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Research Article

Using Machine Learning Algorithms For Classifying Transmission Line Faults

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ABSTRACT

The faults in transmission lines should be identified for attaining high quality energy in electrical power systems. Savings can be made in both time and energy if the transmission line faults are classified accurately. The present study examined phase-ground, phase-phase-ground, phase-phase, phase-phase-phase and no fault cases. Support Vector Machine (SVM), K-Nearest Neighbours Algorithm (KNN), Decision Tree (DT), Ensemble, Linear discriminant analysis (LDA) classifiers were used for classifying the transmission line faults. These algorithms were compared with regard to parameters such as accuracy, error rate, prediction speed and training time. The accuracy and minimum error of SVM and KNN classifiers were 99.7 % and 0.0011 respectively. DT classifier is faster than the other classifiers with a predicted speed of 29000 obs/sec. Whereas LDA had the shortest training time of 0.76992 sec. The results have indicated that SVM, KNN classifiers have similar performances. In addition, the classifiers SVM, KNN acquired minimum error with the highest accuracy compared with the other classifiers. While DT has the highest estimation speed, LDA has the shortest training time.

Introduction

Electrical power systems are the foundation of economy. Many systems including banking, railroad networks, telecommunication and computers cannot operate without electricity. Power systems are comprised of generation, transmission and distribution lines. Transmission lines are the main method of obtaining energy in a reliable manner in power systems. Many external factors such as dirty isolator, falling trees, lightning, wind etc. result in faults in power systems. Faults in transmission lines make up 80-90 % of the faults in power systems [1]. Faults are classified into two as temporary and permanent. If the fault is resolved in a short period of time and normal operation resumes, these types of faults are called temporary faults. Temporary faults should be resolved in the shortest amount of time possible. Faults that develop after short circuits are called permanent faults [2]. Short circuit faults make up 70 % of the faults in electrical system faults and are among the faults that affect consumers the most [3]. These faults such as the increase of power losses, shortening of the duration of using the devices, heating up of the cables etc. may result in significant damages in many electrical transmission systems and devices. Hence, the fault causing the short circuit should be identified as soon as possible along with the faulty phase [4]. It is very important to identify the type, class and position of the fault for protecting the transmission lines [5]. The classification of short-circuit faults in the transmission line is very important for the correct detection of the fault.Thus, the damages that develop in electrical systems are reduced, the quality of power systems is enhanced, system stability is increased. The most fundamental method for reducing faults in energy transmission lines is the accurate classification of short circuit faults [6]. Extended maintenance works lead to economical damages as well as wasting of energy. For this purpose, the maintenance responsible will not have to examine the transmission line in full if the fault can be classified rapidly. The following techniques are used for the classification of faults in transmission lines.

- Impedance measurement
- Traveling wave phenomena

- Artificial intelligence [7]

There are many factors that affect the classification of the fault such as fault type, the starting time of the fault, fault current, stable state of the voltage [8].

Ray and Mishra used SVM for predicting the fault type in long transmission lines. The simulation results illustrated that the suggested method classified the fault type with an accuracy of 99.21 % [9]. Chen et al. suggested the Summation-Wavelet Extreme Learning Machine (SW-ELM) method for classifying the faults in transmission lines and for detecting the position of the fault. The results in the dataset put forth that SW-ELM method classified the faults with an accuracy of 98.22 % [10]. Ekici suggested SVM and wavelet transformation for classifying fault types and predicting the location of the fault. A classification error of lower than 1 % was obtained for a 360km long transmission line [11]. Freire et al. utilized the Hidden Markov Model (HMM), ANNSVM and KNN for classifying the faults in transmission lines. The results proved that the HMM algorithm displayed a better performance compared with classifiers such as ANN, SVM and KNN [12]. Jamehbozorg and Shahrtash suggested the DT algorithm for fault classification. The simulation results put forth that the algorithm was able to classify the faults in a very short amount of time and with high accuracy [13]. Samantaray used a systematic DT based approach for classifying the transmission line faults. The suggested metbhod yielded an accuracy that was better compared with the intuitionistic fuzzy logic[14].Mahanty and Gupta used the methods of wavelet analysis and artificial neural network for classifying the transmission line faults. The simulation results showed that the wavelet method provided better results compared with the artificial neural network [15]. Nguyen and Liao suggested the adaptive neuro-fuzzy inference system (ANFIS) for transmission line fault classification. Satisfactory results were obtained with the designed system [16].

