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Fault Detection and Classification in Transmission Line by using Support Vector Machine Technique

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***Abstract* - Detection and classification of faults in transmission line is of great importance in power system because 80-85% faults occur on transmission line. Detection of faults provides whether system is stable or faulty whereas classification of faults indicates which type of fault is occurred. Both detection and classification suggests accurate and appropriate protection scheme to be implemented. There are numerous techniques used for classifying the faults, but lack of accuracy and processing speed demands new techniques and methods to be invented. In case of new inventions Machine Learning is the latest technique which is taking attention of many researchers. Machine learning includes many algorithms for classification of faults like Naïve Bayes, Support vector machine (SVM), Bagging, Boosting, etc. Also deep learning and neural network techniques are being investigated for most accurate and fast protection scheme. This paper presents the fault detection and classification in transmission line with the help of support vector machine technique. Support vector machine requires less data for training and has fast operation which gives accurate and satisfactory results.**

***Index Terms* - fault detection, fault classification, transmission line, distribution line, machine learning, Support Vector Machine (SVM).**

I. Introduction (Heading 1)

In Power system, transmission and distribution of power is important but to supply it safely and reliably is of prime importance. The conditions which causes the faults in power system like ageing of material with time and some natural events including lightning are unavoidable. These faults can also occur due to manmade activities like sudden opening of isolators, unskilled operation during maintenance, etc. As a result, these undesirable faults should be detected and classified to protect the power system which is the only way to keep power system stable. Detection and classification of faults in transmission and distribution lines is vital for implementing an appropriate protection scheme. Most methods of fault detection and classification depends on the measurement of voltage and current provided by the Potential Transformers (PTs) and Current Transformers (CTs) respectively. Maintenance required for the system and time for clearing faults will be minimized, if protection scheme is accurately implemented. Classification of transmission line faults helps to improve the minimization of frequency of their occurrence.

In transmission line, occurrence of fault on single phase or two phase may lead to tripping of all three phases which is unnecessary operation and should be avoided. The inaccuracy of system in detecting and classifying the faults causes malfunctioning of protective system resulting in tripping of healthy phases. The false tripping of protective system can be minimized or totally avoided if fault detection and classification technique is accurate and fast enough. On the basis that different faults have different voltage and current waveforms so that they can be distinguished from each other and only faulted phase can be tripped without affecting other healthy phases.

A lot of research work and publications is available on detecting and classifying faults on various systems by using number of techniques. Fault on HVDC system by using Support Vector Machine (SVM) in [1], faults on double circuit transmission line by using decision tree based method as in [3], on medium voltage DC shipboard by using wavelets and artificial neural network(ANN) described in [4], unsupervised learning based fault detection on transmission line as in [5] and faults on single circuit transmission line by using symmetrical components of reactive power as in [7]. In each case, various techniques were used and has their own advantages and disadvantages. Some techniques need more training data for having accuracy up to the mark while some techniques give better results with less training data.

II. Support Vector Machines (SVM)

The SVM algorithmic tackles the data complexity problem by searching and selecting the “large margin" separators. In short, a large margin separator separates a training set with a large margin if all the data sample examples lie not only on the correct side of the separating hyperplane but also far away from it. Restricting the algorithm to output a large margin separator can yield a small sample complexity even if the dimensionality of the feature space is high. Whenever there is need of classification some strong machine learning tools are implemented. Support Vector Machine (SVM) is one of those tools which can be used for linear as well as non-linear classifications. SVM is mainly used when classification is to be done between two classes. Also for classification between two classes provides up to the mark accuracy. When some modifications are provided to this tool, SVM can be accurately implemented for multi class classification [2].

SVM is a supervised classification technique from machine learning techniques. It is a classification tool for high dimensional feature spaces. Due to high dimensionality feature it gives rise to problem of sample complexity and computational complexity. The problem of sample complexity in SVM is overcome by searching for ‘large margin separators. Supervised learning means data given to SVM for training must be labelled. Training is carried out by providing past data which is been already classified.

Every input training data is labelled with its classification class. This supervised learning technique takes the past data, train the model on it and finally predicts any test sample data according to training data. SVM depends on the maximum marginal hyperplane between given classes. It maximizes the margin between classes so that accurate classification is done between those classes. The margin between classes also called as hyperplane. The width of hyperplane should be maximum with given training data. SVM focusses on boundary data points which are also considered as Support Vectors form which boundary conditions are defined. SVM is mainly used for linear classification but if there is a non-linear classification then non-linear data is converted into linear data by using proper transformation like converting data from one plane into another plane. Thus converted plane is then classified linearly on the basis of Support Vectors.

Consider there are two linearly separable classes, each containing two instances as shown in Fig. 1. Red Squares indicate one class say class ‘A’ while green triangles indicate another class say class ‘B’. Now there are many possible ways to select a hyperplane from given options. Note that for two dimensional example separation is done by a line and for multidimensional, it is a hyperplane. Here line is stated as hyperplane for generalization. All hyperplanes are eligible for classification of four instances into two classes. Most appropriate and accurate hyperplane must be selected so as to classify any other complicated instances. Support Vectors are the data points or instances that lie closest to the hyperplane. Blue hyperplane is more shifted towards Class ‘A’ instances, hence there may be chances that another instance closer to Class ‘A’ would be classified as Class ‘B’ instance. In green hyperplane, both instances from different classes are closer to green hyperplane. SVM focuses on large margin separation classification, therefore most accurate hyperplane according to SVM technique is dashed black hyperplane. This hyperplane has maximum width from the instances of opposite classes.

