Transmission Line Fault Detection and Classification

Manohar singh, Dr. B.K Panigrahi
Department of Electrical Engineering, Indian Institute of Technology, Delhi
Delhi, India-110016
manoharsingh33@ gmail.com

Dr. R. P. Maheshwari, Member IEEE
Department of Electrical Engineering, Indian Institute of Technology, Roorkee
Roorkee, India-247667
rudrafee@iitr.ernet.i

***Abstract*—Transmission line protection is an important issue in power system engineering because 85-87% of power system faults are occurring in transmission lines. This paper presents a technique to detect and classify the different shunt faults on a transmission lines for quick and reliable operation of protection schemes. Discrimination among different types of faults on the transmission lines is achieved by application of evolutionary programming tools.**

PSCAD/EMTDC software is used to simulate different operating and fault conditions on high voltage transmission line, namely single phase to ground fault, line to line fault, double line to ground and three phase short circuit. The discrete wavelet transform (DWT) is applied for decomposition of fault transients, because of its ability to extract information from the transient signal, simultaneously both in time and frequency domain. The data sets which are obtained from the DWT are used for training and testing the SVM architecture. After extracting useful features from the measured signals, a decision of fault or no fault on any phase or multiple phases of a transmission line is carried out using three SVM classifiers. The ground detection task is carried out by a proposed ground index. Gaussian radial basis kernel function (RBF) has been used, and performances of classifiers have been evaluated based on fault classification accuracy. In order to determine the optimal parametric settings of an SVM classifier (such as the type of kernel function, its associated parameter, and the regularization parameter c), five-fold cross-validation has been applied to the training set. It is observed that an SVM with an RBF kernel provides better fault classification accuracy than that of an SVM with polynomial kernel. It has been found that the proposed scheme is very fast and accurate and it proved to be a robust classifier for digital distance protection.

***Keywords*—Discrete wavelet transforms, Support vector machine (SVMs), Feature extraction, Fault classification accuracy and Ground index.**

I. INTRODUCTION

Fault detection and classification on transmission lines are important task to safeguard electric power systems. A fundamental part of a protective relay is a selector module which classifies the type of fault that has occurred and also to classify the "normal state". Reliable phase selection of the faulted phase is thus vitally important in order to avoid either tripping of the incorrect phase or unnecessary three-phase tripping. Moreover, a necessary requirement of phase selectors is high speed operation as the selection process must be completed in the immediate post-fault period before breaker opens. Traditional phase selection schemes suffer from some drawbacks due to complexity of the system model, lack of knowledge of its parameters, effect of remote-end infeed, fault resistance, mutual-coupling from adjacent parallel lines, etc. They do not have the ability to adapt dynamically to the system operating conditions, and to make correct decisions if the signals are uncertain.

Fault detection and classification is a very challenging task. Different attempts have been made for fault classification including approaches based on traveling waves [1-2], adaptive Kalman filtering [3], fuzzy logic, neural networks[4], and the fusion of different artificial intelligence techniques. Several researchers have proposed different techniques for fault classification of transmission lines using different types of neural networks and their combination with different transforms, such as wavelet and hyperbolic-s [5]. Although the neural-network based approaches have been quite successful in determining the correct fault type, the main disadvantage of neural-network is that it requires a considerable amount of training effort for good performance, especially under a wide variation of operating conditions (such as system loading level, fault resistance, source impedance, etc.). Moreover, another disadvantage of neural-network-based algorithms is that the training may not converge in some cases, as the starting point is chosen at random and can end up in a local minimum [6-7].

This paper presents a new approach for fault detection and classification on transmission lines using SVMs for training with an online wavelet-based preprocessing-stage. The algorithm is based mainly on calculating the RMS value of transient energy of pre-fault and post-fault signals of the three line currents and three line voltages. These preprocessed signals are trained with SVM. Fault classification accuracy is estimated for different loading and for source impedance

II. POWER SYSTEM NETWORK SIMULATION

A. System Studied

The single-line diagram of a power system for a two-terminal is shown in Fig. 1. The generators are represented by equivalent potential source and equivalent source impedance. The transmission line has been represented using the Bergeron line model in PSCAD/EMTDC. The line parameters and source impendence values are given in the Table I and Table II. To ensure proper fault classification, data used for training and testing must be adequate in number. Thus, huge data generation for different faults and system conditions is important for designing a fault classification scheme. The bulk data are generated using multiple run component of PSCAD software. With the help of this component we can use fault resistance, fault inception angle, and fault duration as variable parameter in PSCAD. The generated data is stored in output file option in the project setting option of PSCAD [8].

Different fault on the transmission line are created by using fault block in the PSCAD, fault timing in controlled using the time fault logic block. The fault position on the transmission line is adjusted manually by dividing the line into two parts of required length then fault is applied at point of division. In this way fault are simulated along the line in step of 20% of 120 km long line. Variation of source impendence is simulated by changing the impendence setting option of the source block. The flow of power on the line is controlled by changing the load angle between the two terminals of the line; normally load angle is kept in range of 5 – 20 degree [9-10].

B. *Typical Pyimary wave form*

Data is collected for one cycle of fault, simulation time is adjusted in such a way that 100 samples of fault data are taken for one cycle of fault. Fig. 2 (from top to bottom)) shows wave form of current and voltage signals for a-g, a-b, ab-g, abc-g faults and for no fault.

