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Combined wavelet transforms and support vector machine based fault detection and classification in high voltage transmission lines

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ABSTRACT

Transmission line protection is an important issue in power system engineering because 85 to 87% of power system faults are occurring in transmission lines. This paper presents a novel technique to detect and classify the different operating conditions in high voltage transmission lines to contribute quick and reliable operation of protection schemes. Discrimination among different operating conditions of transmission lines is achieved by combining wavelet transforms with support vector machine. MATLAB(7.3) / Simulink is used to simulate different operating conditions in high voltage transmission lines. The fault conditions considered are single phase to ground fault, line to line fault, double line to ground fault and three phase short circuit conditions. The circuit breaker operation and capacitor switching are the non-fault operating conditions. The discrete wavelet transforsms (DWT) are applied for analysis of simulated three phase current signals, because of its ability to extract information from the transient signal, simultaneously both in time and frequency domain. The wavelet family chosen is Daubechies, filter used – DB2, resolution level -3.The data sets which are obtained from the DWT are used for training and testing the support vector machine (SVM). In this proposed scheme SVM is used as classifier. It has the ability to detect and classify the given operating condition whether it is a fault or non-fault operating condition. It is concluded that this scheme discriminates the six different operating conditions considered in a very clear manner.

Introduction

The complexity in power systems has been increased with the advent of technological advancements as well as fast and vast growth of modern power system networks. Also the users demand for high quality reliable power.

As a result more advanced security control is required. Fault detection is one of important task in security control and the key technique for improving power quality is to remove the faults by protecting equipments as quickly as possible. [1], [2],[3].

Transmission line is one of the main components in every electric power system. It is exposed to environment and possibility of experiencing faults on transmission line is generally higher than the other components.

When fault occurs in a transmission line it is important to detect the fault location and type in order to make necessary repair and to restore power as soon as possible without any maloperation. The time required to detect the fault in the line will affect the quality of power. The speed and accuracy of digital relays of transmission lines can be improved by accurate and fast fault detection and classification. [4], [5], [6].

Studies on high voltage transmission lines fault detection may be classified into the following three methods:

1. Circuit theory based method
2. Travelling theory based method
3. Intelligent systems

Method 1 detects a fault through the nodal voltages, the line currents and the impedance changes.

Method 2 identifies the fault using the return time of the pulse wave.

Method 3 uses several approaches such as expert systems, fuzzy logic and artificial neural network.

Due to many possible causes of fault and the non-linear operation of some power devices under various fault conditions, the first two conventional methods may not be satisfactory in complex transmission lines [7],[8]. The wavelet transform is a relatively new and powerful tool in the analysis of transmission line transient phenomena because of its ability to extract information from the transient signals simultaneously in both time and frequency domain. Recently wavelet transform have been applied to analyze the power system transients as well as fault location and detection problems [7-10].Support Vector Machine (Machine intelligence technique) (SVM) is a relatively new computational learning method based on the statistical learning theory which is mostly used for classification purposes. Hence in this paper the combined wavelet transform and support vector machine based scheme is presented to detect and classify the different operating conditions in a High voltage transmission line. Combined Wavelet-SVM based technique shows a great enhancement in the accuracy of fault classification compared to the conventional techniques.The implementation of the proposed scheme is done by using the flowchart given in figure 1.

Simulation of different operating conditions

In this paper for evaluating the performance of the proposed algorithm, MATLAB (7.3) / Simulink model of the test system is developed (Figure 2) and simulated for different operating

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conditions considered. The test system consists of 110KV source at sending end. At the receiving end one resistive load with power consumption level of 20MW is connected by a high voltage transmission line of 200 km. The specifications of the test system are given in appendix I

The six different operating conditions considered are:

1. Single phase to ground
2. Line to line fault
3. Double line to ground
4. Three phase short circuit
5. Breaker operation
6. Capacitor switching

Single phase to ground fault

In this paper the high voltage transmission line has been simulated by creating phase A to ground fault with ground resistance of 10-3 ohms. The transient current has amplitude, as great as 10 times the normal current value. The simulated fault current waveforms are shown in figure 3 (a).

Line to Line fault

In this the high voltage transmission line (HTL) has been simulated by shunting phase A to B. The transient current has amplitude, as great as 10 times the normal current value. The simulated fault current waveforms are shown in figure 3 (b).

