Fault Detection and Classification on a Hybrid Transmission Line Using Wavelet Packet Energyand RBFNN

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Abstract—*The paper presents a method for detection and classification of fault type on hybrid transmission line. The line consists of an overhead section and an underground cable and is fed from both ends. Wavelet packet energy (WPE) has been extracted from fault current signals for training the radial basis function neural network (RBFNN) to detect and classify faults. The algorithm is fast and accurate as it utilizes only post-fault half cycle current signals recorded at one end of the transmission line. The algorithm need not require identification of fault section for detection and classification of faults in hybrid transmission line irrespective of fault resistances, fault inception angles (FIA), loading angles.*
Keywords— *Hybrid Transmission Line, Feature extraction, Wavelet Packet Energy (WPE), Fault Inception Angle (FIA),Radial Basis Function Neural Network (RBFNN)*

I. INTRODUCTION

The demand of electrical power is increasing with the increase of world population day by day. So it's a big challenge for power engineers to provide good quality of uninterrupted power supply and to detect faults as early as possible. Transmission line with combination of overhead line as well as underground cable behaves like heart of power system. Most of transmission line faults are short circuit faults and usually most of fault occurs in overhead line since it is open to atmosphere. Most of the faults on transmission lines are single-line-to-earth faults, followedby phase-phase, double-phase-earth and three phase faults.

Back-propagation neural network (BPNN) based fault classification with Clarke transformation in presented in [1]. Here daubechies4 (Db4) is used as a mother wavelet along with alpha and beta modal value of currents. A fault classification technique on a transmission line based on discrete wavelet transform (DWT) is presented in [2]. A combination of fuzzy-neuro technique and kernel principal component analysis is used for transmission line fault using wavelet transform and fuzzy k-Nearest Neighbor (Fuzzy-KNN). Heuristic fuzzy system with decision-tree (DT)-fuzzy is exploited for fault classification in transmission lines [14]. Travelling wave based fault classification method is used in [15]. But this method requires data recording at very high sampling rate for accuracy of the proposed method. Fault classification on a combined transmission line of overhead system and underground cable requires quite different approach as travelling wave velocity and characteristics impedance are different for an overhead line and underground cable.

The present article has proposed a wavelet packet energy (WPE) and radial basis function neural network (RBFNN) based fault classification method on a hybrid transmission line irrespective of fault section identification. The wavelet packet energy has been extracted from fault current signals recorded only at one end of the transmission line and fed to RBFNN for training. Proposed method has been verified for different type of faults, fault inception angles, fault resistances and loading angles.

II. WAVELET PACKET ENERGY

Wavelet packet decomposition (WPD) is very useful tool for non stationary fault signal which is transient in nature and contains high frequency components. It's popularly used for signal processing, data compression and feature extraction which consequently decrease the complexity. In WPD, for n level decomposition both the detail and approximation coefficients are decomposed in n + 1 possible ways and hence it provides better resolution than DWT. A three level wavelet packet decomposition tree is shown in the Fig. 1.

A Wavelet packet function can be obtained from sequence functions satisfying the scaling function and the wavelet function [16] and is represented by

$$W_{j,n,k}(t) = 2^{-j/2} S_n(2^{-j}t - k) \qquad (1)$$

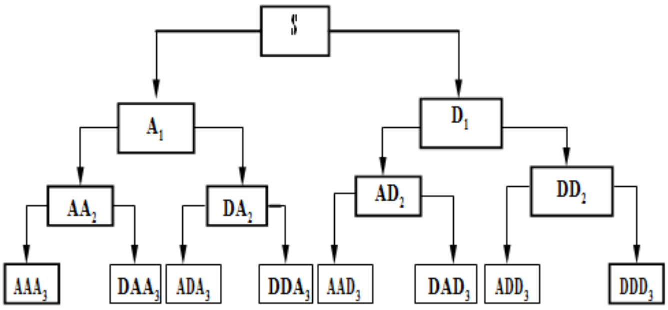

Fig. 1. Wavelet packet decomposition tree

Where k, j and n are time localization parameter, scale parameter and modulation parameter respectively. The wavelet packet coefficients of a signal f(t) are computed by taking the inner product of the signal and the particularwavelet packet function as

$$W_{j,n,k} = < f(t), W_{j,n,k}(t) > = \int f(t) W_{j,n,k}(t) dt \qquad (2)$$

WPD decomposes the non-stationary and stationary signal utilizing both low and high frequency components with rich collection of abundant information of WPD coefficients. The energy of a wavelet packet node is obtained by summing the square of coefficients in each frequency band corresponding to the node.