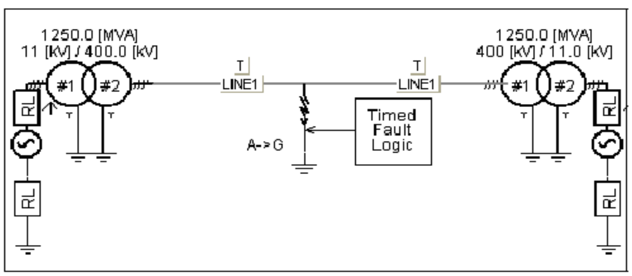


Fig.1. Transmission Line Model

Table I
Transmission line Parameters

Positive sequence resistance R1 Ω/KM	0.02056
Zero sequence resistance R1 Ω/KM	0.16270
Positive sequence inductance X1 Ω/KM	0.000096
zero sequence inductance X0 Ω/KM	0.003885
Positive sequence Capacitance C0, F/KM	2.50290e-05
Zero sequence Capacitance C0, F/KM	3.19500e-05

Table II
Source Parameters

Parameters	Source 1	Source 2
Positive sequence impendence	5∟85	10∟85
Zero sequence impendence	10∟85	20∟85

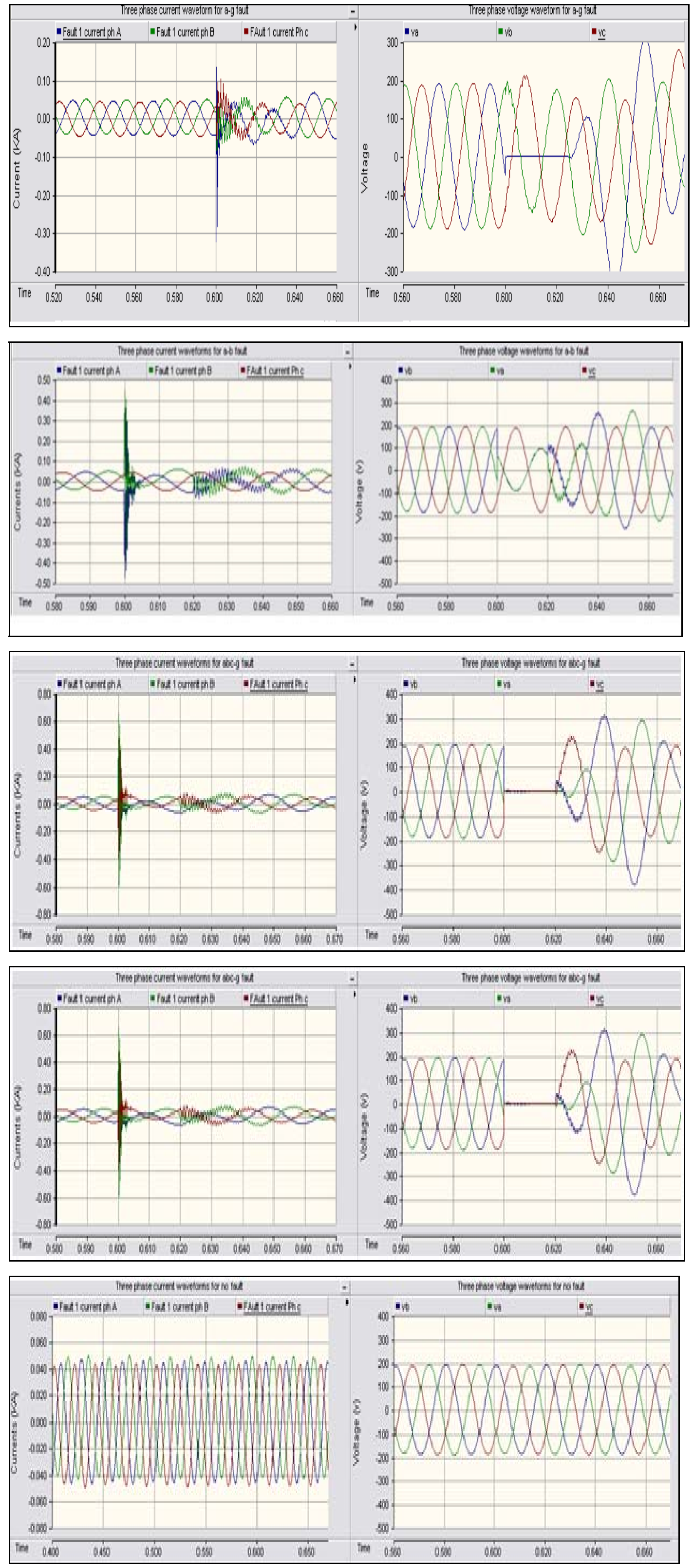


Fig.2. Simulation of shunt types of faults

III. WAVELET TRANSFORM

Wavelets are functions that satisfy the requirements of both time and frequency localization. The necessary and sufficient condition for wavelets is that it must be oscillatory, must decay quick1y to zero and must have an average value of zero. In addition, for the discrete Wavelet transform considered here, the Wavelets are orthogonal to each other [11]. Wavelets can provide multiple resolutions in both time and frequency. The signals can be accurately reproduced with the Wavelet analysis using relatively small number of components. The analyzing wavelets are called the "mother wavelets" and it's dilated and translated versions are called the "daughter wavelets". It has a digitally implementable counterpart called the discrete Wavelet transform (DWT). The generated waveforms are analyzed with Wavelet multi-resolution analysis (MRA) to extract sub-band information from the simulated transients. Daubechies Four (db-4) wavelet is used in this work for the analysis as it closely matches the signal to be processed which is of utmost importance in wavelet applications. Wavelet co-efficient of the signal are obtained by the decomposition of a discrete fault current and voltage signals using Mallat's algorithm [12].

