagram of fault analysis system. Here at Power station 11kV power is generated, this power is transfer to the electric tower through transmission line. Basically at every 100Km between tower we placed our fault detection system. And if any fault occurs in this range of area, then our system can detect the fault in that area. Else if the transmission line is safe then this power is distributed to user.

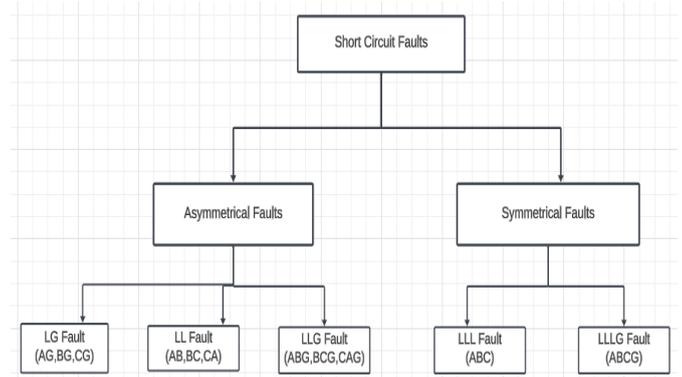


Fig. 1.2 Short Circuit Faults

Types of Electric Faults

An electric fault refers to an abnormality or disruption in the flow of electric current, often caused by equipment malfunctions, short circuits, or other irregularities, leading to potential damage and interruptions in the electrical system. There are mainly two types of faults –

1. Open-Circuit Fault
2. Short-Circuit Fault

1. Open Circuit Fault

The open-circuit fault is a fault where there is failure of one or two conductors.

2. Short-Circuit Fault

A short circuit fault occurs when there is an unintended direct connection between two points in a circuit with low resistance. This often happens due to insulation failure, damaged wiring, or the contact of conductive materials.

There are mainly two types of Short circuit fault –

1. Symmetrical Fault
2. Unsymmetrical Fault

96-97 % of Short circuit faults are Unsymmetrical Faults.

- LG Fault = Single line-to ground fault
- LL Fault = line-to-line fault
- LLG Fault = Double line-to-ground fault
- LLL Fault = line- line -line fault
- LLLG Fault = Triple line-to-ground fault

2. LITERATURE SURVEY

The existing literatures on electric fault detection using machine learning emphasizes the significance of real-time monitoring. Research highlights successful applications of supervised learning in distinguishing fault types. Integrating ML for precise fault localization emerges as a promising avenue, contributing to enhanced grid reliability and minimized downtime in transmission lines.

Jianping Yang proposed an optimized decision tree algorithm to predict line faults by conducting a correlation analysis of line run data attributes and using mutual information to evaluate the impact of various factors on line tripping.

In research paper of 2022, The three classifiers, Random Forest, XGBoost and Decision tree are producing high accuracies, while Logistic Regression and SVM are producing realistic accuracy results. As a result of its ability to predict events in the most efficient manner, random forest is currently ideally

outperforming other models in terms of fault detection, just as what was learned in the literature review.

Research paper by Shahriar Rahman Fahim and colleagues is a notable contribution, focusing on the deployment of Artificial Neural Networks (ANNs) for fault diagnosis in power transmission lines. Here fault prediction of line fault is done using optimized decision tree and hybrid neural network.

3. METHODOLOGY

3.1 Functional Analysis

1. User Authentication and Access Control:

User authentication to ensure authorized access to the system.

2. Model Selection:

Model selection for classification tasks can significantly affect the performance of the predictive model. We choosing an appropriate Classification algorithm among Decision tree and Random Forest to serve as the foundation for detecting electrical faults.

3. Data Input and Output:

Users would be able to input real or any value of current and voltage of three phase circuit for detection. The system would display the results for input data including whether the fault is happening or not and also give the type of fault.

Inputs- [Ia, Ib,Ic,Va,Vb,Vc]

Output – [G C B A]

Examples :

[0 0 0 0] – No Fault

[1 0 0 1] -LG fault (Between Phase A and G)

[0 0 1 1] -LL fault (Between Phase A and B)

[1 0 1 1] – LLG fault (Between Phases A ,B and G)

[0 1 1 1] -LLL fault (Phase A, B and C)

[1 1 1 1] -LLLG fault (Three Phase Symmetrical fault)

4. Feedback and reporting

Allows users to provide feedback on the system's performance and report issues or concerns.

3.2 Datasets

We start with collecting and acquiring all the datasets for the project. It involves a combination of searching, downloading and possibly preprocessing the data

Following are a detail list of sources through which we are going to do this:

➤ **Public Repositories:** We use two datasets, are available on public repositories like Kaggle and GitHub

➤ **Research Papers:** Checking the research papers that introduced or used the datasets we're interested in. Authors often provide download links or instructions in the papers.

