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Fault Detection in a Series Compensated Transmission Line using Discrete Wavelet Transform and Improvement

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Abstract: Fault detection and separation mainly concerned about monitoring the system, checkingand examining when the fault has occurred and mentioning the type of fault and its location. Fault detection is useful in determination that a problem has occurred within a specific channel or area of operation. For the improvement of safety, and efficient advanced systems of supervision, fault-detection and fault diagnosis become very important for many technical processes. In this paper a Discrete Wavelet Transform (DWT) and Principal Component Analysis (PCA) are used to detect a discontinuity of currents due to the fault, and then the features for fault diagnosis are mentioned for fault detection in a series compensated transmission line. Relevance vector machine(RVM) is used for the classification of faults. Also the location of fault is detected using two ended impedance method. The different types of faults are created using MATLAB/Simulink.

Keywords: Fault detection; relevance vector machine; series compensated transmission line; wavelet component analysis.

I. INTRODUCTION

Transmission and distribution lines are important links between generating units and consumers. They are exposed to atmosphere, hence chances of occurrence of fault in transmission line is very much high, which must be immediately sorted out in order to minimize damage caused by it. Also fault location in electric power distribution systems (EPDS), however, because of their specific algorithmic and operational characteristics, still place some chalenges. Several methods are proposed in the recent years for performing the power system fault detection and location identification. Some of the techniques are bridge circuit method [1], surface wave [2, 3], Petrinets [4], wavelet transform approach [5-10], neural network approach [11-13], artificial intelligence [14], graph methodology [15], real time [16] and statistical methodology. Singh et al presented a software fault prediction at design phase. Here, various software matrics related to the modules level fault were utilized for Detection of fault prone modules [17]. Medoued et al classified an induction machine faults based on time-frequency representation and PSO. The feature vector size was optimized with the PSO algorithm. the classifier was designed based on ANN [18]. Kong et al formulated a fault tolerant control of five-phase induction motor under the single phase open circuit. The control methods were developed based on the third harmonic current injection [19].where as most of time , FL in EPDS is many times performed by visual inspection, field methods and brute force methods [20]. These techniques are not feasible on underground systems and require a long time in large distribution networks.

II DISCRETE WAVELET TRANSFORM

Wavelet based charectaristics will be taken from EMG signal. Different standard wavelets have been tried and Daubechies wavelet (‘db10’) was declared to be the most suitable for the analysis of EMG signals. Different forms result in different changes in the coefficients.The wavelet transform is a convolution of the wavelet function $\psi(t)$ with the signal x(t). Orthonormaldyadic discrete wavelets are associated with scaling functions $\varphi(t)$. The scaling function can be convolved with the signal to produce approximation efficients S. The discrete wavelet transform (DWT) can be written as

$$T_{m,n} = \int_{-\infty}^{\infty} x(t)\psi_{m,n}(t)dt.$$

The wavelet transform is calcualted separately for different segments of the time-domain signal at different frequencies. Multi-resolution analysis: analyzes the signal at different frequencies giving different resolutions MRA is designed to give good time resolution and poor frequency resolution at high frequencies and good frequency resolution and poor time resolution at low frequencies Good for signal having high frequency components for short durations and low frequency components for long duration .e.g. images and video frames. The 1-D wavelet transform is given by :

$$W_f(a,b) = \int_{-\infty}^{\infty} x(t)\psi_{a,b}(t)dt$$

The inverse 1-D wavelet transform is given by:

$$x(t) = \frac{1}{C}\int_{0}^{\infty}\int_{-\infty}^{\infty} W_f(a,b)\psi_{a,b}(t)db\frac{da}{a^2}$$

$$\text{where } C = \int_{-\infty}^{\infty}\frac{|\psi\omega)|^2}{\omega}d\omega < \infty$$

Discrete wavelet transform (DWT), which transforms discrete time signal to a discrete wavelet representation. it converts an input series x_0, x_1, $..x_m$, into one high-pass wavelet coefficient series and one low-pass wavelet coefficient series (of length n/2 each) given by:

$$\mathbf{H_i} = \sum_{m=0}^{k-1} \mathbf{x_{2i-m}} \cdot \mathbf{s_m(z)} \qquad (1)$$

$$\mathbf{L_i} = \sum_{m=0}^{k-1} \mathbf{x_{2i-m}} \cdot \mathbf{t_m(z)} \qquad (2)$$

where $s_m(Z)$ and $t_m(Z)$ are called wavelet filters, K is the length of the filter, and i=0, ..., [n/2]-1.Such transformation will be applied recursively on the low-pass series until the efficient number of iterations is reached.