Due to the unique feature of providing multiple resolutions in both time and frequency by wavelets, the sub-band information can be extracted from the original signal. When applied to faults, this sub-band information of faulted power system is seen to provide useful signatures of faults, so that fault classification can be done elegantly. By randomly shifting the point of fault on the transmission line, a number of simulations are carried out employing PSCAD/ EMTDC. The generated time domain signal for each case is analyzed using Wavelet transform. From the different decomposed levels [13-17]. Only first level output is considered for the analysis. As the absolute values of the summation of first level output for all the inception angles considered in the analysis are found higher as compared to that of other level outputs. It indicates that the total area under the characteristics of first level outputs is more than that of other level outputs. Another reason for the first level output to be selected as the parameter for fault Classification is due to discrimination in transient energy content of faulty and healthy signals is higher as compare to other levels. Moreover, as the sampling time considered in the analysis is 0.0002 s which corresponds to a sampling frequency of 5 kHz and the total number of wavelet levels considered is 6, therefore, 6^{th} level wavelet output corresponds to a frequency band of 70 – 160 Hz. Level 1 corresponds to frequency band of 1.25 – 5 kHz, which are rich in higher order harmonics, predominant in case of faults. The RMS value of transient energy of current and voltage signals is utilized as a feature for detection and discrimination among the faults**.** However, the fault is to be discriminated from other types of transient disturbances before using the classification algorithm.

IV. SUPPORT VECTOR MACHINE

Support vector machines (SVMs) were first introduced by Vapnik [19-20] in the late 1960's as a part of his development of statistical learning theory. Support vector machines are a type of hyper-plane classifier which attempts to find an optimal separating hyper-plane for the input training data. When formulated under SVMs the optimal hyper-plane is the decision boundary that attains the maximum margin of separation between the two classes. Optimal hyper-plane under these conditions can be uniquely determined by solving a constrained optimization problem whose solution has an expansion

$$w = \sum_i a_i x_i$$

which is the weighted sum of the training patterns that lie on the margin [24]. The training vectors which lie on the margin are referred to as the support vectors. Formally, given a set of features vectors x_i and corresponding class labels y_i we form the index pair $\{(x_i, y_i)\}$ where $x_i \in R$ and $y_i \in \{+1,-1\}$. We denote those input features x_i with label +1 as belonging to Class 1 and those feature vectors with label -1 as belonging to Class 2. In the linearly separable case we can find a hyper-plane which is able to separate the training data. This separating hyper-plane will take on the following form,

$$f(x) = wx + b$$

Where $w_i \in R$ and is the normal vector to the separating hyper-plane and $b \in R$ is the scalar bias. Hence, if x belongs to Class 1(+1 label) then $f(x) \geq 0$ and conversely if x belongs to Class 2 (-1 label) we have $f(x) \leq 0$. Consequently, we have the following constraints,

$$y_i(w_i x_i + b) \geq 0 \quad \text{for i= 1…n}$$

for a weight vector w and bias b we define the margin separation ρ as the separation between the hyper-plane and the closest feature vector. In particular an SVM finds the separating hyper-plane which maximizes the margin of separation ρ. The idea behind maximizing the margin of separation is rooted in concepts of structural risk minimization.

Roughly, when the margin of separation is maximized the generalization error on unseen test data tends to its minimum value [21-25].

The SVM classifier is also defined as

$$f(x) = w\Phi(x) + b \qquad (1)$$

where $\Phi(x)$ is a mapping function to map the input pattern x into higher dimensional space $\mathcal{H}$. This classifier $f(x)$ is linear in terms of the transformed data, but non-linear in terms of the original data

Following non-linear transformation, for the parameters of the decision function $f(x)$ the minimization of following cost function is

$$j(w,b) = \frac{1}{2}\|w\|^2 + c\sum_i \xi_i$$

Subjected to constraints

$$y_i(w.\phi(x_i) + b \geq 1 - \xi \quad \text{For i = 1…n} \qquad (2)$$

The solution to minimize the above cost function subject to the constraints in Eq. (2) is given from following dual:

Maximize

$$L_d = \sum_i \alpha_i - \frac{1}{2}\sum_{i,j} \alpha_i \alpha_j y_i y_j \phi(x_i)\phi(x_j)$$

$$L_d = \sum_i \alpha_i - \frac{1}{2}\sum_{i,j} \alpha_i \alpha_j y_i y_j k(x_i, x_j) \quad (3)$$

Where $k(x_i, x_j)$ known as kernel, is a non-linear function and is defined as

$$k(x_i, x_j) = \phi(x_{i,} x_j) \quad (4)$$

Subjected to constraint

$$0 \le \alpha_i \le c$$

$$\sum_i \alpha_i y_i = 0 \quad (5)$$

Solution is given as

$$w = \sum_i^{N_s} \alpha_i y_i \phi(x_i)$$

where N_s is the number of support vectors.