The aim of this study is to determine which type of fault is the algorithm in the case of phase-earth, phase-phase-earth, phase-phase, phase-phase-phase and no faults occurring in the transmission line. It was observed as a result of a literature survey that many classifiers have been used for electrical fault classification. However, a study could not be found which utilizes all of the classifiers of SVM, KNN, DT, Ensemble, LDA which compares their performances. In most studies, the performance of algorithms used to classify failures has been evaluated in terms of accuracy, sensitivity, error rate and predictive value. However, in this study, estimation speed and training time were added together with these parametric measurements. SVM, KNN, DT, Ensemble, LDA algorithms have proven shortcomings and their superiority over each other.

The present study was organized as follows. Section 2 explains the SVM, KNN, DT, Ensemble, LDA classifiers and their performance criteria. Section 3 explains the data analysis and simulation results. Whereas Section 4 summarizes the study results.

Methodology

Support Vector Machine

SVM is an algorithm developed by Vladinir Vapnik which is used for non-linear classification and regression. SVM is the linear separation hyperplane of the data at point $(x_{i,}\ y_i)$. $x_{i1}, x_{i2,\cdots}, x_Q$ is the feature vector; i=1, ⋯,n , p denotes the number of features, n is the number of trainings, y_i is the class label. The best hyperplane is the distance to the best training data points. Observations from the side margin and hyperplane are known as support vectors. The position of the hyperplane depends on these observations. The position of the hyperplane changes when the position of even one of these observations changes. Linear separation of the hyperplane results in optimal classification. However, since the data in different classes are not clear most of the time, linear classification will most likely lead to erroneous results [17]. SVMs have been used in many areas ranging from image perception, classification, fault analysis, regression and text perception. This algorithm aims to setup a nonlinear hyperplane using nonlinear input data. SVM displayed a better performance compared with the traditional statistical models in many applications such as pattern recognition, classification and analysis. Different kernel functions such as radial basis function, function polynomial, and linear are used in SVM models. The features of the SVM method are as follows:

- SVM is responsive and reliable
- Can model non-linear data.
- Requires less assembly than other models
- Used in regression, pattern recognition and classification problems [18].

K-Nearest Neighbours Algorithm

KNN is the most frequently used algorithm for the classification of data objects. The distance between test and training data identify the nearest neighbour in KNN algorithm. In KNN, k denotes the classifier indicating the number of neighbours of which the classification is affected. As an example, if k=1 it is assigned to the class of the nearest neighbour. Distance functions such as Minkowsky, Euclid, Manhattan, Chebyshev and City-block are used in KNN algorithm. The steps of the KNN algorithm are indicated below:

- Calculate the nearest k neighbour number.
- Calculate the distance between the training data and the test data.
- Order the distances subject to the kth minimum distance.
- Classify the nearest neighbours.

- Predict the new data object with the help of the nearest neighbours [19].

$T = \{(x_1, y_1), (x_2, y_2), \cdots, (x_N, y_N)\}$ is the training set and N is the number of training data. $x_i \epsilon R^d$ feature vector, $y_i \in Y = \{c_1, c_2, \cdots c_m\}$ classification label, $i = 1,2, \cdots, N$. $N_{k(x)}$ x is the k nearest neighbor with x input data. The voting process is as follows:

$$y = argmax \sum_{x_i \epsilon N_{k(x)}} I(y_i = c_j) \; i = 1,2, \cdots, N \qquad (1)$$

I denotes the indicator function [20].

$$I = \begin{cases} 1, & y_i = c_i \\ 0 & else \end{cases} \qquad (2)$$

Decision Tree

DT is a classifier comprised of learning and classification. DT learns during the learning stage how a DT can be formed from a series of training sets. Whereas in the classification stage, the data are classified via DT. A DT consists of nodes, branches and leaves. Figure 1 shows a four-dimensional attribute space and a DT example for two classes.