3.3 Project Process Modeling

Incremental Model

Our project “An Intelligent Approach of Predicting Faults and its types for Power Transmission Line” is following the Incremental Model for process modelling. Incremental modeling is an iterative approach to model development where

the model is built in small, manageable increments or parts.

Here's how we can apply an incremental model to the process of developing a predictive model for electric fault detection:

1. Initial Planning.
2. Data Collection and Initial Model.
3. Evaluation and Feedback.
4. Iterative Model Improvement.
5. Validation and Testing.
6. Incremental Feature Addition.
7. Scalability Consideration.
8. Documentation.
9. Monitoring and Maintenance.
10. Future Enhancements.

4. PROPOSED SYSTEM

Architecture

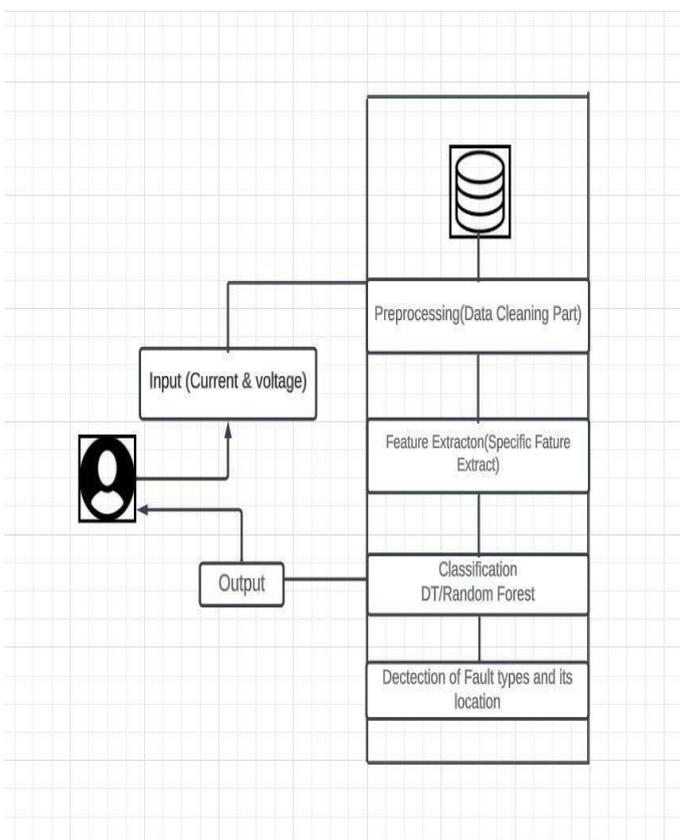


Figure 4.1: Architecture Diagram

System Overview

The system is ML-Based web application and the project aims to explore and develop a comprehensive system for detection and classification of electric faults using Decision tree and Random forest, so we can compare the metrics of both algorithm to developed a more precise appropriate system.

Key Components:

1. **User Interface (UI):** Has a user-friendly interface for users to interact with the system. User can give the input (current and voltage) in their respective area and see is if their possibility of fault will happen or not.
2. **Dataset of Current and Voltage:** Collecting the diverse dataset of three-phase power transmission line having attributes of current and voltage of each phase.
3. **Train and Test split:** Splitting the dataset into 70-30 or 75-25 percentage. Larger portion will be of training while smaller will be of test.
4. **Decision Tree:** A decision tree is one of the most powerful tools of supervised learning algorithms used for both classification and regression tasks. It breaks down a dataset into smaller subsets based on specific features, creating a tree-like structure. At each node, the algorithm makes decisions, and the branches represent possible outcomes.
5. **Random Forest:** Random Forest is a classifier that contains a number of decision trees on various subsets of the given dataset and takes the average to improve the predictive accuracy of that dataset. Each tree is trained on a random subset of the data and features, and the final prediction is determined by a majority vote or averaging, making it a robust and versatile algorithm for classification and regression tasks.

6. Performance Evaluation: Conducting the performance evaluation to get the accuracy and reliability of our two detection mechanisms using standard evaluation metrics to measure the performance.

5. CONCLUSIONS

In conclusion, the application of decision tree algorithms for detecting and locating electric faults in transmission lines demonstrates promising results in terms of accuracy and interpretability. Decision trees offer interpretability and transparency in understanding fault patterns, while random forests harness the collective intelligence of multiple decision trees to enhance accuracy and robustness. It has achieved his goal of Predicting electrical faults in distribution networks using online data helps in avoiding long interruptions for the consumers which could increase satisfaction. The fault localization algorithm based on decision tree principles provided satisfactory precision in pinpointing fault locations along the transmission lines. The accuracy of Decision tree or random forest in more as compare to other classifiers such as Logistic Regression and SVM.

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