The kernel function in an SVM plays the central role of implicitly mapping the input vector (through an inner product) into a high-dimensional feature space. In the present study, radial basis functions (RBFs)) have been used. They are defined as follows

$$k(x, y) = e^{\left(-\gamma\|x-y\|^2\right)} \quad \text{Where } \gamma = \frac{1}{2\sigma^2} \quad (6)$$

V. PROPOSED FAULT CLASSIFICATION SCHENE

A 400kv, 50 Hz power system shown in Fig.1, consisting of two sources representing two areas connected by 128 km long transmission line is used for simulation studies. Faults take place at different position of transmission line. All the data is collected from sending end of the system. Simulations of faults which occur at 0.6 sec are shown in Fig. 2. . Fault signals (voltages and currents) are collected for a cycle at 50 Hz. These signals are taken in discrete form, 100 samples of current and 100 samples of voltage are taken for all three phases for all 11 types of faults [25].

The proposed scheme makes use of SVM classifier for detection and classification of fault. Fig. 3 shows the flow chart of proposed algorithm. The fault classifier has three classifiers for each phase. The extracted features are fed to these classifiers and their output indicates the type of fault. The voltages and currents signal are sampled at a frequency of 5 kHz. The RMS value of transient energy of voltages and currents are extracted using db4 as mother wavelet. The decomposition is performed at level 1, which contains rich. harmonics of order 25-50 Hz. From the wavelet decomposition of simulated signals (voltage and current), it is clearly detectable that RMS values of transient energy of current signals for faulty phases is much more as compare to healthy phases. Then these RMS value of transient energy of current and voltage are exported to support vector machine model for training. The output of each SVM indicates weather a particular phase is involved in fault or not [34].

Ground fault detection is carried through detection of Zero-Sequence component. Phases which do not involve the ground has almost zero, zero-sequence component, where as for phases involving ground have observable amount of zero-sequence component.

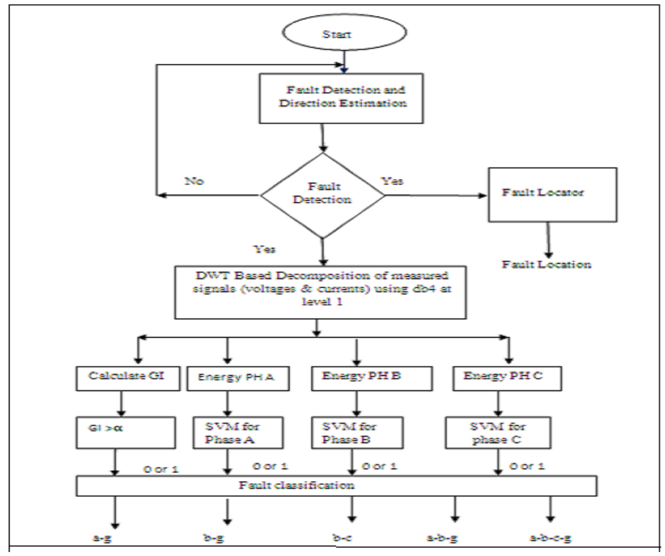


Fig 3. Fault detection and classification algorithm

A. Data Generation

For training and testing of SVM, the fault simulation has been carried out on transmission system as shown in Fig.1. PSCAD software is used to simulate the faults on the transmission line. Table III shows the different conditions that are simulated on transmission line for data generation used for training the SVMs and Table IV shows condition corresponding to the data simulated for testing the trained models.

Table III

Line and system parameters used for generation of training patterns

Fault type	a-g, b-g, c-g, a-b, b-c, c-a, a-b-g, b-c-g, c-a-g, a-b-c and a-b-c-g
Fault location (KM)	25.6, 51.2, 76.8 and 102.4 (128 KM line length)
Fault resistance (Ω)	0 , 25 , 50 , 75 , 100 , 125 and 150
Fault inception angle (0')	0, 45, 90, 135, 180, 225, 270, 315 and 360
Load angle variation (0')	10% and 20% (source 1)

Table IV

Line and system parameters used for generation of testing patterns

Fault type	a-g, b-g, c-g, a-b, b-c, c-a, a-b-g, b-c-g, c-a-g, a-b-c and a- b-c-g
Fault location (KM)	19.2 and 57.6
Fault resistance ( )	5 Ω, 30 Ω, 55 Ω, 80 Ω, 105 Ω, 135 Ω and155Ω
Fault inception angle (0')	0, 60, 120, 180, 240, 300 AND 360
Load angle variation (0')	5% and 15% (source 1)

B. Selection of mother wavelet for feature Extractions

The Daubechies family is one of the most suitable wavelet families in analyzing power-system transients although there are no definite criteria for the selection of wavelets; the best choice is a wavelet that most strikingly exhibits the phenomena to be studied. It has been found that db4, with its characteristic as the shortest wavelet in its family, is an excellent choice to detect abrupt change in RMS value of transient energy of the pre-fault and post-fault signals. Even though other families of wavelet-transform also give change in transient energy of the pre-fault and post-fault signals, but this change is more in case of db4 mother wavelet. Hence db4 is used as mother wavelet. The Fig.4.shows the variation of wavelet coefficients decomposed at level 1 using db4 as mother wavelet. On the top of Fig. 4 comparison of phase 'a" fault current for single line to ground fault vs. normal load current is shown, middle corresponds to phase 'b' current and bottom to phase 'c' current for the same type of fault.