Double line to ground fault

This condition has been created by shunting phase A and B to ground with ground resistance of 2*10-3 ohms. The simulated fault current waveforms are shown in figure 3 (c).

Three phase short circuit

This condition has been created by shunting phase A, B and C. The simulated fault current waveforms are shown in figure 3 (d).

Breaker Operation

This condition has been created by opening the circuit breaker at the receiving end of the transmission line. The simulated fault current waveforms are shown in figure 3 (e).

Capacitor Switching

This condition has been simulated by shunting the capacitor with rating of 2*10-6, in the receiving side of the transmission line. The simulated fault current waveforms are shown in figure 3 (f).

The simulated three phase current waveforms for the different operating conditions are shown in Figure 3(a)-(f).

Fault classification based on multi resolution wavelet transforms and support vector machine (svm)

A.Wavelet transforms (wt)

WT is a relatively new processing tool, which performs time localization of different frequency components of a given signal. Therefore, by using WT, both time and frequency resolution of a given signal is accomplished. WT performs this task by using some unique analyzing functions, called mother wavelets. The unique property of the mother wavelets is that for high-frequency components, the time intervals would be short whereas for low frequency components, the time intervals would be longer. Thus, WT is a quite useful technique for characterizing and analyzing the power system transient signals. There are different types of mother wavelets available in the literature, such as Harr, Daubechies (db), Coiflet (coif), symmlet (sym), etc. The choice of the mother wavelet plays a major role in the characterization of the signal under study. The mother wavelet, whose characteristics matches closely with the signal under consideration, would be the best choice. For studying power system fault signals, it has been reported in the literature that db wavelet is the most suitable one [11-13].Therefore, in this paper also, db wavelets have been used for the first stage analysis of the fault current signals.

In this paper the wavelet that is named Discrete Wavelet Transform (DWT) by two scale factor was used. For any function (f), mathematical representation of DWT can be written as,

$$f(t)=\sum_{k} C_{j0,k}\phi_{j0,k}(t)+\sum_{j>j0}\sum_{k} W_{j,k}\, 2^{j/2}\psi(2^{j}t-k)$$

where, ψ is the mother wavelet.

B. Artificial neural network (ann)

Artificial neural network (ANN) is made up of many computational processing elements called neurons or nodes. These nodes operate in parallel and are connected together in topologies that are loosely modeled after biological neural systems [14], [15]. The training of ANN is carried out to associate correct output responses to particular input pattern. A popular model for ANN is multilayered feed forward back propagation. The multi-layer perceptron has the ability of handling complex and non-linear input-output relationship with hidden layer. Here in this paper multi-layer feed forward networks are chosen to process the prepared input data which were obtained from wavelet transform.

C. Support vector machine (svm)

C.1 Introduction

Support Vector Machine (Machine intelligence technique) (SVM) is mostly used for classification purposes. SVM is a relatively new computational learning method based on the statistical learning theory. SVM-based classifiers have good generalization properties compared to conventional classifiers, because in training the SVM classifier the structural misclassification risk is minimized, whereas traditional classifiers are usually trained so that the empirical risk is minimized. [4], [11].

C. 2 Support vector machine for classification

Let n-dimensional input x_i, (i=1……M), (M is the number of samples) belong to class-I or Class-II and associated labels be y_i =1 for Class I and y_i=-1 for Class II, respectively. For linearly separable data, we can determine a hyper plane f(x) =0 that separates the data. This gives the equation 2

$$f(x)=w^{T}x+b=\sum_{j=1}^{n}w_{j}x_{j}+b=0$$

where ‘w’ is an n-dimensional vector and ‘b’ is a scalar.

The vector ‘w’ and the scalar ‘b’ will determine the pos ition of the separating hyper-plane. Function sign (f(x)) is also called the decision function. A distinctly separating hyper-plane satisfies the constraints f(xi) ≥1 if yi=+1 and f(xi) ≥ -1 if yi=-1 .These results in, equation (3).

$$y_i f(x_i)=y_i\left(w^{T}x_i+b\right)\geq 1 \text{ for i=1.......M}$$

The separating hyper- plane that creates the maximum distance between the plane and the nearest data is called as the optimal separating hyper -plane. From the geometry of the optimal separating hyper- plane of two datasets the geometrical margin is found to be.Taking into account the noise with slack variables ξi and error penalty C, the optimal hyper plane can be found by solving the following convex quadratic optimization problem, Minimize