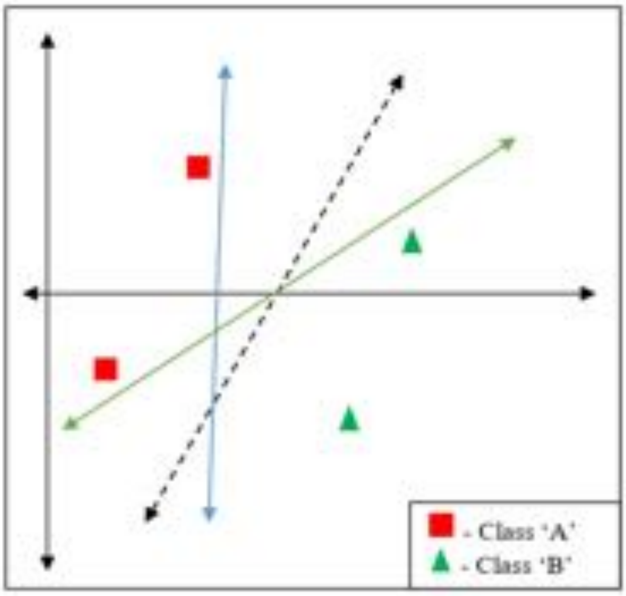


Fig. 1 Demonstration of Classification by using SVM

Now this hyperplane is selected with visual understanding but for computers there must be some mathematical equation which can fit for selected hyperplane.

Consider a two class training data set $\{x_i, y_i\}^N_{i=1}$ consisting N number of data points. xi is the i^{th} real valued input data point and y_i is the respective class of x_i with value of either +1 or −1. +1 belong to one class and -1 belong to another class. A hyperplane, separating these points into their classes, can be given by the equation

$$\boldsymbol{w}^T\boldsymbol{x}_i + \boldsymbol{b} = 0 \quad \text{...} (1)$$

where, $\boldsymbol{w}$ = weight vector

$\boldsymbol{b}$ = bias factor

This equation represents the separating hyperplane for two different classes. This equation requires ‘$\boldsymbol{w}$’ and ‘$\boldsymbol{b}$’ values which can be obtained by training. Training is given for two classes with past data. This equation gives the maximum width of separation between two classes [1]. The *separation margin* (m) is given by

$$m = \frac{2}{||w||} \text{...} (2)$$

For better separation, maximum value of ‘m’ should be increased with training with, reducing value of $\boldsymbol{w}$ to its minimum value. Hence, for linearly separable data, the SVM can be constructed by maximizing $v(\boldsymbol{w})$ where

$$V(\boldsymbol{w}) = \frac{1}{2}\boldsymbol{w}^T\boldsymbol{w} \text{...} (3)$$

Subject to

$$y_i(\boldsymbol{w}^T\boldsymbol{x}_i + \boldsymbol{b}) \geq 1 \quad (4)$$

SVMs, in general, are used for classifying between two classes. Thus it is a two-class classifier algorithm. The best technique for multi-class classification is provided by the construction of multi-class SVMs, where we build a two-class classifier over a feature vector (x, y) derived from the pair consisting of the input features and the class of the data. At test time, the classifier chooses the class $y = \arg\max_{y'} \boldsymbol{w}^T \phi(x, y')$. The margin during training is the gap between this value for the correct class and for the nearest other class [1].

III. Simulation Model

The general model for detection and classification of transmission line faults is represented as shown in fig. 2.

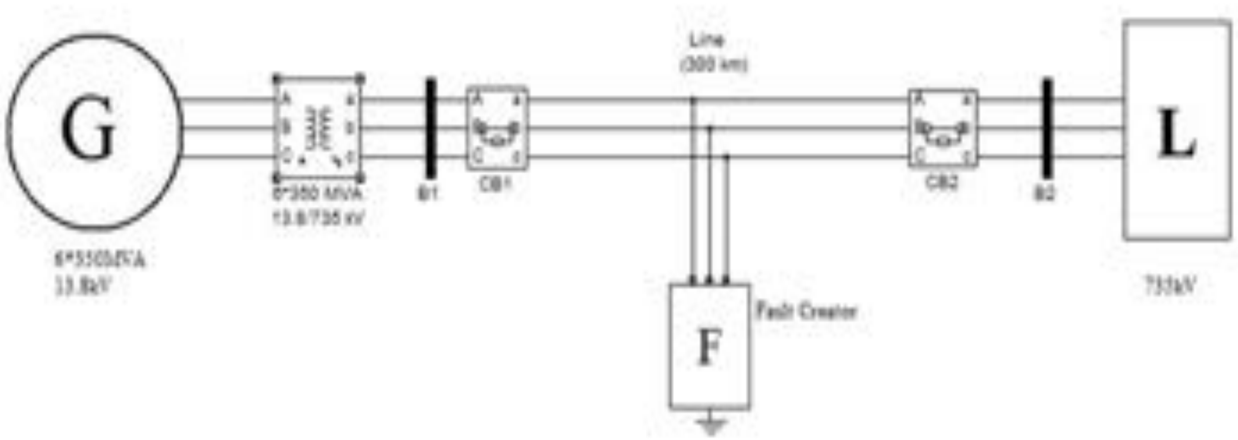


Fig. 2. Three Phase Transmission Line Network for fault detection and classification