$$E_{j,n} = \sum_{k=1}^{L} W_{j,n,k}^2 \qquad (3)$$

Where k = L is the number of WPD coefficients in each node for j level wavelet packet decomposition with $n = 0, 1, 2, \ldots (2^j - 1)$.

III. RADIAL BASIS FUNCTION NEURALNETWORK

A radial basis function neural network (RBFNN) is a feed forward network consisting of three layers i.e. input layer, hidden layer and output layer. It consists of highly interconnected neurons for pattern classification with the help of large number of trained offline data. In supervised learning technique conformal mapping is take place between input layer to hidden layer and then linear mapping from hidden layer to output layer which is used to calculate the Euclidean distance between the centre and the input vector and then the result is passed to the radial basis function. For an input x, the output of the network can be represented as

$$d_i = w_{oi} + \sum_{j=1}^{h} \omega_{ji} \Phi (||x - c||, \beta_j) \qquad (4)$$

Where, i = 1….m and j = 1,…..,h. w_{0i} is the biasing term, H is the number of hidden units, is the weight between the jth hidden node and the ith output node, is the centre of the jth hidden node, is the real constant known as spread factor and is the activation function. Here Gaussian radial basis function is used as activation function represented in (5) for the jth hidden unit

$$\Phi(z_i, \beta_i) = \exp(-z_j^2/\beta_j^2), \qquad z_i = ||x - c_i|| \qquad (5)$$

In the present work, the normalized current energies of first four WPD frequency bands for each phase are fed to RBFNN for detection and classification of faults. Thus input layer of this RBFNN has 12 inputs and the output layer has one output i.e. fault classification as shown in Fig. 2. In neural network, error goal is achieved leading to fast convergence irrespective of selection of neurons which is created by hidden layer.