Minimize $\boxed{\frac{1}{2}\left\|W^{-2}\right\|+c\sum_{i}^{M}\xi_i}$

subject to

$$y_i\left(w^T x_i + b\right) \geq 1 - \xi_i, \quad \text{for i=1…………M}$$

$$\xi_i \geq 0, \quad \text{for all i}$$

where ξi is measuring the distance between the margin and the xi. xi are lying on the wrong side of the margin. The calculations can be simplified by converting the problem with Kuhn–Tucker conditions into the equivalent Lagrange dual problem, which will maximize,

$$w(\alpha) = \sum_{i=1}^{M}\alpha_i - \frac{1}{2}\sum_{i,k=0}^{M}\alpha_i\alpha_k y_i y_k x_i^T x_k$$

subject to,

$$\sum_{i=1}^{M} y_i\alpha_i = 0, c \geq \alpha_i \geq 0, \quad \text{i=1….,M}$$

The number of variables of the dual problem is the number of training data. Let us denote the optimal solution of the dual problem with α* and w*.

According to the Karush–Kuhn–Tucker theorem, the equality condition in (4) holds for the training input–output pair (xi,yi) only if the associated α* is not 0. In this case the training example xi is a support vector (SV).

Usually, the number of support vectors is considerably lower than the number of training samples making SVM computationally very efficient. The value of the optimal bias b* is found from the geometry:

$$b^* = -\frac{1}{2}\sum_{SVs} y_i\alpha^* i\left(s_1^{\,T} x_i + s_2^{\,T} x_i\right)$$

where s1 and s2 are arbitrary support vectors (SVs) for Class I and Class II, respectively.

Only the samples associated with the SVs are summed, because the other elements of optimal Lagrange multiplier α* are equal to zero.

The final decision function will be given by

$$f(x) = \sum_{SVs}\alpha_i y_i x_i^{\,T} x + b^*$$

Then unknown data example ‘x’ is classified as follows:

x€{ class –I if f(x) ≥0
class-II otherwise

SVM can also be used in nonlinear classification tasks with application of kernel functions.

The data to be classified is mapped onto a high-dimensional feature space, where the linear classification is possible.

The use of kernel methods provides powerful way of obtaining nonlinear algorithms capable of handling non-separable datasets in the original input space.

Different types of kernels used to train the support vector machine (SVM).

D. Extraction of co-efficients using wavelet transforms

The simulated three phase current signals obtained for various operating conditions in Simulink are given as input to the wavelet transforms to decompose into series of wavelet co-efficients (both approximation & detailed coefficients).The sampling time for simulated waveforms is 0.001seconds and the sampling frequency is 103Hz..

Wavelet Type used : One-dimensional Discrete Wavelet Transforms (DWT)
Family chosen : Daubechies
Filter used : DB2
Resolution level : 3

DB2 filter is chosen for decomposition process because this type of filter reproduces the same original signal after reconstruction. The approximate and detail co-efficients are extracted for six different operating conditions at five decomposition levels (d1, d2, d3, d4, d5).These extracted detailed coefficients at level d3, are used to train the neural network and support vector machine (SVM) to discriminate six different operating conditions because these coefficients are identified as much suitable for fault classification by trial and error. Also the frequency bandwidth for d3, is in power frequency range (55.75 Hz to 111.5 Hz).These extracted detailed coefficients at level d3 for all the six operating conditions are used for the study. For instance detailed coefficients obtained at level d3 for single phase to ground fault condition are shown in appendix II.

E. Fault Classification Using ANN

E1. Development of ANN architecture

A three level BP (Back Propagation) network with sigmoid activation function performs as a classifier in this paper. The input layer has 15 input nodes corresponding to the extracted detailed co-efficients of each operating condition considered .The hidden layer has 33 nodes. The output layer has 3 nodes corresponding to the three phases A, Band C.

E2. Training and Testing

A number of 540 wavelet co-efficient data groups (90 co-efficients from each operating condition) of simulated waveforms corresponding to six different operating conditions are obtained. Out of them 340 data are used for training and the remaining 200 of them are chosen as test samples. The developed ANN was trained to classify abovesaid six different operating conditions and the simulation results obtained are shown in Table 1. The output indication is interpreted as follows:

0 – indicates fault condition
1 – indicates non-fault condition

The misclassification rate for different operating conditions is tabulated in Table 2.From the results it is found out that the overall accuracy of 96.43% is obtained after 923 iterations. The momentum factor used was 0.85.