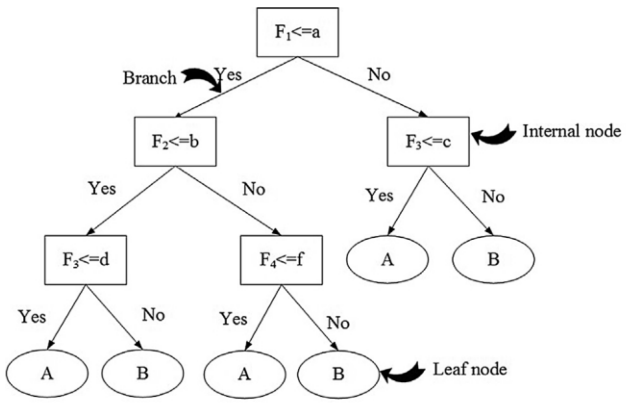

Figure 1. Decision tree classifier flowchart

Each node represents the attribute test, each branch represents the output of the attribute test and each leaf represents classification [21].Decision tress are classified into two groups as classifier and regression trees. Classifier trees are used for predicting a discrete variable whereas regression trees are used to predict continuous variables. The most important advantage of DT is that the general process time is short when there is no need for variable transformations. In addition, it can easily model the complex relations between the variables and decision makers can make rapid interpretations. Trees should be formed and the branches should be pruned in order to model DT. In order to generate an ideal DT, first a DT is developed with the largest size after which the pruning process is conducted subject to the ideal pruning threshold. The tree will grow based on certain criteria in DT prior to pruning. A full tree will be formed and sub-trees will be pruned based on certain criteria [22]. If the attribute cuts the space with a hyperplane parallel to the axis it is known as a single variable tree, whereas if it divides in a skewed manner it is known as a multivariate tree.DT is frequently preferred due to its ease of use, efficiency and success in classification [23].

Ensemble

Ensemble classifier is based on the principle of generating and conjoining of multiple classifiers to reach the optimum solution of a problem [24]. The main idea behind the ensemble methodology is assigning different weights to different classes and conjoining all classifiers. A weight value is assigned for each opinion and all opinions are joined prior to coming to a decision. Knowledge consistency and classification dependency are very important while developing a classifier. Different classifiers have different interpretations regarding a sample and all classifiers are independent of each other [25]. The ensemble acquires the ability for prediction after completing the training [26]. Ensemble classifier is used in many applications due to its performance in classifying complex data [27].

Linear Discriminant Analysis

LDA analyses different object groups subject to more than one variable and determines the differences between them. It contains a dataset, predictors and different measurements with class labels. Prediction values are classified based on the information in the old data set. Training data are known as the observations in the class labels. LDA network is trained via training data. Some classifications in the training set are wrong. Re-substitution error is calculated for identifying the ratio of these misclassifications. Misclassification sets are calculated using the confusion matrix in the training set. The confusion matrix is comprised of predicted class labels and known class labels [28]. Discriminant is used for classifying low dimension samples with the same attributes from the LDA large dimension attribute space. Samples of different types are tried to be used as much as possible in order to ensure that the classification is accurate.

$$\sum_{i=1}^{c} P(i) E\{(u_i - x)(u_i - x)^T \mid x \in class\ i\} \qquad (3)$$

$$s_b = \sum_{i=1}^{c} P(i)(u_i - u)(u_i - u)^T \qquad (4)$$

$$N = n_1 + n_2 + \cdots n_c x_1, x_2, x_3, \cdots, x_m \quad P(i) R^n \qquad (5)$$

X represents the dataset, n_i ith class, c sample space class,u_i ith class mean vector, u average of all data, S_w in-class distribution,S_b intra-class distribution [29].

Performance Criteria

SVM, KNN, DT, Ensemble and LDA algorithms have been used for the classification of faults in electrical power systems. f_p, f_n, t_n, t_p respectively denote wrong positive, wrong negative, real negative and real positive. The following metrics have been used for measuring the performances of these algorithms.

