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Decision Tree Based Fault Classification for Transmission Line Analysis

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Abstract: Transmission lines forms the backbone of the transmission and distribution networks which powers the nation. No modern society can imagine its existence without power supplies which runs everything ranging from consumer electronics to bullet trains. This research paper focuses on classifying faults on electric power transmission lines. fault classification has been achieved by using decision tree and study on their result is done. The simulation studies have been carried out by using MATLAB fuzzy-logic toolbox.
Keywords: fault classification, transmission line, power, lightning, Decision tree.

I. INTRODUCTION

This document is a template. For questions on paper guidelines, please contact us via e-mail. The use of high capacity electrical generating power plants and concept of grid, i.e. synchronized electrical power plants and geographical displaced grids, required fault detection and operation of protection equipment in minimum possible time so that the power system can remain in stable condition. The faults on electrical power system transmission lines are supposed to be first detected and then be classified correctly and should be cleared in least fast as possible time. The protection system used for a transmission line can also be used to initiate the other relays to protect the power system from outages.

A good fault detection system provides an effective, reliable, fast and secure way of a relaying operation. Therefore, a transmission system should have design in accordance with the process of fault classification where it could be classifying easily and it would be possible to isolate the faulty section easily. Application of machine learning algorithms on the transmission line for fault classification and location identification has been explored in many research. Decision tree is one of the most popular supervised learning models for knowledge discovery. Decision trees are used to make decisions for the unseen cases with the help of the model build with the trained classes.

II. DECISION TREE

The first applications of DT in power systems were concerned with voltage security assessment. Transient stability analysis, power transformer protection and high impedance fault detection. This method provides a useful tool for fault analysis independent of the protection system. DTs that utilize voltage and current phasors as predictor variables and the target variable is the fault point.

DT is constructed in a top-down recursive divide-and-conquer manner. Each tree consists of many nodes. These nodes are divided into two kinds: internal nodes and terminal nodes. Each internal node is generated from another internal node and is surely generator of two or many internal or terminal nodes. Terminal node also known as leaf node is generated from an internal node but does not generate any node and as compared to other algorithms decision trees requires less effort for data preparation during pre-processing. It does not require normalization of data and scaling of data as well.

Missing values in the data also does not affect the process of building a decision tree to any considerable extent. Decision trees give a straightforward visualization of data. Figure 2.1 illustrates an example of a decision tree.

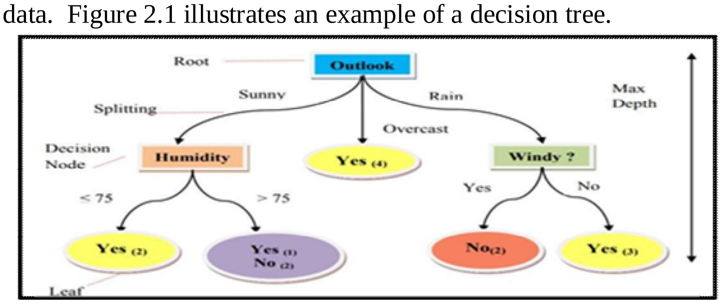

Fig 1 Simple Decision Tree

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A. Flowchart & Algorithm

Dataset was divided into two datasets (75%/25%, training/testing) to avoid any bias in training and testing. Of the data, 75% was used to train the ML model, and the remaining 25% was used for testing the performance of the proposed activity classification system. Algorithm of Decision Tree:

1) Step 1 - Creating a Power Transmission Line Models in MATLAB Simulink, obtaining data for various types of faults by manually adjusting the resistances; and saving the fault data in an MS-Excel File.
2) Step 2 - Importing the libraries and packages in Google Colab.
3) Step 3 - Mounting the fault data to Google Colab server.
4) Step 4 - Merging all the data into a 2D Data Structure (Data Frame)
5) Step 5 - Finding all entries of unique fault types and assigning class labels to all types of faults.
6) Step 6 -Separating/ Splitting the train data and test data, i.e., current values and fault types by specifying division of all data (75:25).
7) Step 7 - Importing Random Forest Classifier with specific estimators and depth.
8) Step 8 - Fitting the data into the compiled model, i.e., training the model using the initially defined parameters.
9) Step 9 - Training the model on the given set of data and testing on the other set of data separated out from the original data.
10) Step 10-Predicting the values using the trained model and finding the accuracy based on how many times the data was predicted correctly.
11) Step 11-Print the Accuracy Score, Classification Report and Confusion Matrix of the training process.