III RELEVANCE VECTOR MACHINE AND FAULT ANALYSIS

In mathematics, a relevance vector machine (RVM) is a machine learning technique that 33uses Bayesian inference to obtain parsimonious solutions for regression and classification The RVM has an identical functional form to the support vector machine, but provides probabilistic classification. It is actually same Gaussian process model with covariance function:

$$k(\mathbf{x},\mathbf{x}') = \sum_{j=1}^{N}\frac{1}{\alpha_j}\varphi(\mathbf{x},\mathbf{x}_j)\varphi(\mathbf{x}',\mathbf{x}_j)$$

Where φ is the kernel function (usually Gaussian), and $\mathbf{x}_1,\ldots,\mathbf{x}_N$ are the input vectors of the training set. Compared to that of support vector machines (SVM), the Bayesian formulation of the RVM avoids the set of free parameters of the SVM (that basically require cross-validation-based post-optimizations). However RVMs use expectation.

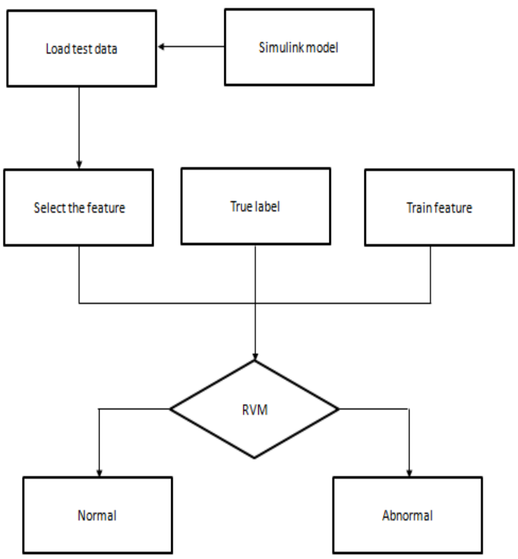

Fig.1. flow chart RVM classification

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maximization (EM) like learning method and are therefore at risk of local minima. This is different from the standard sequential minimal optimization (SMO)-based algorithms employed by SVMs, which are guaranteed to find a global optimum (of the convex problem).

IV SIMULATION RESULTS

A. Without fault

The figure2. shows grid voltage and current. The energy associated with approximate and detailed coefficients are calculated below. These energies are the reference parameters. If any change in these parameters is seen, the phase is declared as faulty.The energy of approximate coefficients and detailed coefficients of each phase and zero currents for without fault condition are mentioned below.

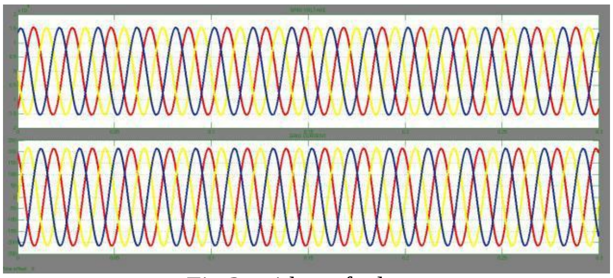

Fig.2. without fault

TABLE I

Phase	R	Y	B	Zero
E_{CA}	99.997	99.997	99.997	99.995
$E_{CD}(wf)$	.002	.002	.002	.005

No fault coefficient

B.L-G faults

The L-G faults occur in transmission system are R-G, Y-G and B-G faults. For example R-G fault has been taken into consideration. The above figure describe the voltage and current waveforms of RG fault system. The R phase signals is having more transients than other phases.The approximate and detailed coefficients are calculated and energy associated with each phase and ground is listed out. From the table it is clear that the energy associated with detailed coefficients of R phase and ground are changed and thus this is an R-G fault system.