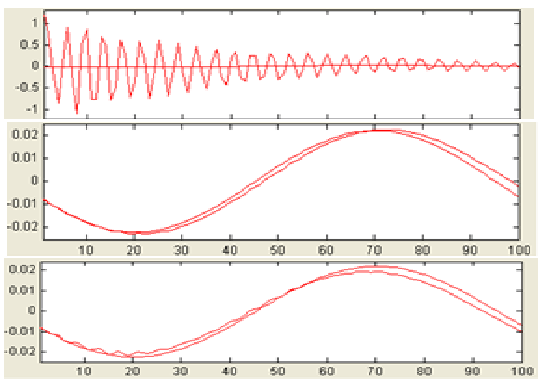


Fig.4. Discrete Samples of fault currents

C. Feature extraction

The proposed fault classification technique is based on RMS value of transient energy of the detail coefficient of the respective phases of voltage and current signals. Considering a sampling frequency of 100 samples/cycle of a 50 Hz fundamental frequency signal, the measured signals (three voltages and three currents) are decomposed into approximation (A1) and detail coefficients (D1) using a db4 mother wavelet. Decomposition is performed up-to 10 levels; the details coefficients extracted by wavelet transform at level 1 decomposition have more value of transient energy under fault duration as compare to pre-fault signals. Hence fault classification can be done more effectively using transient energy of these details coefficients at level-1 of voltage and current signals. Fig. 5, Shows the complete decomposition of fault signal up-to level 6 for phase "a" current and voltage signal when a-g fault occur at 50% of line length. Fig. 6 gives value of transient energy of samples corresponding to different simulated signals. The shaded potion shows that transient energy of fault phase 'a' current on left side and voltage on right side when phase "a-g' fault takes place[35-36].

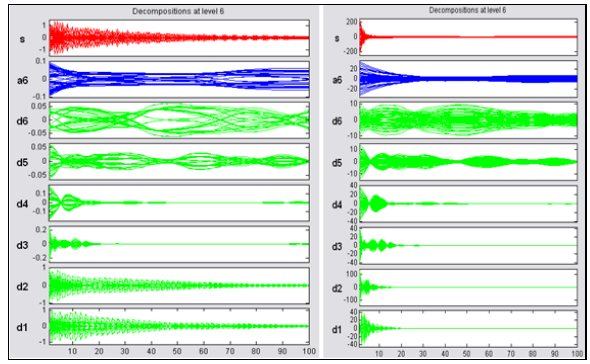
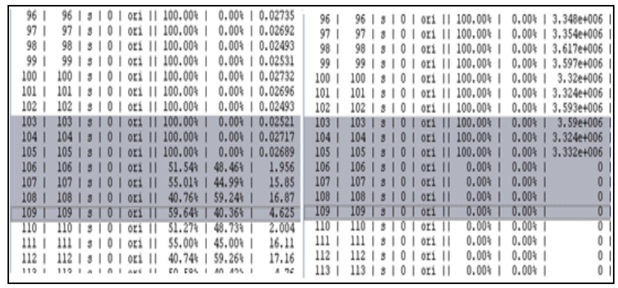


Fig.5. Wavelet coefficients of phase "a" for a-g



96	96	s	0	ori	100.00%	0.00%	0.02735
97	97	s	0	ori	100.00%	0.00%	0.02692
98	98	s	0	ori	100.00%	0.00%	0.02493
99	99	s	0	ori	100.00%	0.00%	0.02531
100	100	s	0	ori	100.00%	0.00%	0.02732
101	101	s	0	ori	100.00%	0.00%	0.02696
102	102	s	0	ori	100.00%	0.00%	0.02493
103	103	s	0	ori	100.00%	0.00%	0.02521
104	104	s	0	ori	100.00%	0.00%	0.02717
105	105	s	0	ori	100.00%	0.00%	0.02689
106	106	s	0	ori	51.54%	48.46%	1.956
107	107	s	0	ori	55.01%	44.99%	15.85
108	108	s	0	ori	40.76%	59.24%	16.87
109	109	s	0	ori	59.64%	40.36%	4.625
110	110	s	0	ori	51.27%	48.73%	2.004
111	111	s	0	ori	55.00%	45.00%	16.11
112	112	s	0	ori	40.74%	59.26%	17.16
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

96	96	s	0	ori	100.00%	0.00%	3.348e+006
97	97	s	0	ori	100.00%	0.00%	3.354e+006
98	98	s	0	ori	100.00%	0.00%	3.617e+006
99	99	s	0	ori	100.00%	0.00%	3.597e+006
100	100	s	0	ori	100.00%	0.00%	3.32e+006
101	101	s	0	ori	100.00%	0.00%	3.324e+006
102	102	s	0	ori	100.00%	0.00%	3.593e+006
103	103	s	0	ori	100.00%	0.00%	3.59e+006
104	104	s	0	ori	100.00%	0.00%	3.324e+006
105	105	s	0	ori	100.00%	0.00%	3.332e+006
106	106	s	0	ori	0.00%	0.00%	0
107	107	s	0	ori	0.00%	0.00%	0
108	108	s	0	ori	0.00%	0.00%	0
109	109	s	0	ori	0.00%	0.00%	0
110	110	s	0	ori	0.00%	0.00%	0
111	111	s	0	ori	0.00%	0.00%	0
112	112	s	0	ori	0.00%	0.00%	0
113	113	s	0	ori	0.00%	0.00%	0

Fig.6.Transient energy of current and voltage for phase "a" for a-g fault

D. Scaling for feature extraction

The input patterns (training and test patterns) are normalized to [+1,-1] before inputting to the SVM module [40]. The main advantage is to avoid attributes in greater numeric ranges dominate those in smaller numeric ranges. Another advantage is to avoid numerical difficulties during the calculation. Because kernel values usually depend on the inner products of feature vectors, large attribute values might cause numerical problems