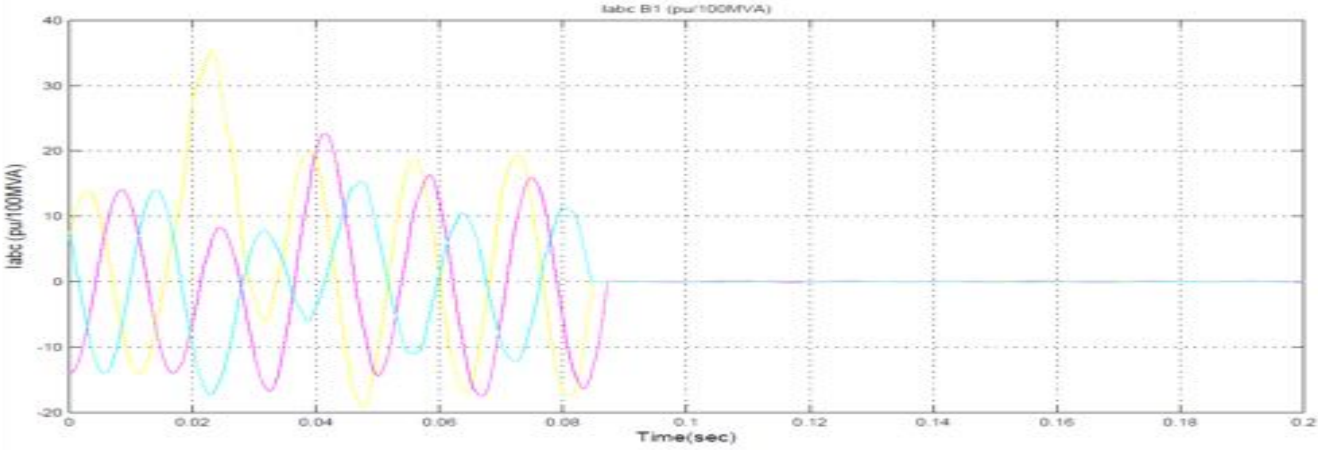
A three phase, 735 kV, 60 Hz power system is delivering power from generating station consisting of six 350 MVA generators to network connected to variable load through 300 km transmission line. First bus B1 at generation side, second bus B2 is at load side. The CB1 and CB2 are the two line-circuit breakers. Voltages and Currents are measured on both buses B1 and B2. The *Fault Creator* block is used execute user desired fault on the transmission line and the data of fault is stored in workspace of MATLAB. There are 11 short circuit faults which can be occurred in transmission line and are mainly focused in this paper. These faults are named as Line to Ground fault(LG), Double Line to Ground fault(LLG), Triple line to ground fault(LLLG), Line to Line fault(LL) and Triple Line fault(LLL). Table 1 specifies the details of given model. The fault resistance varies with the fault location hence current and voltage waveforms changes their magnitude but the pattern of waveforms remains the same which is sufficient for SVM to detect the fault and classify it from given fault types.

Table 1. Model Specifications

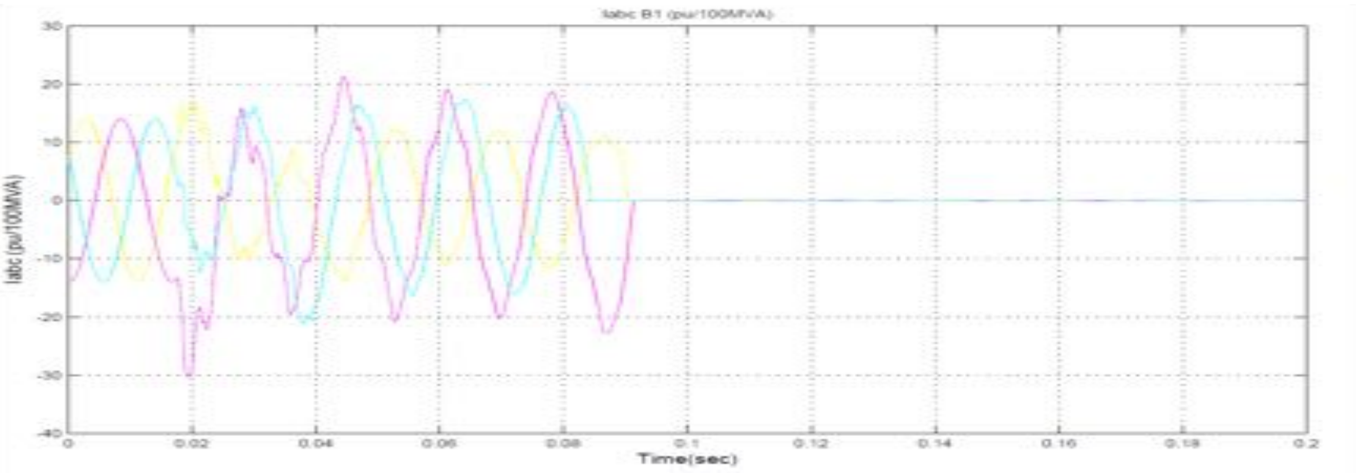
Parameter	Values
Base Voltage of System	735 kV
Base Power of system	100 MW
Transmission line	735 kV, 300 km, 60 Hz

As discussed earlier, waveforms of current and voltage shows same patterns for same faults at same time instance with different fault resistance. Here in this fault detection and classification methods by using SVM, only current waveforms at Bus B1 is considered which is sufficient enough to classify the fault types.