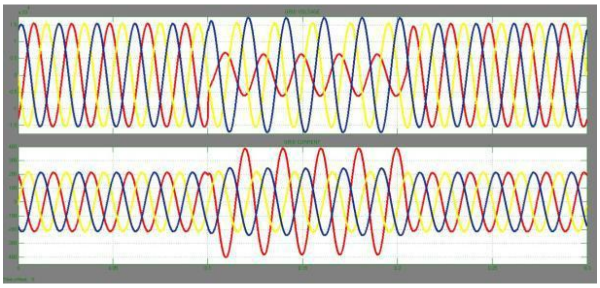

Fig.3. R-G fault

TABLE III

Phase	R	Y	B	Zero
E_{CA}	99.992	99.997	99.997	99.999
$E_{CD}(wf)$	.002	.002	.002	.005
$E_{CD}(R-G)$	**.008**	.002	.002	**.001**

R-Gfault coefficient

C.LLfault

The L-L fault occur in transmission system are R-Y fault, RB fault and Y-B fault. For example Y-B fault has been taken into consideration. The figure shows the voltage and current waveforms of Y-B fault system. The Y and B phase signals having more transients than other phases The approximate and detailed coefficients are calculated and energy

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associated with each phase and ground is mentioned below. From the table it is obvious that the energy associated with detailed coefficients of Y phase and B phase are changed and thus this is a Y-B fault system.

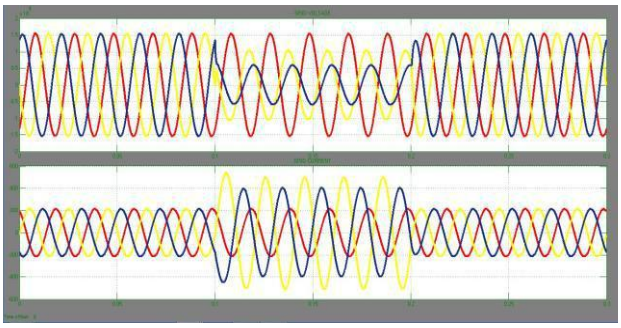

Fig.4. Y-B fault

TABLE IIIII

Phase	R	Y	B	Zero
E_{CA}	99.998	99.996	99.993	99.999
$E_{CD}(wf)$	.002	.002	.002	.005
$E_{CD}(Y-B)$	.002	**.004**	**.007**	.005

Y-B fault coefficient

D. L-L-G faults

The figure shows the voltage and current waveforms of RB-G fault system. The R, B and zero signals having more transients than other phases The approximate and detailed coefficients are calculated and energy associated with each phase and ground is listed below. From the table, it is clear that the energy associated with detailed coefficients of R B phases and ground is changed and thus this is an R-B-G fault system.

TABLE IVV

Phase	R	Y	B	Zero
E_{CA}	99.99	99.998	99.993	99.999
$E_{CD}(wf)$	.002	.002	.002	.005
$E_{CD}(R-B-G)$	**.01**	.002	**.007**	**.001**

R-B-G fault coefficient

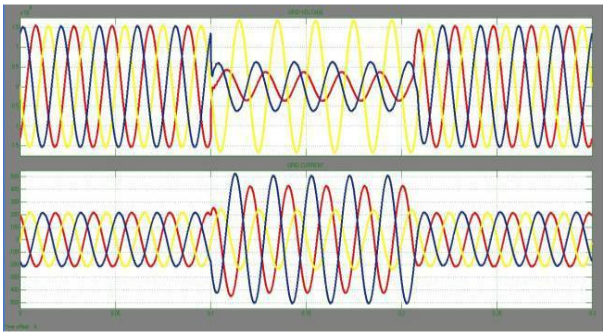

Fig.5. R-B-G fault

E.Three phase faults

Three phase faults occurs in transmission system are RYB faults and R-Y-B-G faults. Simulation results of RYB faults and R-Y-B-G faults are discussed. The figure shows the voltage and current waveforms of R-Y-B fault system. The R, Y and B phase signals having more transients than other phases The approximate and detailed coefficients are calculated and energy associated with each phase and ground is listed out below. From the table it is obvious that the energy associated with detailed coefficients of R, Y and B phases changed and thus this is an R-Y-B fault system The figure shows the voltage and current waveforms of RYB-G fault system. The R, B and B phase and ground signals having more transients as compare to other phases.