E. Performance Evaluation

1. Parameter Selection and Training

Once the training samples are obtained, the next step is to determine the optimal parametric settings of the SVM. In this process, the type of kernel function, its associated parameter, and the regularization parameter C must be decided. To optimize these parameters, five-fold cross-validation [44] has been applied to the training set. This procedure consists of the following steps. First, randomly divide all of the available samples in the training set into five equal-sized subsets. Second, for each model-parameter setting, train the SVM classifier five times; during each time, one of the subsets is held out in turn while the rest of the subsets are used to train the SVM. This trained-SVM classifier is then tested using the held-out subset, and its accuracy values are recorded. Finally, the model with the highest accuracy is adopted. Various parameters for the SVM (such as regularization parameter C, sigma of RBF, etc.) are varied as C from 1 to 10000, and sigma of RBF from 2000 to 0.02, to choose the best parameters for SVM. For C = 10 and σ = 20 gives the maximum accuracy.

Table V
Selection of parameters for RBF kernel function

C	Accuracy variation with various value of sigma (σ)					
1	2000	200	20	2	0.2	0.02
10	96.7532	96.7532	**98.7013**	87.9870	88.0345	90.2597
100	96.7532	96.7532	98.7013	97.0779	87.9897	89.6104
1000	96.7532	96.7532	98.7013	96.4286	96.1039	87.9870
10000	96.7532	96.7532	98.7013	96.4286	96.1039	96.1039

2. Ground Detection in Ground faults

Usually, it is not possible to identify the involvement of ground using voltage and current signals. Therefore, the ground fault involvement detection task is carried out using zero-sequence current (I_0). For detecting the involvement of ground fault, a ground detection index (GI) is proposed. Where $I_{pha}, I_{phb}, I_{phc}$ are phase currents?

$$GI = I_0 = \frac{1}{3}(I_{pha} + I_{phb} + I_{ph\,c})$$

When the value of GI index is more than the threshold (α) of 0.025 for fault resistance of 5 Ω, it indicates the involvement of fault with ground. The variation of zero-sequence current for different types of faults is calculated. It is seen from Fig.7 that for a fault involving ground (L-G); the value of GI is much above the threshold value. Whereas, for a fault not involving ground (L-L), the value of GI is much below the threshold value [35].

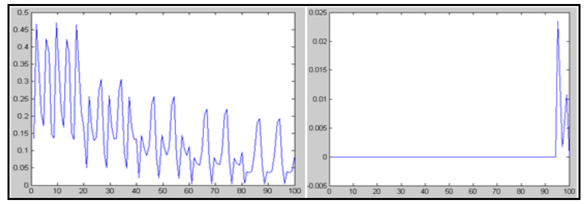


Fig.7 Zero sequence current component for a-g and a-b faults

3. Fault Classification Performance

The variation of fault classification accuracy for different types of fault at different fault location is tabulated in Table VI. Variation of source (S2) impendence at receiving end as shown in Table III, is also taken into account. For model generalization the line parameter of another line is also taken into consideration. Training and Testing samples are collected for all the possible conditions that occur on the transmission line. Testing samples are different from the training samples. These training samples are trained through SVM structure, and are tested against the different testing samples.

The classification accuracy is between 90-100%. When source variation and parameter variation are taken into account the classification accuracy falls marginally. But this can be improved by training the SVM for mixed training data of variable source impendence and line parameter on a another line. Results are shown in Table VII for different training and testing samples. Following are notation used in Table VII.

K Training data at 50% and 20% of line length
L Training data at 50%, 20% and 40%of line length
M Training data at 50%, 20%, 40% and 60%of line length
N Training data at 50%, 20%, 40%, 60% and 80%of line length
O Training data at 50%, 20%, 40%, 60% and 80% of line length and source variation at receiving end as shown in Table III

Table VI
Detailed fault classification result for different training samples and testing samples for different fault location

Line length in (%)	Training samples	Testing samples	TP PhA	TN PhA	TP Ph B	TN Ph B	TP Ph C	TN PhC	Accuracy Ph A (%)	Accuracy Ph B (%)	Accuracy Ph C (%)
50	1848	308	304	04	304	04	307	01	98.7013	98.7013	99.6753
20	1848	1155	1137	18	937	218	1155	00	98.4416	81.1255	100.0000
20	6853	1155	1108	47	1155	00	1155	00	95.9307	100.0000	100.0000
40	1848	1155	1155	00	1119	36	1155	00	100.0000	96.8831	100.0000
40	6853	1155	1146	09	1155	00	1155	00	99.2208	100.0000	100.0000
60	1848	1155	1130	25	924	231	1144	11	97.8355	80.0000	99.0476
60	6853	1155	1115	40	1155	1155	1150	05	96.5368	100.0000	99.5671
80	1848	1155	1106	49	891	264	1115	40	95.7576	77.1429	96.5368
80	6853	1155	1107	48	1155	00	1150	05	95.8442	100.0000	99.5671

Table VII
Fault classification result for different training samples and testing samples for different fault location, including source variation