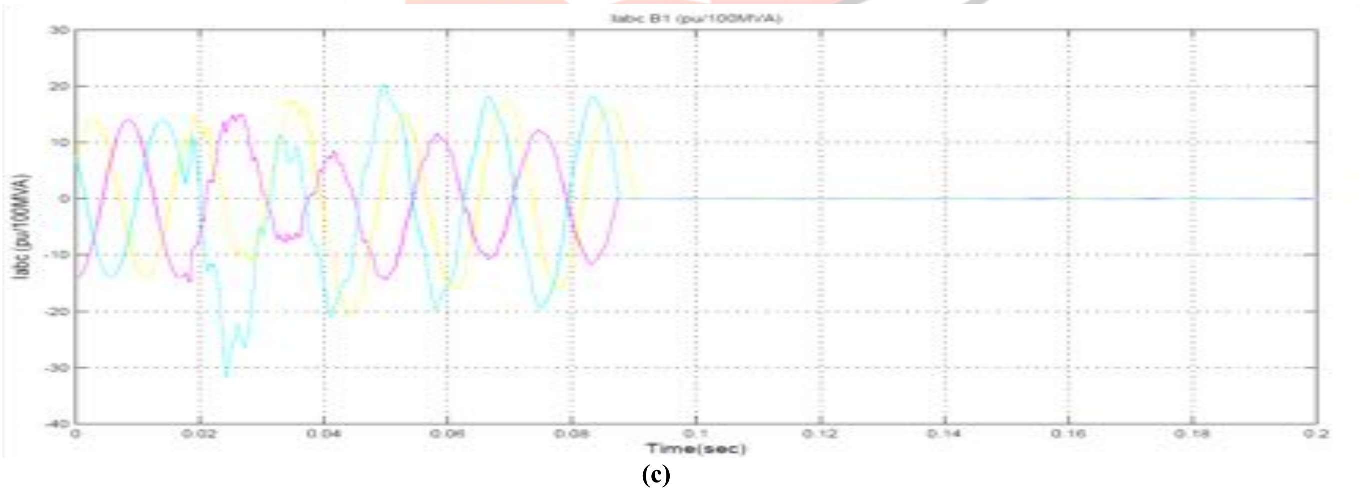
Each type of fault is set to occurred on given model and their current waveforms data on bus B1 is taken from workspace for training purpose. Current waveforms for each type of faults differ from each other and hence convenient for training for given fault types. Current waveforms for each fault are shown as follows,



(a)



(b)

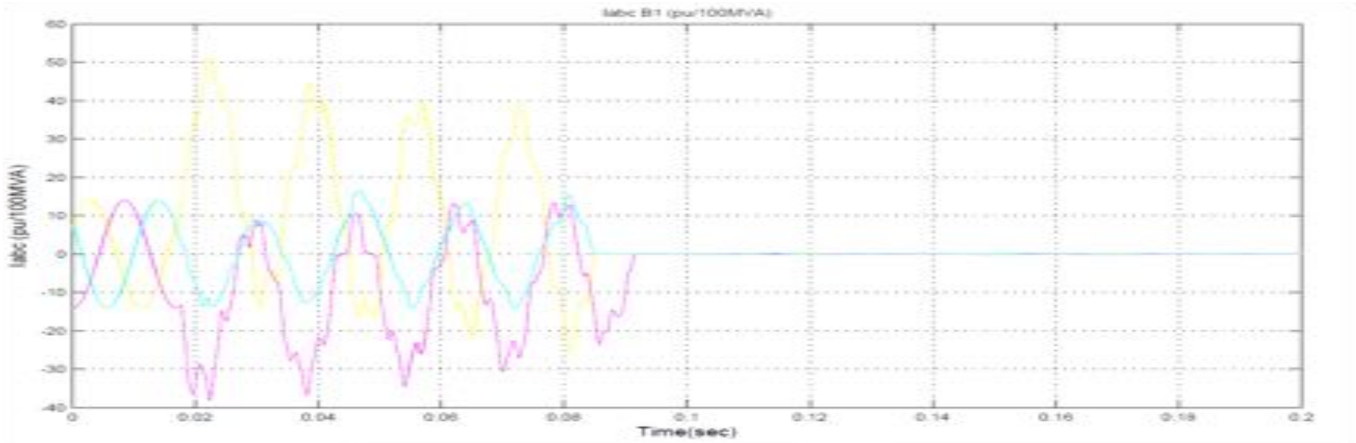


(c)