Accuracy (ACC) is a parameter that defines the accurate classification ratio:

$$ACC\% = \frac{t_n+t_p}{t_n+f_p+f_n+t_n} \tag{6}$$

Sensitivity (Sen) is the parameter defining sensitive classification [30].

$$Sen\% = \frac{t_p}{t_p+f_n} \times 100 \tag{7}$$

Error ratio (ERR) is the ratio of the wrong positive and wrong negatives to the total number of calculations [31].

$$ERR = \frac{f_n+f_p}{t_p+f_p+f_n+t_n} \tag{8}$$

Simulation Results and Data Analysis

Data Analysis

In this study phase-earth, phase-phase-to-ground, phase-phase, phase-phase-phase and no-fault conditions were investigated. Table 1 presents the fault types in power systems. G in Table 1 represents ground whereas A, B, C represent the three phases. Table 2 shows the input and output values for the simulation. A total of 2100 data have been used in the study. However, Table 2 shows only a portion of the data. The input values of the simulation $I_a, I_b, I_c, V_a, V_b, V_c$ and the output values have been considered as the fault classes. The parameters of the SVM algorithm are given in Table 3, the parameters of the KNN algorithm are given in Table 4, the parameters of the Decision tree algorithm are given in Table 5, the parameters of the LDA algorithm are given in Table 6, and the parameters of the Ensemble algorithm are given in Table 7. These algorithms used of the data 70% as training data and 30% as test data. Single-phase fault Class 1 fault, phase-phase-earth fault Class 2 fault, phase-phase fault Class 3 fault, phase-phase-phase fault Class 4 fault, no fault Class 5 fault has been accepted. These data are taken from the kaggle date set. Data set was given to SVM, KNN, Decision tree, LDA, Ensemble algorithms and confusion matrix was obtained. Based on this matrix, accuracy, precision and error rate were calculated for each class.

Table 1. Power system error class [32]

Fault type	G	C	B	A
A-Gnd (Type 1)	1	0	0	1
A-B-Gnd (Type 2)	1	0	1	1
A-B (Type 3)	0	0	1	1
A-B-C (Type 4)	0	1	1	1
No fault (Type 5)	0	0	0	0

Table 2. Input and output values of the power system[32]

I_a	I_b	I_c	V_a	V_b	V_c	Class
-151	9	85	0.40075	-0.13293	-0.26781	1
-336	-76	18	0.312732	-0.12363	-0.1891	1
-502	-174	-80	0.265728	-0.1143	-0.15143	1
-593	-217	-124	0.235511	-0.10494	-0.13057	1
-643	-224	-132	0.209537	-0.09555	-0.11398	1
-83	42	38	0.41693	-0.06644	-0.35049	2
-304	243	42	0.097053	0.089765	-0.18682	2
-487	377	29	-0.13245	0.203226	-0.07078	2
-603	439	9	-0.24861	0.263483	-0.01487	2
-620	423	0.61	-0.22692	0.254651	-0.02773	2
41	-93	55	0.51751	-0.00369	-0.51383	3
42	-105	65	0.518491	-0.00807	-0.51042	3
43	-105	65	0.511217	0.003798	-0.51501	3
43	-100	59	0.499096	0.025105	-0.5242	3
44	-95	53	0.487527	0.045052	-0.53258	3
-99	44	57	0.412305	-0.09152	-0.32078	4
-342	218	125	0.095905	-0.00347	-0.09243	4
-526	347	181	-0.13109	0.05679	0.074304	4
-633	416	218	-0.24598	0.084683	0.161301	4
-639	412	229	-0.22452	0.07558	0.148943	4
61	-22	21	0.36632	-0.56718	0.200859	5
48	-23	21	0.367341	-0.56426	0.196916	5
34	-23	21	0.368258	-0.56117	0.19291	5
20	-24	21	0.369086	-0.55792	0.18883	5
7	-25	21	0.370321	-0.5545	0.184184	5

Table 3. SVM parameters

Preset	Kernel function	Kernel scale	Box constraint level	Multiclass method	Standardize data
Cubic SVM	Cubic	Automatic	1	One-vs-One	True

Table 4. KNN parameters

Preset	Number of neighbors	Distance metric	Distance weight	Standardize date
Fine KNN	1	Euclidean	Equal	True

Table 5. Decision tree parameters

Preset	Maximum number of splits	Split criterion	Surrogate decision splits
Complex Tree	100	Gini diversity index	off