Line length	Training samples	Testing samples	TP Ph A	TN Ph A	TP Ph B	TN Ph B	TP Ph C	TN Ph C	Accuracy Ph A (%)	Accuracy Ph B (%)	Accuracy Ph C (%)
K	2998	201	153	48	186	15	172	29	76.1194	92.5373	85.5721
L	4158	509	496	14	505	04	508	01	97.4460	99.2141	99.8035
M	5313	710	641	69	694	16	703	07	90.2817	97.7465	99.0141
N	6468	911	791	120	893	18	905	06	86.8276	98.0241	99.3414
O	6853	1112	1077	35	1094	18	1106	06	96.8525	98.8309	99.4040
P	8008	1313	1078	253	1202	111	1118	195	82.1021	91.5461	85.1485

VI. CONCLUSION

In this paper, an accurate technique of identification and classification of faults on transmission line has been proposed. The method utilizes the samples of current and voltage extracted from the fault point. Wavelet transforms is used to extract the transient energy feature from these sampled signals. This feature vector then acts as input to the SVM for training. The proposed scheme was found to be immune of fault resistance, fault inception angle, change in load, lightning disturbance, auto-reclosing action, and even CT saturation as the transient energy content in these action is very low due to their very short existence time The proposed scheme is also free from many difficulties that are faced by traditional neural networks approaches, such as generalization

The proposed scheme can be extended for locating the exact location of fault and classification of fault on a series compensated lines, but a few more features may be required for the training of SVM.

REFERANCE

[1] D. W. P. Thomas and C.Christopulo, "Ultra-high speed protection of series compensated lines," IEEE Transactions on Power Delivery, Vol. 7, pp. 139–145, January 1992.

[2] Jamil, M. Thomas, M. S. Moinuddin and P. Kumar, "Fuzzy approach to fault classification for transmission line protection," Proc. IEEE Tencon 99 Conf., Vol. 2, pp. 1046–1050, September 1999.

[3] A. A. Girgis, A. A. Sallam and A. Karim, El-Din, "An adoptive protection scheme for advanced series compensated (ASC) transmission lines," IEEE Transaction on Power Delivery, Vol. 13, No. 2, pp.414–420, April 1998.

[4] B. Das and J. V. Reddy, "Fuzzy-logic-based fault classification scheme for digital distance protection," IEEE Transactions on Power Delivery, Vol. 20, pp. 609–616, April 2005.

[5] R. N. Mahanty and P. B. Dutta Gupta, "A fuzzy logic based fault classification approach using current samples only," Int. J. Elect. Power Syst. Res., Vol. 77, pp. 501–507, 2007.

[6] H. Wang and W. W. L. Keerthipala, "Fuzzy-neuro approach to fault classification for transmission line protection," IEEE Transactions on Power Delivery, Vol. 13, No. 4, pp. 1093–1104, October 1998.

[7] P. K. Dash, S. R. Samantaray and G. Panda, "Fault classification and section identification of an advanced series-compensated transmission line using support vector machine," IEEE Transactions on Power Delivery, Vol. 22, No. 1, pp. 67–73, January 2007.

[8] PSCAD/EMTDC Version 3.08, Winnipag, MB, Canada: Manitoba HVDC Research Centre.

[9] PSCAD/EMTDC Power System Simulation Manual, Winnipeg, Mb, Canada S. Haykin, Neural Networks- A Comprehensive Foundation, Second Edition Englewood Cliffs, NJ: Prentice-Hall ,1999

[10] Michel Misiti, Yves Misiti, Georges Oppenheim and Jean-Michel Poggi, "Wavelet Tool box 4 matlab user's Guide," March 2008.

[11] G. Strang and T. Nguyen, "Wavelet and Filter Banks" Cambridge, MA: Wellesley-Cambridge, 1996

[12] Daubechies, "Ten Lectures on wavelet," Philadelphia, PA: Soc. Industrial Application Math., 1992.

[13] C. H. Kim and R. Aggarwal, "Wavelet transform in power system," IET Power Engineering Journal, Vol.15, pp. 193-200, August 2001.

[14] C. S. Burrus, R. A. Gopinath, and H. Guo, "Introduction to Wavelets and Wavelet Transform: A primer. Englewood Cliff," NJ: Prentice-Hall.1998.

[15] T. M. Lai, L. A. Snider and E. Lo, "wavelet transform based relay algorithm for the detection of stochastic high impedance faults," ELSEVIER Transaction on Electric Power System Research, pp. 626-633.

[16] T. M. Lai, L. A. Snider, E. Lo, and D. Suntanto, "High-impedance fault detection using discrete wavelet transform and frequency range and rms conversion," IEEE Transactions on Power Delivery, Vol.20, No.1, pp. 397-407, January2005.

[17] Chunju Fan, K. K. Li, W. L. Chan and Weiyong Yu, "Study of protection scheme for transmission line based on wavelet transient energy," Electrical Power & Energy System, Vol.28, pp. 459-470, 2006.

[18] Fernando H. Magnago and Ali Abur, "Fault location using wavelet," IEEE Transactions on Power Delivery, Vol. 13, No. 4, October 1998.