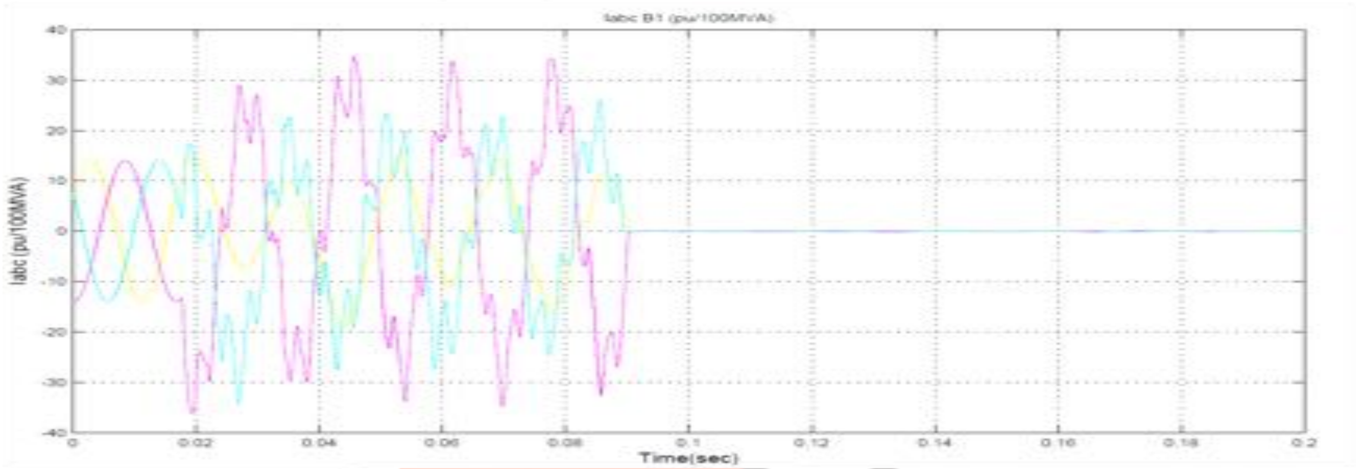
Fig. 3 (a) Phase A to ground fault, (b) Phase B to ground fault, (c) Phase C to ground fault

These are the current waveforms at bus B1 for Line to ground faults. In line to ground faults, line on which fault occurs in three phase transmission line can be phase A, phase B and phase C. The faulty phase shows disturbed current waveform than other healthy phase currents. Thus fault on each phase shows slight difference in their current waveforms with respect to others. This slight difference allows SVM to classify the fault types.

Similarly, double line to ground faults also shows slight differences between them so that they can be classified from each other. This fault includes any two phases shorted to the ground hence can be of three types namely phase A-B to ground, phase B-C to ground and phase A-C to ground. Current waveforms for these faults are as follows



(a)



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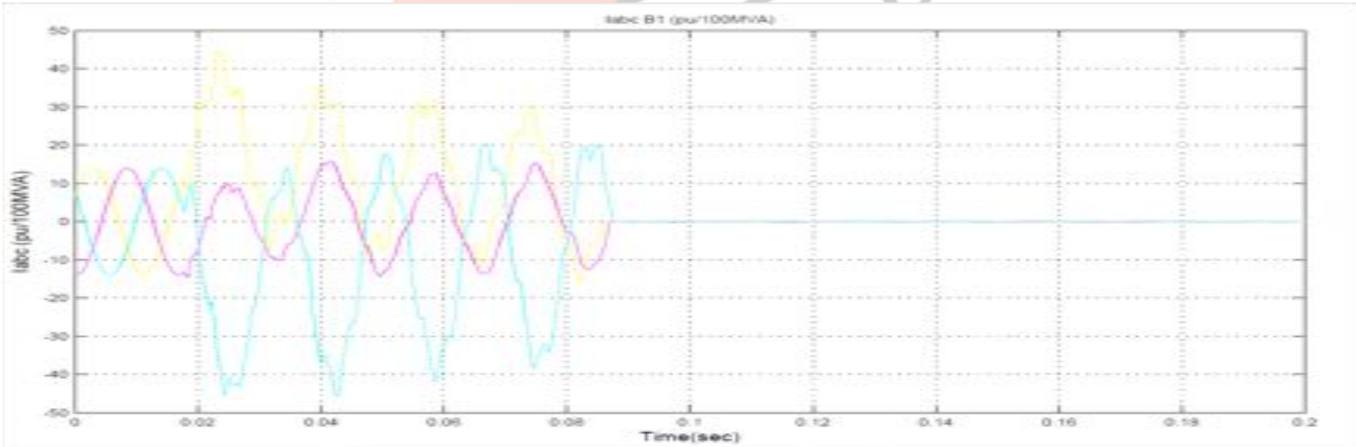
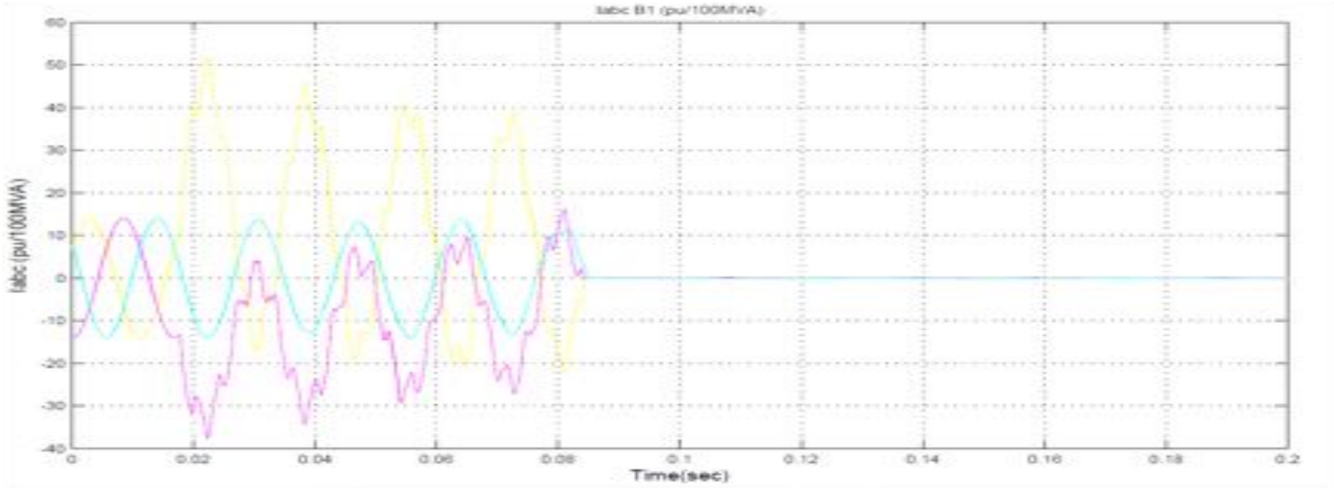