Table 6. LDA parameters

Preset	Regularization
Quadratic Discriminant	Diagonal covariance

Table 7. Ensemble parameters

Preset	Ensemble method	Learner type	Maximum number of splits	Number of lerners	Learnin rate
Boosted Tree	Adaboost	Decision tree	20	30	0.1

Simulation Results

In this study, 5 fault types in power transmission lines were examined. SVM, KNN, Tree, LDA, Ensemble classifiers have been used for classifying these faults. Figure2 shows confusion matrix of SVM classifier, Figure3 shows confusion matrix of KNN classifier, Figure4 shows confusion matrix of Decision decision tree classifier, Figure5 shows confusion matrix of LDA classifier and Figure6 shows confusion matrix of Ensemble classifier. These results have helped us in determining the accuracy, sensitivity and error ratio of the algorithms. Table 8 presents the accuracy values for the SVM, KNN, decision tree, LDA, Ensemble classifiers. An accuracy of 99.8 % has been attained for the first 3 fault types with SVM and KNN. However, while SVM yielded the highest accuracy for the 4th fault type with 99.8 %, KNN provided the highest accuracy for the 5th fault type with 100 %. The Ensemble algorithm is in the 1st failure, and the LDA algorithm is in the 2nd, 3rd, 4th, 5th failure obtained the worst accuracy value. Table 9 shows the sensitivities for the classifiers SVM, KNN, decision tree, LDA, Ensemble. The sensitivity of classifiers displayed different performances for each fault type. The best sensitivity of the classifiers was 100 % whereas the worst sensitivity was 88 %. Table 10 shows the error ratio for the SVM, KNN, decision tree, LDA, Ensemble classifiers. The minimum error ratio of the SVM and KNN algorithms for the first 3 fault classes was 0.011. While the error ratio for the SVM algorithm was 0.0017 for the 4th fault type, KNN algorithm error rate was 0 for the 5th fault type. Table 11 presents the accuracy, prediction speed and training time for the SVM, KNN, decision tree, LDA, Ensemble classifiers. The results were 99.7 % for SVM, KNN with the best accuracy, best prediction speed for decision tree with 29000obs/sec and the shortest training time for LDA with 0.76992 sec. When we compare the Ensemble algorithm with other algorithms, it has the lowest prediction speed of 4000obs/sec and the highest training time of 10,621sec.