[19] Vladimir N. Vapnik, "An overview of statistical learning theory," IEEE Transactions on Neural Networks, Vol.10, No.5, 1999

[20] C. Cortesand and V. Vapnik, “Support vector network,” Machine Learning, Vol. 20, pp. 273-297, 1995.
[21] C. J. C. Burges, “A tutorial on support vector machine for pattern recognition,” Data Mining and knowledge Discovery, Vol.2, No.2, pp. 121-167, 1998.
[22] Haykin Simon “Neural networks: A comprehensive foundation”, 2nd Edition, Prentice-Hall, Inc., 1999.
[23] Chih-Wei Hsu and Chih-Jen Lin, A, “Comparison of methods for multiclass support vector machines,” IEEE Transactions on Neural Networks, Vol.13, No.2, March 2002.
[24] Chih-Wei Hsu and Chih-Jen Lin, “LIBSVM: A library for support vector machines,” 2001
[25] Joe-Air Jiang, ching-Shah chen, and Chih-Wen Liu, “A new protection scheme for fault detection, direction discrimination, classification, and location in transmission lines,” IEEE Transactions on Power Delivery, Vol.18, No.1, pp. 1253-1261, January 2003.
[26] U. Parikh, R. P. Maheshwari, B. Das and B. Bhalja, “A new fault classification technique for protection of series compensated transmission lines,” International Conference on Power System Protection, CPRI, Bangalore, India, 20–21 February 2007.
[27] R. K. Aggarwal, Q. Y. Xuan, A. T. Johns, R. W. Dunn and A.Bennett, “A novel fault classification technique for double-circuit lines based on a combined unsupervised/supervised neural network,” IEEE Transactions on Power Delivery, Vol. 14, No. 4, pp. 1250–1256, October 1999.
[28] Bhavesh, Bhalja and R. P. Maheshwari, “Trends in adaptive distance protection of multi – terminal and double-circuit lines,” Int. J. Elect. Power Components Syst., Vol. 34, pp. 603–617, June 2006.
[29] Bhavesh, Bhalja and R. P. Maheshwari, “Protection Of Double Circuit Line Using Wavelet Transform,” IE Journal-EL, Vol. 87, pp. 67-70 September 2006.
[30] Bhavesh, Bhalja and R. P. Maheshwari, “Philosophy of protection for multi-terminal and double-circuit lines,” Int. Conf. on Computer Applications in Electrical Engineering Recent Advances, Roorkee, India, Sept. 28-October 1, 2005, pp. 582-588.
[31] Yi, Hu, Damir, Novosel, Murari Mohan Saha, and Volker Leitloff, “An Adaptive Scheme For Parallel Line Distance Protection,” IEEE Transactions on Power Delivery, Vol. 17, No. 1, pp. 105-110 January 2002.
[32] Xiangning Lin, Hanil Weng, and Bin Wang, “Identification of cross country fault of power transformer for fast unblocking of differential protection,” IEEE Transactions on Delivery, Vol. 24, No. 3, pp. 1079-1086 July 2009.
[33] Bhavesh, Bhalja and R. P. Maheshwari, “New differential protection scheme for tapped transmission line,” IET Gener. Transm. Distr., Vol. 2, pp. 271–279, 2008
[34] Bhavesh, Bhalja and R. P. Maheshwari, “Wavelet-based fault classification scheme for a transmission line using a support vector machine,” Electric Power Components and Systems, Vol.36, Pp. 1017-1030, 2008.
[35] V. S. Kale, S. R. Bhide, R. P. Bedekar and G. V. K. Mohan, “Detection and classification of faults on parallel transmission lines using wavelet transform and neural network,” International Journal of Electric and Electronics Engineering Vol. 1, pp.364-368, 2008.
[36] P. S. Bhowmik, P. Purkait, K. Bhattacharya, “A novel wavelet transform aided neural networks based transmission line fault analysis method,” Electrical Power & Energy System, Vol.31, No. 5, pp. 213-219, 2009.
[37] Robert Salat and Stanislaw Osowski, “Accurate fault location in the power transmission line using support vector machine approach,” IEEE Transaction on Power Sysyem, Vol.19, No.2, May 2004.
[38] S.M. De Souza, A.P. Alves da Suva, and A.C.S. Lima, “Attribute selection for fault location recognition in transmission lines,” IEEE Power Engineering Society General Meeting, pp. 6, October, 2006.
[39] Thomas Dalstein and Bernd Kulicke, “Neural Network Approach to Fault Classification for High Speed Protective Relaying,” IEEE Transactions on Power Delivery, Vol.10, No. 2, pp. 1002-1011, April 1995.
[40] C. H. Kim and R. Aggarwal, “Wavelet transform in power system,” IET Power Engineering Journal, Vol.15, pp. 193-200, August 2001.
[41] B. Ravikumar, H. P. Khincha, D. Thukaram, “An intelligent approach using support vector machines for monitoring and identification of faults on transmission systems,” IEEE Power India Conference, pp. 184-190, 05, June, 2006.
[42] P. K. Dash, A. K. Pardhan, and G. Panda, “Application of minimal radial basis function neural networks to distance protection,” IEEE Transactions on Power Delivery, Vol.16, No. 1, pp. 68-74, January 2001.
[43] R. N. Mahanty, P. B. and Dutta, “Application of radial basis function neural networks to fault classification and location in transmission lines,” IEE Proc. Gener. Transm. Distrib., Vol.151, No. 2, March 2004.
[44] Jeo-Air Jiang, Ching-shan Chen, and chin-Wen Liu, “A new protection technique for fault detection, direction discrimination, classification, and location in transmission lines,” IEEE Transactions on Power Delivery, Vol.18, No. 1, pp. 34-42, January 2003.
[45] A. S. Omar Youssef, “New algorithm to phase selection based on wavelet transform,” IEEE Transactions on Power Delivery, Vol.17, No.4, pp. 908-914, October 2002.