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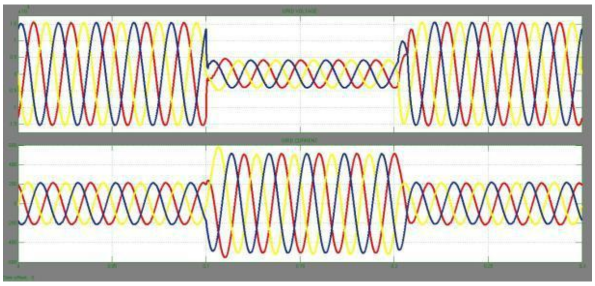

Fig.6. R-Y-B fault

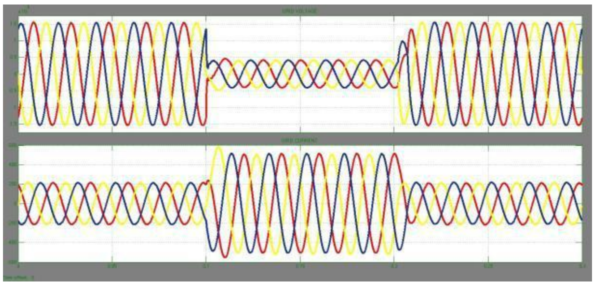

Fig.7. R-Y-B-G fault

TABLE V

R-Y-B fault coefficient

Phase	R	Y	B	Zero
E_{CA}	99.99	99.992	99.991	99.995
$E_{CD}(wf)$	.002	.002	.002	.005
$E_{CD}(R-Y-B)$	**.01**	**.008**	**.009**	.005

TABLE VI

Phase	R	Y	B	Zero
E_{CA}	99.99	99.992	99.992	99.999
$E_{CD}(wf)$	.002	.002	.002	.005
$E_{CD}(RYB-G)$	**.01**	**.008**	**.008**	**.001**

R-Y-B-G fault coefficient

TABLE VII

	A-g	**B-g**	**C-g**	**AB-g**	**BC-g**	**AC-g**	**AB**	**BC**	**AC**	**ABC-g**
Average error, %										
0 –15	0.23	0.23	0.24	0.23	0.23	0.23	0.23	0.23	0.23	0.23
20– 35	0.24	0.24	0.24	0.24	0.24	0.23	0.24	0.24	0.23	0.23
40– 60	0.25	0.25	0.25	0.25	0.25	0.24	0.24	0.25	0.24	0.24
65– 80	0.26	0.26	0.27	0.26	0.26	0.26	0.26	0.26	0.26	0.26
85– 100	0.27	0.28	0.29	0.28	0.28	0.28	0.27	0.28	0.28	0.28
Maximum error, %										
0 –15	0.37	0.37	0.36	0.35	0.35	0.34	0.34	0.35	0.34	0.34
20– 35	0.39	0.38	0.38	0.37	0.37	0.36	0.36	0.37	0.36	0.36
40– 60	0.42	0.42	0.41	0.40	0.40	0.40	0.38	0.40	0.40	0.39
65– 80	0.45	0.45	0.45	0.44	0.45	0.44	0.41	0.43	0.44	0.44
85– 100	0.49	0.50	0.51	0.50	0.50	0.49	0.45	0.47	0.49	0.50

percentage error in fault location

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V CONCLUSIONS

This paper describes the features and benefits of wavelet multi resolution analysis in combination with relevance vector machine for precise classification and location of single line to ground fault. The method takes energy of spectrum D1 and D5 for two consecutive data windows for classification and location of faults. Wavelet transform is used to get details D1 and D5 of the current signals. Relevance vector machine classification method used to classify the faults. After classification, information of fault signals are used to locate the fault. Simulation process were performed for every possible fault conditions with faults at different phases, at different locations and at different fault inception angles and performance of the proposed scheme was checked out. The classification of faults was exact and the location of the faults was identified with above 92% precision. This work deals with fault classification and detection for single line to ground faults, but the proposed algorithm and scheme can be streched to other faults also with similar effectiveness.

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