(c)

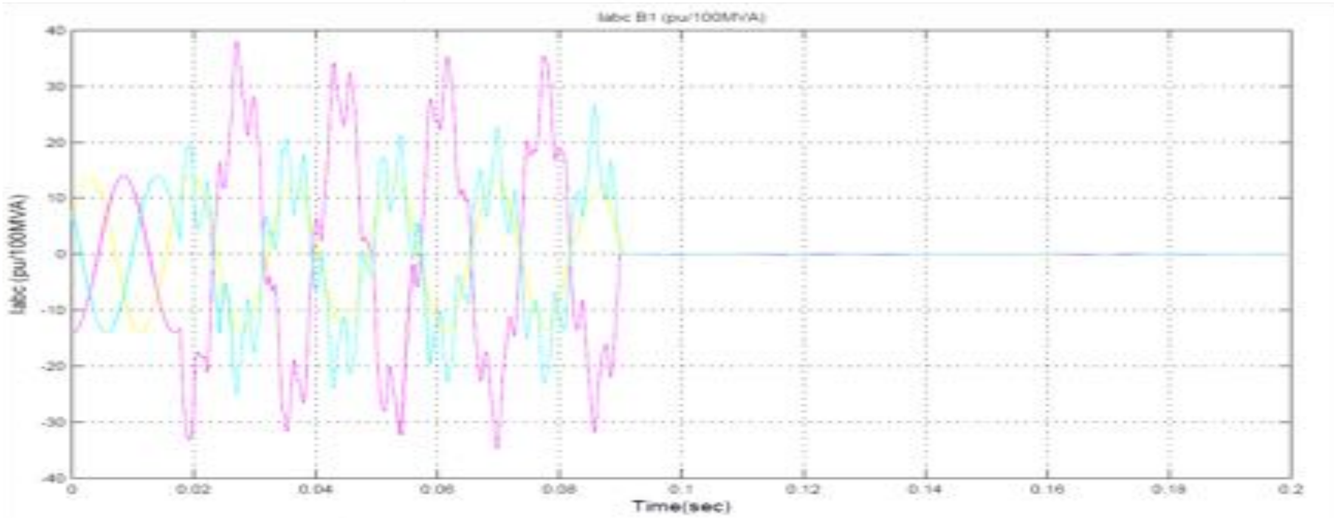
Fig. 4 (a) Phase A-B to ground, (b) Phase B-C to ground, (c) Phase A-C to ground

This shows that those phases on which fault occurs have the distorted current waveforms and hence fault can be distinguished and classified by analyzing that distortion in specific phases. Consider Phase A-B to ground fault, only phase A and B are more distorted than phase C current waveforms while in case of Phase B-C to ground, distortion can be seen in phase B and phase C than phase A. This allows us to classify double phases to ground fault amongst 3 types of faults namely Phase A-B to ground, Phase B-C to ground and Phase A-C to ground.