III.DESIGNING OF DECISION TREE MODEL

We have developed our own model based on decision tree architecture, and have used it to train the standard dataset values without any pre-processing, i.e., the input data have not been manipulated. The sample data set of these numbers are as shown below

	A	B	C	D	E
1	t	ia	ib	ic	Fault Type
2	0	-37.8457	3.87942	33.96632	ABFAULT
3	0.00045	-29.4199	0.176654	29.24329	ABFAULT
4	0.0009	-22.7446	-3.03521	25.77977	ABFAULT
5	0.00135	-17.292	-5.83186	23.12384	ABFAULT
6	0.0018	-12.697	-8.25776	20.95476	ABFAULT
7	0.00225	-8.71132	-10.3364	19.04774	ABFAULT
8	0.0027	-5.17057	-12.078	17.24854	ABFAULT
9	0.00315	-1.97049	-13.4846	15.45512	ABFAULT
10	0.0036	0.950556	-14.5549	13.60436	ABFAULT
11	0.00405	4.879243	-15.5505	10.67131	ABFAULT
12	0.0045	6.994418	-15.876	8.881541	ABFAULT
13	0.00495	8.92996	-15.8743	6.944375	ABFAULT
14	0.0054	10.69093	-15.5568	4.865839	ABFAULT
15	0.00585	12.24117	-14.9294	2.6882	ABFAULT
16	0.0063	13.54902	-14.0045	0.455478	ABFAULT
17	0.00675	14.58786	-12.8005	-1.78737	ABFAULT
18	0.0072	15.33659	-11.3413	-3.9953	ABFAULT
19	0.00765	15.78	-9.65595	-6.12404	ABFAULT
20	0.0081	15.90904	-7.77806	-8.13098	ABFAULT
21	0.00855	15.72239	-5.78059	-9.9418	ABFAULT
22	0.009	15.22054	-3.62296	-11.5976	ABFAULT

The hyper parameters that are kept constant are as follows: Class weight=None; criterion='gini'; max depth = 100; max features = auto; max leaf nodes = None; max samples = None; min samples split = 2 n; estimators = 1000. In this research paper fault analysis for two different cases (LL fault and LG fault) at various fault resistance are considered.

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1) *Case I:* Fault analysis for LL fault at various fault resistance
a) Fault analysis of LL (AB, BC, CA) at fault resistance 25Ω:

TABLE I
TRAINING AND TESTING SAMPLES FAULT ANALYSIS OF LL

No. of Training Samples	2703
No. of Testing samples	903
No. of Output Classes	3(AB,BC,CA)
Accuracy	0.495

The Classification Report of the testing on Dataset based on the training data:

TABLE II
CLASSIFICATION REPORT FOR AB, BC, CA AT 25Ω FAULT RESISTANCE

Class	Precision	Recall	F1-Score	Support
Zero	0.39	0.49	0.43	84
One	0..55	0.55	0.59	107
Two	0.45	0.46	0.46	110
Avg/total	0.50	0.49	0.49	301

Here, Precision is the number of correct positive results divided by the number of all positive results returned by the classifier, Recall is the number of correct positive results divided by the number of all relevant samples (all samples that should have been identified as positive), F1-Scoreis a measure of test accuracy and is the harmonic average of Precision and Recall. The Support values are the number of samples of that particular class that have been analysed while testing. A Confusion Matrix displays the number of data correctly classified according to their class. The Confusion Matrix of the testing data is:

TABLE III
CONFUSION MATRIX OF THE MODEL FOR LL FAULT

	ZERO	ONE	TWO
ZERO	41	12	31
ONE	24	59	24
TWO	40	21	49

b) Fault analysis of LL (AB, BC, CA) at fault resistance 25Ω ,50Ω:

TABLE IV
TRAINING AND TESTING SAMPLES FAULT ANALYSIS OF LL

No. of Training Samples	10827
No. of Testing samples	3609
No. of Output Classes	3(AB,BC,CA)
Accuracy	92.18

The Classification Report of the testing on Dataset based on the training data:

TABLE V
CLASSIFICATION REPORT FOR AB, BC, CA AT 25Ω AND 50Ω,75Ω,100Ω

Class	Precision	Recall	F1-Score	Support
Zero	0.91	0.94	0.93	408
One	0.92	0.91	0.92	386
Two	0.93	0.91	0.92	409
Avg/total	0.92	0.92	0.92	1203

A Confusion Matrix displays the number of data correctly classified according to their class. The Confusion Matrix of the testing data is:

TABLE VI
CONFUSION MATRIX OF THE MODEL FOR LL FAULT

	ZERO	ONE	TWO
ZERO	385	12	11
ONE	18	353	15
TWO	21	17	371

c) Fault analysis of LL (AB, BC, CA) at 25Ω,50Ω,75Ω,100Ω,150Ω fault resistance

TABLE VII
TRAINING AND TESTING SAMPLES FAULT ANALYSIS OF LL

No. of Training Samples	16239
No. of Testing samples	5415
No. of Output Classes	3(AB,BC,CA)
Accuracy	94.84

The Classification Report of the testing on Database based on the training data is:

TABLE VIII
CLASSIFICATION REPORT FOR AB, BC, CA AT 25Ω, 50Ω,75Ω,100Ω,150Ω.