F. Fault Classification Using SVM

Faults on the line are simulated for six operating conditions including different fault impedance values ranges from 20 Ω - 500 Ω. The extracted detailed co-efficients of various operating conditions at level d3, are given as input to support vector machine. It classifies the given six different operating conditions whether the given operating condition is a fault or non- fault. The output of the SVM is 1 or -1.Here 1 indicates fault condition -1 indicates non fault condition.

A number of 360 wavelet co-efficient data groups (60 co-efficients from each operating condition) of simulated waveforms corresponding to six different operating conditions are obtained. Out of them, 180 data are used for training and the remaining 180 data are chosen as test samples. The penalty parameter (C) is taken as 10 by trial and error, in this problem. The quantity C is always greater than zero. If the parameter C is small, the separating hyper plane tends to maximize the margin (m), while the larger C will cause hyper plane to minimize the number of misclassified points. The kernel functions chosen here are linear and polynomial with the order of 2.The necessity to choose the kernel function is to convert the linearly non-separable data into linearly separable one.

Table 3 shows the results for fault classification for six different operating conditions. From Table 3, it is understood that misclassification occurs for bc-g fault condition with linear kernel and for abc fault condition with polynomial kernel function. For all the remaining operating conditions output is exactly correct. To rectify this other type of kernel function is used for classification and from the results obtained it is inferred that for bc-g fault condition with polynomial kernel function the classification is exactly correct. Similarly for abc fault condition linear kernel function is more suitable one. So it is understood that according to the fault condition the suitable kernel function must be selected.

In the study it is found that the overall accuracy for fault classification is approximately 98%.This value is obtained by taking the mean average value of % classification rate of various cases. The vectors satisfying the constraint with equality sign in the equation (4) are termed as support vectors. These vectors are needed to determine the decision surface or the separating hyper plane. Usually the number of support vectors considered must be less than number of training samples to make SVM computationally very efficient. The classification rate for different operating conditions is tabulated in Table 4.The SVM classifications for the six different operating conditions are shown in appendix III.

Analysis of results

In the first stage, an ANN architecture is developed and a combined WT and ANN (WNN) based scheme is trained and tested to classify the six different operating conditions of high voltage transmission line. Then a combined WT and SVM (support vector machine) based scheme is trained and tested to classify the same six different operating conditions of high voltage transmission line. From the simulation results obtained, it is inferred that the used DB2 Discrete Wavelet Transforms is very efficient in extracting the features. The overall classification accuracy obtained for SVM is approximately 98%. The execution time taken for SVM based scheme is also less than 1 second ie. 0.1 second. But the overall classification accuracy for ANN based scheme is 96.43%. The convergence is obtained after 923 iterations. The momentum factor used was 0.85 by using back propagation architecture. The execution time for ANN architecture was approximately 60 seconds. The simulation work is done in Intel Pentium dual core, 2.8GHz, 1 GB RAM computing system. Hence this proposed combined WT-SVM technique will provide more accurate results than the WNN based scheme. Moreover it has high-speed response and better ability of discriminating the different operating conditions.

Conclusion and future work

In this proposed work, a new algorithm for discriminating different operating conditions in high voltage transmission line is proposed. This proposed algorithm combines the use of the wavelet transforms and support vector machine (SVM). The use of Multi resolution Analysis (MRA) Wavelet transforms is proved to be very efficient in extracting the very crucial time frequency features from different simulated current signals. The extracted features at level d3 are used for classification since d3 is the power frequency band. In this work SVM is trained to result in most optimized classifier. It classifies the given six different operating conditions considered, (single phase to ground fault, line to line fault, double line to ground fault, three phase short circuit, capacitor switching, circuit breaker operation) and indicates whether it is a fault or non-fault operating condition. Thus the proposed method for fault detection and classification in high voltage transmission line shows promising security and reliable protection operation by preventing the missing operation and false tripping of protective devices. In future this work shall be extended for more complicated transmission lines with compensating devices including different fault parameters like fault inception angle and auto-reclosure condition.