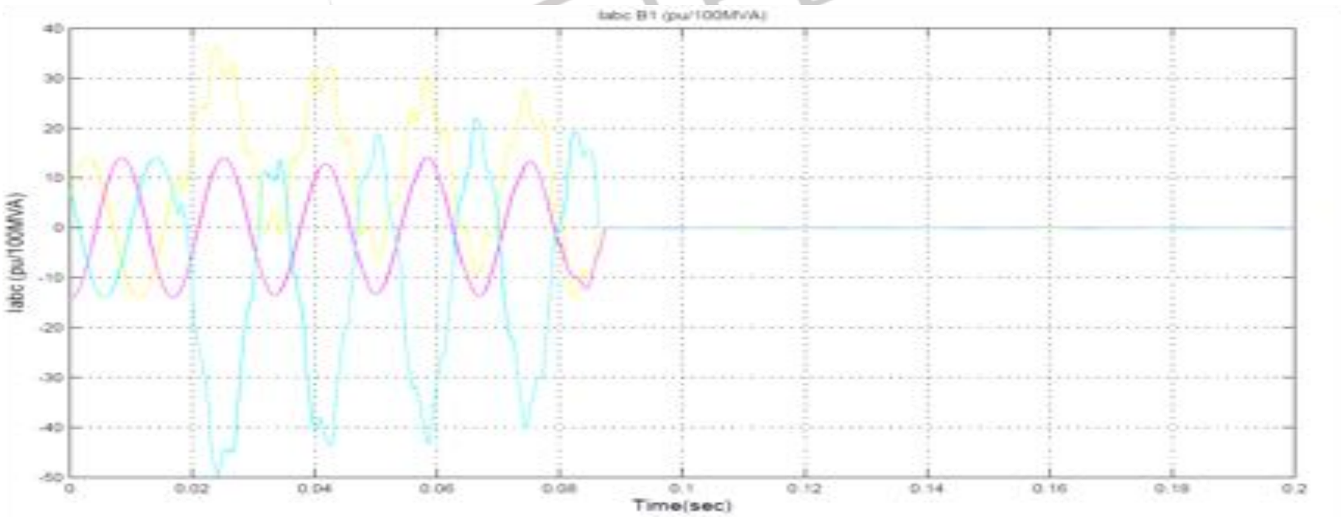
The line to line fault without ground also occurs on transmission line which is of 3 types Phase A to B, Phase B to C and Phase A to C. Only those phases show current distortion on which fault occurs. Current Waveforms for these type of faults are as follows



(a)



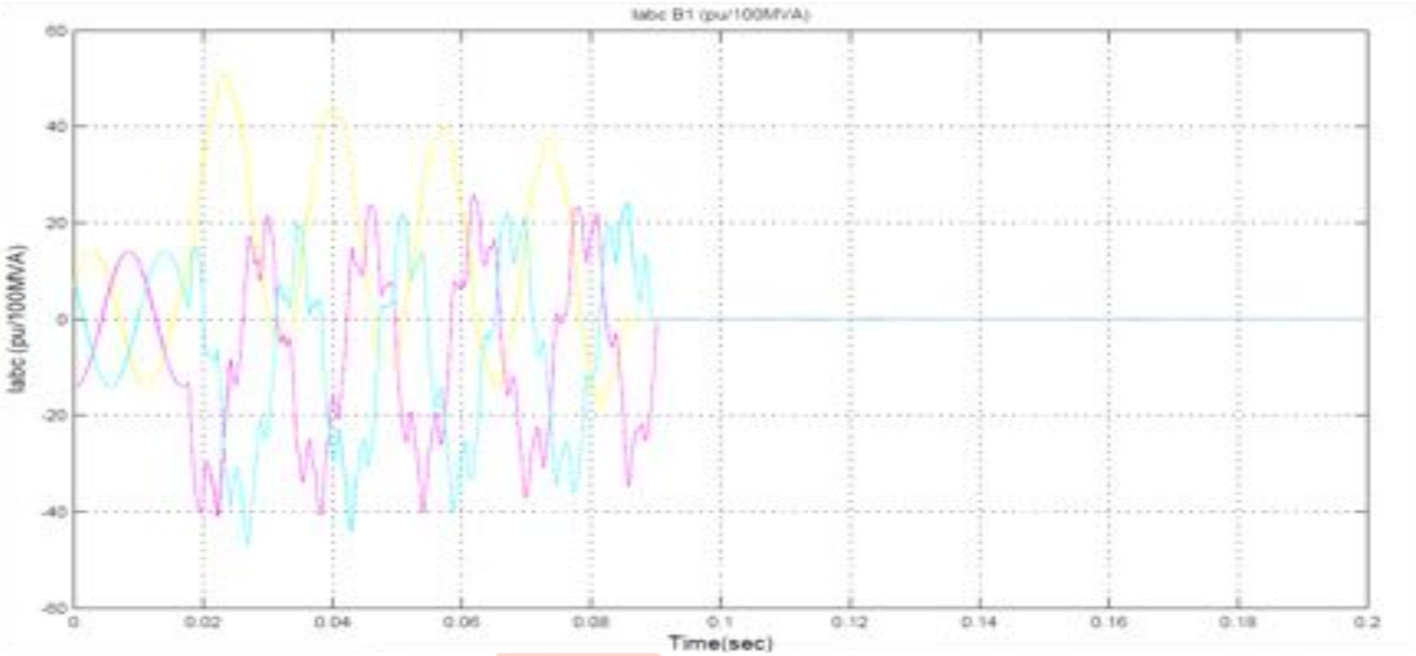
(b)