Class	Precision	Recall	F1-Score	Support
Zero	0.95	0.96	0.96	597
One	0.96	0.94	0.95	604
Two	0.93	0.95	0.94	604
Avg/total	0.95	0.95	0.95	1805

A Confusion Matrix displays the number of data correctly classified according to their class. The Confusion Matrix of the testing data is:

TABLE IX
CONFUSION MATRIX OF THE MODEL FOR LL FAULT

	ZERO	ONE	TWO
ZERO	573	5	19
ONE	17	565	22
TWO	13	17	574

d) Fault analysis of LL (AB, BC, CA) at 25Ω,50Ω,75Ω,100Ω,150Ω,200Ω fault resistance:

TABLE X
TRAINING AND TESTING SAMPLES FAULT ANALYSIS OF LL

No. of Training Samples	18945
No. of Testing samples	6318
No. of Output Classes	3(AB,BC,CA)
Accuracy	94.25

The Classification Report of the testing on Dataset based on the training data is:

TABLE XI
CLASSIFICATION REPORT FOR AB, BC, CA AT 25Ω, 50Ω,75Ω,100Ω,150Ω,200Ω

Class	Precision	Recall	F1-Score	Support
Zero	0.93	0.97	0.95	679
One	0.96	0.93	0.94	729
Two	0.94	0.93	0.93	701
Avg/total	0.94	0.94	0.94	2106

A Confusion Matrix displays the number of data correctly classified according to their class. The Confusion Matrix of the testing data is:

TABLE XII
CONFUSION MATRIX OF THE MODEL FOR LL FAULT

	ZERO	ONE	TWO
ZERO	655	8	13
ONE	21	676	32
TWO	27	20	654

TABLE XIII
ACCURACY TABLE OF FAULT CLASSIFICATION AT LL FAULT:

FAULT TYPE	RESISTANCE	ACCURACY
AC ,BC,CA	25Ω	49.50
AC ,BC,CA	25Ω,50 Ω	82.39
AC ,BC,CA	25Ω,50Ω ,75Ω	89.59
AC ,BC,CA	25Ω,50 Ω ,75Ω,100 Ω	92.18
AC ,BC,CA	25Ω,50 Ω ,75Ω,100 Ω,150Ω	94.84
AC ,BC,CA	25Ω,50 Ω, 75Ω,100 Ω,150Ω 200Ω	94.25
AC ,BC,CA	25Ω,50 Ω, 75Ω,100 Ω,150Ω 200Ω,300Ω	94.15
AC ,BC,CA	25Ω,50 Ω, 75Ω,100 Ω,150Ω 200Ω,300Ω, 400Ω	88.52
AC ,BC,CA	25Ω,50 Ω, 75Ω,100 Ω,150Ω 200Ω,300Ω, 400Ω, 500Ω	89.91

TABLE XIV
ACCURACY AT FAULT CLASSIFICATION OF AB, BC, CA AT COMBINE FAULT RESISTANCE

Fault Type	Resistance	Accuracy
AB, BC, CA	25 Ω	49.50
AB, BC, CA	50 Ω	48.83
AB, BC, CA	75 Ω	47.74
AB, BC, CA	100 Ω	46.17
AB, BC, CA	150 Ω	46.84
AB, BC, CA	200 Ω	48.17
AB, BC, CA	300 Ω	47.34
AB, BC, CA	400 Ω	47.17
AB, BC, CA	500 Ω	48.17

2) Case II: Fault analysis for LG fault at various fault resistance
a) Fault analysis of LG (AG, BG, CG) at 25Ω fault resistance:

TABLE XV
TRAINING AND TESTING SAMPLES FAULT ANALYSIS OF LG

No. of Training Samples	2706
No. of Testing samples	903
No. of Output Classes	3(AG,BG,CG)
Accuracy	0.47

The Classification Report of the testing on Dataset based on the training data is

TABLE XVI
CLASSIFICATION REPORT FOR AG, BG, CG AT 25Ω FAULT RESISTANCE

Class	Precision	Recall	F1-Score	Support
Zero	0.43	0.49	0.46	84
One	0.50	0.47	0.48	107
Two	0.49	0.46	0.47	110
Avg/total	0.47	0.47	0.47	301

A Confusion Matrix displays the number of data correctly classified according to their class. The Confusion Matrix of the testing data is:

TABLE XVII
CONFUSION MATRIX OF THE MODEL FOR LG FAULT

	ZERO	ONE	TWO
ZERO	41	21	22
ONE	25	353	15
TWO	29	10	51

b) Fault analysis of LG (AG, BG, CG) at 25Ω ,50,75Ω,100Ω,150Ω,200 fault resistance