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Appendix I

Source data at sending end	
Voltage	110KV
Phase angle	30°
System Frequency	50Hz

Load data at receiving end	
Voltage	110KV
Power factor	Unity power factor
Power consumption level	20MW

Transmission line data	
Length	200km
Voltage	110KV
Resistance/ph/km	0.16 ohm
Reactance/ph/km	0.25 ohm
Shunt admittance/ph/km	$1.5*10^{-6}$ mho

Appendix II

Data sets(Extracted detailed co-efficients) for single phase to ground fault condition

Phase-a	Phase-b	Phase-c
-520.95	95.465	236.03
262.68	-301.75	24.917
227.27	283.26	-287.01
-502.34	-69.372	318.3
500.59	-160.6	-187.86
-141.76	339.04	-113.51
-128.24	-173.57	169.3
350.5	-43.824	-169.93
-2.3129	-1.8335	4.1464
3.098	-63.548	60.45
79.358	15.849	-95.20
-72.262	111.47	-39.208
-45.557	-37.773	83.33
-36.329	-49.802	86.13
110.55	-52.57	-57.98
-5.8455	90.691	-85.091
-90.282	63.618	26.653
-38.952	-54.31	93.286
76.352	-84.831	8.4764
66.998	22.502	-89.52
-49.954	93.557	-43.576
86.562 17.515	12.974	73.574
70.042	-88.127	70.601
77.918	-47.825	-45.65
-15.801	70.63 73.951	-88.15
-93.955	-41.248	12.484
-24.631	-92.501	93.205
56.072	-44.678	22.415
1.3652e-006	90.882	-33.13
0.000214	50.761	-75.163
0.1284	-70.387	43.171
-23.18	-2.3736	95.018
4.8186	7.35e-007	-53.56
96.882	0.00011509	-2.1157e-006
28.817	0.12283	-0.000331
-117.11	-11.578	-0.24945
-90.446	-47.124	25.306
-12.34	55.7238	31.981
130.31	55.829	-55.901
59.154	43.078	-47.748
-42.752	-22.566	40.696
-107.76	-73.731	62.84
49.4	-9.2645	49.023
92.265	43.747	-67.721
94.587	75.996	-57.743
25.47	-6.6237	-19.561
-119.8	-46.591	64.065
	-63.341	53.642
	17.362	-15.149
	60.268	-62.447
		-48.298 9.561

Appendix III

Support Vector Classification details while doing classification of six different operating conditions using SVM

1. Single phase to ground fault condition (phase a-g)

Execution time	:	0.1 seconds
Status	:	OPTIMAL_SOLUTION
|w0|^2	:	0.000005
Margin	:	929.329277
Sum alpha	:	0.000005
Support Vectors	:	2 (66.67%)
predictedY =		-1 1 1 -1 1 1 -1 1 1 err : 0 err : 0 err : 0

2.Lline to line fault condition(phase b-c)

Execution time	:	0.1 seconds
Status	:	OPTIMAL_SOLUTION
|w0|^2	:	0.000005
Margin	:	: 282.902313
Sum alpha	:	0.000050
Support Vectors	:	: 0 (0.0%)
predictedY =		1 -1 -1 1 -1 -1 1 -1 -1 err : 0 err : 0 err : 0

3.Double line to ground fault condition(phase bc-g)

Execution time	:	0.1 seconds
Status	:	OPTIMAL_SOLUTION
|w0|^2	:	0.000005
Margin	:	859.374082
Sum alpha	:	0.000005
Support Vectors	:	3 (100.0%)
predictedY =		1 1 -1 1 -1 -1 1 -1 -1 err : 1 err : 0 err : 0

4. Three phase short circuit (phases abc)

Execution time	:	0.1 seconds
Status	:	OPTIMAL_SOLUTION
|w0|^2	:	2.351455
Margin	:	1304.252
Sum alpha	:	0.2985
Support Vectors	:	3 (100.0%)
predictedY =		-1 -1 -1 -1 -1 -1 -1 -1 -1 err : 0 err : 0 err : 0

5.Circuit breaker operation

Execution time	:	0.1 seconds
Status	:	OPTIMAL_SOLUTION
|w0|^2	:	0.004562
Margin	:	296.10673
Sum alpha	:	0.004562
Support Vectors	:	2 (66.7%)
predictedY =		1 1 1 1 1 1 1 1 1 err : 0 err : 0 err : 0

6.Capacitor switching

Execution time	:	0.1 seconds
Status	:	OPTIMAL_SOLUTION
|w0|^2	:	19.212167
Margin	:	0.456291
Sum alpha	:	19.212167
Support Vectors	:	3 (100.0%)
predictedY =		1 1 1 1 1 1 1 1 1 err : 0 err : 0 err : 0