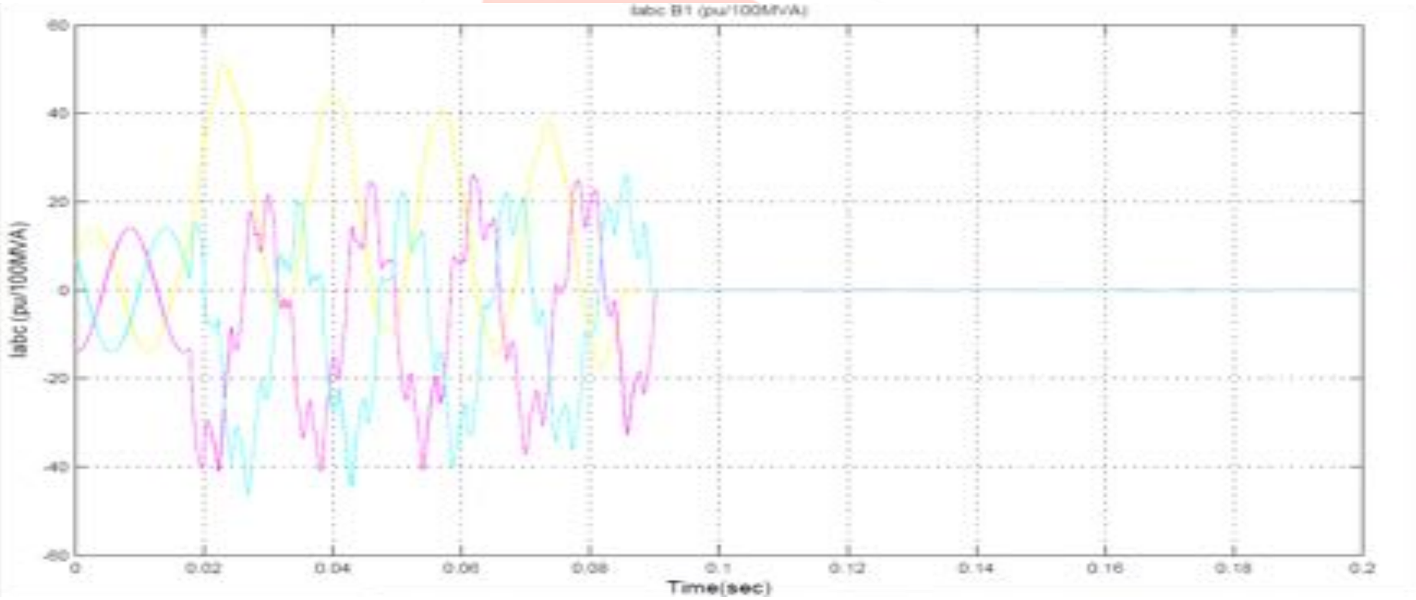
(c)

Fig. 5 (a) Phase A to B, (b) Phase B to C, (c) Phase A to C

There are two types of faults for three phase fault. One is three phase fault without ground and another is three phase to ground fault. Current waveforms for these faults are as follows



(a)



(b)

Fig. 6 (a) Three phase without ground, (b) Three phase to ground

In three phase fault without ground and with ground, the difference between their waveforms is very acute but SVM is able to distinguish them and classify them. Three phase without ground currents have slightly higher magnitude than three phase fault with ground.

The difference in waveforms are important for detection and classification of the fault types. If any two fault types show similar current waveforms, then their few instantaneous data are similar. These similarities can lead to misclassify the fault types. The detection is identified if the current waveforms are different than normal three phase current waveforms. The classification is done with the help of SVM technique which compares the current data with each pre-defined classes. Thus after comparing it can classify the most relevant class to the given test sample. More the training data more will be the accuracy of SVM technique. In this paper only current waveforms are considered for fault detection and classification. If more parameters are considered, then accuracy will increase. Parameters like current, voltage, resistances can play important role in classification due to their varying nature with fault type and location. Meaningless parameters must be ignored like length of line, size of conductors, type of conductors, etc.

IV. Fault Classification

As discussed earlier, SVM is implemented for classification of faults. There are 11 types of faults from which one fault type is to be assigned to test data through detection and classification. These fault types are shown in Table 2. Those faults can be represented as binary code having values '1' when fault occurs on that line and '0' when line does not participate in fault. This binary code is convenient to recognize the fault but one can choose to have string name if required. Each binary code belongs to certain specific class type like '1101' code represents 'Phase A-B to Ground' fault and fault number or fault class number four.

Table 2. Fault Types Classes

Faults	3 phase binary values				Class
	A	B	C	G	
Phase A to Ground	1	0	0	1	1
Phase B to Ground	0	1	0	1	2
Phase C to Ground	0	0	1	1	3
Phase A-B to Ground	1	1	0	1	4
Phase B-C to Ground	0	1	1	1	5
Phase A-C to Ground	1	0	1	1	6
Phase A to B	1	1	0	0	7
Phase B to C	0	1	1	0	8
Phase A to C	1	0	1	0	9
Phase A-B-C	1	1	1	0	10
Phase A-B-C to Ground	1	1	1	1	11

In general, SVM is used to classify between two classes but to classify amongst 11 faults, some modifications is done where 'if else' conditions are used. Thus fault types are divided into two classes each and break down into smaller and smaller class. Consider first 11 faults are divided into two classes, first is with ground and second is without ground fault. Then it is further divided into two classes, first single phase fault and second multi-phase fault. Multi-phase fault further divided into two classes namely double phase and triple phase faults. Thus this process continues and fault occurred on the system is identified and classified into an accurate class.

V. RESULTS AND DISCUSSION

In the given model, simulation is done and instantaneous data of fault current on bus B1 is taken from workspace in MATLAB and then trained to get SVM classifier model. More the training more will be the accuracy of model but more training requires more data and time which can also increase the cost. Model should be such a that it will require minimum training data and maximum accuracy which is tough. SVM is capable of giving much higher accuracy with lower training data.

The given model is trained with only one fault occurrence for each class. If more number of training data is given, then accuracy will increase. Single instance training to the model gives good results. Model can identify and classify accurately with varying fault resistance and ground resistance within certain limits.

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