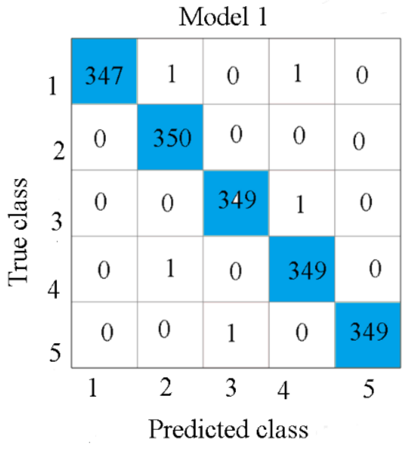

Figure 2. SVM classifier

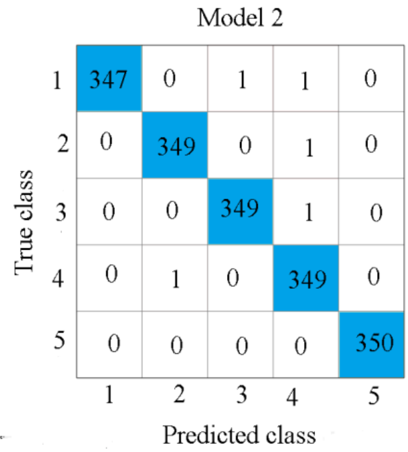

Figure 3. KNN classifier

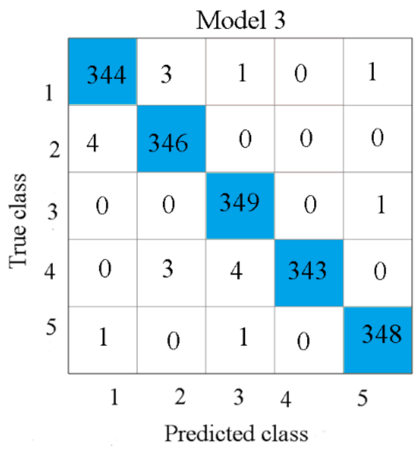

Figure 4. Decision tree classifier

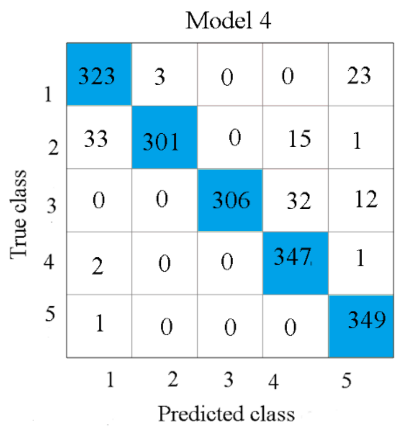

Figure 5. LDA classifier

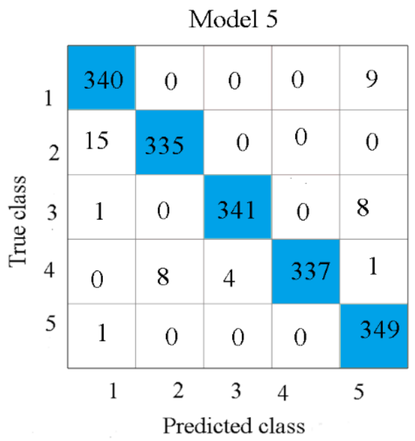

Figure 6. Ensemble classifiers

Table 8. Accuracy of the algorithms

Algorithm	Class1	Class2	Class3	Class4	Class 5
SVM	**0.998**	**0.998**	**0.998**	**0.998**	**0.999**
KNN	**0.998**	**0.998**	**0.998**	**0.997**	**1**
Decision Tree	0.994	0.994	0.995	0.995	0.997
LDA	0.964	**0.970**	**0.974**	**0.971**	**0.978**
Ensemble	**0.985**	0.986	0.992	0.992	0.989

Table 9. Sensitivity of the algorithms

Algorithm	Class1	Class2	Class3	Class4	Class 5
SVM	**0.994**	**1**	0.997	0.997	0.997
KNN	0.994	0.997	0.997	0.997	**1**
Decision Tree	0.985	0.988	0.997	0.98	0.994
LDA	0.899	0.99	**1**	0.88	0.997
Ensemble	0.952	0.957	0.988	**1**	0.997

Table 10. Error rate of the algorithms

Algorithm	Class1	Class2	Class3	Class4	Class 5
SVM	**0.0011**	**0.0011**	**0.0011**	**0.0017**	0.0005
KNN	**0.0011**	**0.0011**	**0.0011**	0.0022	**0**
Decision Tree	0.0057	0.005	0.004	0.004	0.002
LDA	0.035	0.029	0.025	0.028	0.021
Ensemble	0.0148	0.013	0.0074	0.007	0.997

Table 11. Performance of the algorithms

Algorithm	Accuracy	Prediction speed	Training Time
SVM	**99.7**	7000obs/sec	8.4807sec
KNN	**99.7**	18000obs/sec	1.1106sec
Decision Tree	98.9	**29000obs/sec**	1.341sec
LDA	93	14000obs/sec	**0.76992sec**
Ensemble	97.3	**4000obs/sec**	**10.621sec**

Conclusion

Phase-ground, phase-phase ground, phase-phase, phase-phase-phase from among the most frequently observed faults in electrical networks along with the no-fault states have been examined. While the algorithms are classifying the failures, the the superiorities and weakness of SVM, KNN, decision tree, LDA, Ensemble algorithms are determined.In addition, the success of these algorithms for classifying the faults was also examined. These algorithms were examined with regard to performance, accuracy, sensitivity, error rate, prediction speed and training times. SVM and KNN algorithms showed similar performances. These algorithms showed 99.7% accuracy while classifying the failures. Also, the error rates of SVM and KNN algorithms are very close to each other. The KNN algorithm has a faster estimation speed and shorter training time than the SVM algorithm. Decision tree algorithm has faster prediction time than other algorithms. LDA algorithm has the shortest training time. The Ensemble algorithm has the slowest prediction speed and the longest training time.

In further studies, different failure classes and performances of different algorithms will be examined.

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