TABLE XVIII
TRAINING AND TESTING SAMPLES FAULT ANALYSIS OF LG

No. of Training Samples	16239
No. of Testing samples	5415
No. of Output Classes	3(AG,BG,CG)
Accuracy	0.94

The Classification Report of the testing on Dataset based on the training data is:

TABLE XIX
CLASSIFICATION REPORT FOR AG, BG, CG AT 25Ω ,50Ω,75Ω,100Ω,150Ω,200Ω

Class	Precision	Recall	F1-Score	Support
Zero	0.94	0.96	0.95	597
One	0.96	0.92	0.94	604
Two	0.92	0.94	0.93	604
Avg/total	0.94	0.94	0.94	1805

A Confusion Matrix displays the number of data correctly classified according to their class. The Confusion Matrix of the testing data is as shown below:

TABLE XX
CONFUSION MATRIX OF THE MODEL FOR LG FAULT

	ZERO	ONE	TWO
ZERO	571	4	22
ONE	20	557	27
TWO	17	17	570

c) Fault classification (AG, BG, CG) at 25Ω, 50Ω, 75Ω, 100Ω, 150Ω, 200Ω, 300Ω fault resistance:

TABLE XXI
TRAINING AND TESTING SAMPLES FAULT ANALYSIS OF LG

No. of Training Samples	18945
No. of Testing samples	6318
No. of Output Classes	3(AG,BG,CG)
Accuracy	0.93

The Classification Report of the testing on Database based on the training data is

TABLE XXII
CLASSIFICATION REPORT FOR LG AT 25Ω AND 50Ω,75Ω,100Ω,150Ω,200Ω,300Ω

Class	Precision	Recall	F1-Score	Support
Zero	0.94	0.95	0.94	708
One	0.94	0.93	0.94	701
Two	0.93	0.94	0.93	697
Avg/total	0.94	0.94	0.94	2106

A Confusion Matrix displays the number of data correctly classified according to their class. The Confusion Matrix of the testing data is

TABLE XXIII
CONFUSION MATRIX OF THE MODEL FOR LG FAULT

	ZERO	ONE	TWO
ZERO	671	16	21
ONE	21	651	29
TWO	22	23	6521

TABLE XXIV
ACCURACY TABLE OF FAULT CLASSIFICATION FOR LG FAULT

Fault Type	Resistance	Accuracy
AG, BG, CG	25 Ω	47.17
AG, BG, CG	50 Ω	48.17
AG, BG, CG	75 Ω	47.84
AG, BG, CG	100 Ω	48.83
AG, BG, CG	150 Ω	47.84
AG, BG, CG	200 Ω	46.84
AG, BG, CG	300 Ω	45.18
AG, BG, CG	400 Ω	46.17
AG, BG, CG	500 Ω	46.17

TABLE XXV
ACCURACY TABLE AT COMBINE FAULT RESISTANCE

FAULT TYPE	RESISTANCE	ACCURACY
AG ,BG,CG	25Ω	47.17
AG ,BG,CG	25Ω,50 Ω	82.89
AG ,BG,CG	25Ω,50Ω ,75Ω	89.03
AG ,BG,CG	25Ω,50 Ω ,75Ω,100 Ω	92.93
AG ,BG,CG	25Ω,50 Ω ,75Ω,100 Ω ,150Ω	93.88
AG ,BG,CG	25Ω,50 Ω, 75Ω,100 Ω ,150Ω 200Ω	94.15
AG ,BG,CG	25Ω,50 Ω, 75Ω,100 Ω ,150Ω, 200Ω,300Ω	93.44
AG ,BG,CG	25Ω,50 Ω, 75Ω,100 Ω ,150Ω, 200Ω,300Ω, 400Ω	93.14
AG ,BG,CG	25Ω,50 Ω, 75Ω,100 Ω ,150Ω, 200Ω,300Ω, 400Ω, 500Ω	94.12

IV. CONCLUSIONS

Decision tree approach has been presented for the classification of different types of fault faults. Simulation was carried out on a 400kV, 3 phase and 300km line to support the results of the proposed technique for getting dataset of different types of fault current. To improve the accuracy of the fault diagnosis, especially in case of network topology variations, random forest (RF) containing DTs is used to increase robustness of diagnosis. the proposed technique gives quick, correct, robust fault classification of the LL, LG type of short circuit event occur in transmission line using data collected at post fault current. Uniqueness of this technique is that large no data is collected to classify different type of fault; optimized value of random forest classifier is used to improve the accuracy of model to classify different type of faults. The simulation result shows that maximum accuracy for LG fault classification is (94.15%) for LL fault classification is (94.84%).

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