

Machine Learning Approach to Detect and Classify Power Line Fault

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Abstract—In recent years, precise fault detection and localization of the power system are focused as the major research interest to ensure system protection and enhance the power quality. To protect power transmission line, identification of faulty phases is necessary and fault should be cleared accurately and reliably as fast as possible. Digital signal processing methods has made it easier to analyze faulty signal and efficiently detect precise fault. In this paper, we present machine learning approaches to detect and classify power line fault from the voltage and current signal.

Index Terms—Empirical mode decomposition (EMD), Hilbert Huang transform (HHT).

I. INTRODUCTION

MODERN power suppliers aim at providing reliable and high quality power to the consumer. Fault occurrence in power systems creates impediment to this regard. Since faults can-not be avoided, it is evitable to recognize the faults and restore the supply of power by clearing the fault [1]. The major fault scenarios that are observed in power transmission line are Single line-to-ground faults, Line-to-line faults, Double line-to-ground faults and three phase faults. These fault occurs mainly due to the lightening, falling trees on line and equipment male function. For the protection of power system, a protection scheme based on the operation of relays and circuit breakers has been developed. Various computational tools based on signal processing techniques has been employed for the proper functioning of protective devices. But, recently with the development of digital signal processing techniques and evolution of machine learning algorithm, every system is turning into an intelligent system [2]. In this paper, we have presented how a power system can be intelligent to detect and classify fault by itself. The rest of the paper is organized as follows: In section II, we have demonstrated machine learning approaches to detect and classify faults. We have studied feature extraction method in brief there. We have concluded our article in section III.

II. PROPOSED APPROACH

A. Workflow for Detecting and Classifying Fault

Recent advancements in the sensors for collecting various data popularize machine learning algorithms for decision making purpose. It has achieved paramount importance in complex, large and heterogeneous data processing where manual investigation may arise ambiguity. Over the years, various

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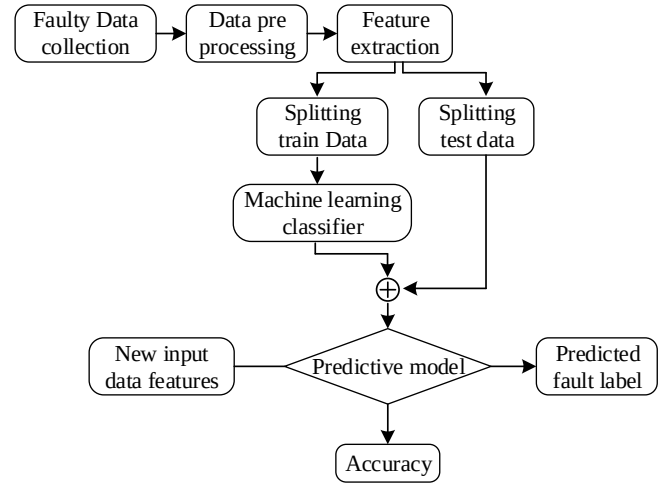


Fig. 1. Proposed methodology.

machine learning algorithms have been developed in order to perform classification, regression, and in general pattern recognition. Among these the most common algorithms are the support vector machine (SVM), the neural networks, the k-nearest neighbor (KNN), the logistic regression, the decision tree, the random forests, the linear discriminant analysis (LDA), the case-based reasoning, the naive Bayes, and the fuzzy logic [3]. In the following figure, methodology using machine learning algorithm to classify the fault is given below:

B. Feature Selection and Predictive Model Generation

Over the years, many soft computing techniques including Fourier Transform, Wavelet Transform and S-Transform are emerged as the popular techniques to detect the transient of power system network [4], [5]. Necessary features are extracted from these techniques. These extracted features are employed to train the machine learning classifier namely ANN and Fuzzy logic as well to detect and classify precise fault. Power system fault detection based on Wavelets and artificial neural networks (ANN) have been proposed in [6]. But the methods are limited due to having low accuracy during high impedance faults and when the fault inception angle is near zero [7]. Wavelet based combined fuzzy logic classifier is also introduced in the literature [8] for classification of faults of power system. Heavy load on power system also limits the accuracy of Fuzzy logic classifier [9]. Recently, EMD and HHT has been proposed for feature extraction instead of

TABLE I
FAULT CLASSIFICATION LOGIC TABLE.

A phase	B phase	C phase	Fault type
0	1	1	AG
1	0	1	BG
1	1	0	CG
0	0	1	AB
1	0	0	BC
1	1	0	CA
1	1	1	ABC

wavelets of voltage and current signal. The best features for the intended purpose are:

- 1) Energy distribution of instantaneous amplitude.
- 2) Standard deviation of amplitude.
- 3) Standard deviation of phase.

80% features out of the whole data set are splitted for training and the rest are kept for testing in general. Then, the trained data set are feeded into any of the machine learning classifier to train and generate the predictive model for detecting and classifying fault. Based on the Following logic table faults are classified.

C. Performance Measures for Classification

To properly evaluate the validity of the model we need to use proper performance measurement. In case of classification task we use precision, recall and F-score for each class defined by following equations. All these metrics may be obtained from confusion matrix. Precision represents as the number of examples correctly classified as class divided by the number of all the examples labeled by the classifier. Recall is the number of examples correctly classified as class divided by the number of all the examples of class in the data. F-score is a harmonic mean of the above.

$$\text{Precision} = \frac{\text{True Positives}}{\text{Total Predicted Class}} \quad (1)$$

$$\text{Recall} = \frac{\text{True Positives}}{\text{Total Example of Class}} \quad (2)$$

$$\text{Fscore} = \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (3)$$

III. CONCLUSION

In this paper we have studied in details how EMD and HHT assists to extracts features from voltage and current signal. Employing those features how machine learning algorithm can be applied detect and classify the fault. We have also demonstrated performance parameter to check our predictive model which will ensure the validity of our predictive model.

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