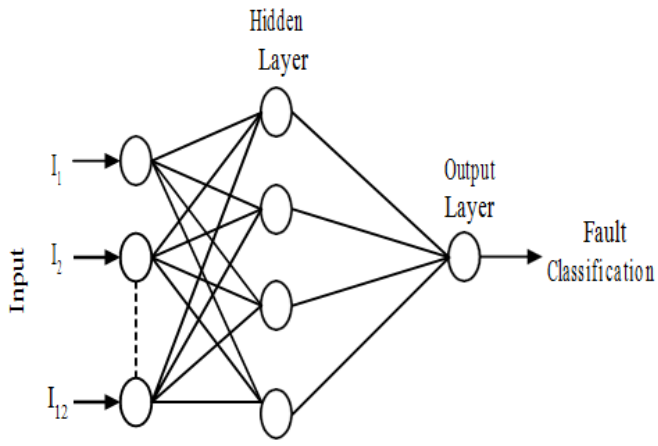

Fig. 2. Architecture of radial basis function neural network

IV. TRANSMISSION NETWORK UNDER CONSIDERATION

In the present work, a 400kV, three phases, 50Hz power system network fed from both ends is simulated using ATP/EMTP software and the single line diagram of the power system is shown in Fig. 3. The length of the proposed transmission line is 140 km, of which over head section is 100 km and under-ground section is 40 km. Faults have been initiated at 10 km interval starting from 10 km from Bus 1 in over head section and at 5 km interval in under- ground cable section for training. The faults have also been created at 10 locations on the over head section and 7 locations on the under-ground section. Positive, negative and zero sequence components of resistance, inductance and capacitance are used in transmission line modeling. BCTRAN model of transformers (Tr1, Tr2 & Tr3) are used in EMTP simulation. The voltages of the two alternators (Alt1 & Alt2) are considered as $V_1 = 21\angle 0^0$ kV and $V_2 = 21\angle(-10^0)$ kV. Two three phase balanced load of rating of 800MVA, 0.92 lagging power factor (load1) and 100MVA, 0.87 lagging power factor (load 2) are connected at the Bus 2 of the transmission line. Three single line to ground (SLG) faults, three double line (LL) faults, three double line to ground (LLG) faults and one three phase fault (LLLG) with fault resistance (R_f) of 0 Ω, 20 Ω and 150 Ω at different fault inception angle (FIA) of 0^0 and 90^0 and loading angle (δ) of 10^0 and 20^0 have been simulated. Only fault current signals are recorded at Bus-1 with sampling frequency of 100 kHz. Current waveforms for three phase fault at a distance 60 km away from Bus-1 with fault resistance 0 Ω,FIA = 90^0 and loading angle = 10^0 is shown in the Fig. 4.

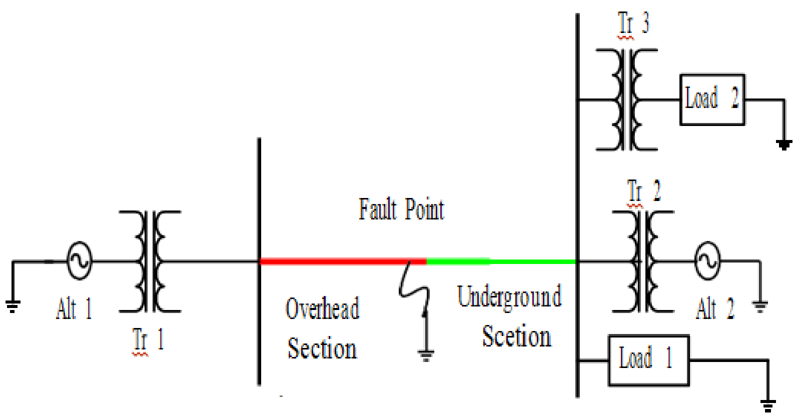

Fig. 3. Single line diagram of the transmission system underconsideration

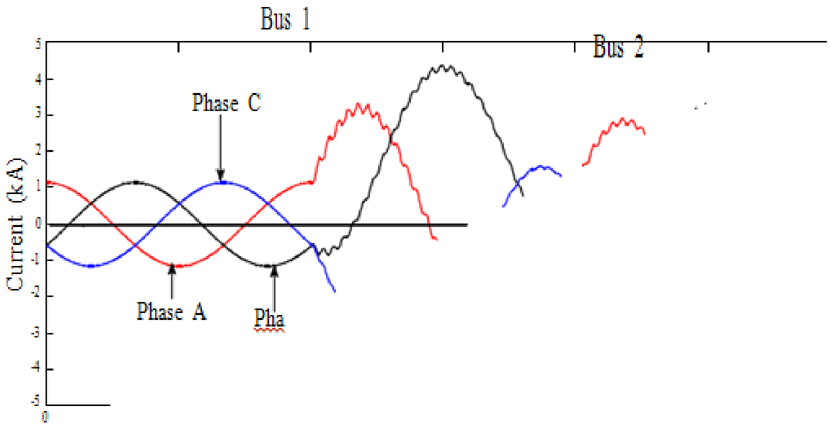

Fig. 4. Current waveform for three phase fault at 60 km with FIA 90^0,

V. FEATURE EXTRACTION AND FAULTCLASSIFICATION

The wavelet packet Decomposition has been used for feature extraction from the fault currents recorded at Bus 1 with the help of 3rd level decomposition with mother wavelet db1 is performed in MATLAB software. Energies of fault current at first four nodes of wavelet packet decomposition tree (Fig. 1) i.e., AAA3, DAA3, ADA3, and DDA3 are calculated and these are used as fault features for detection and classification of different types of faults on the transmission line. Few sample features are shown in Table I. After normalization, the extracted features are fed to RBF neural network designed in MATLAB for detection and classification of faults on the hybrid transmission line. The flowchart of the proposed fault detection and classification algorithm is shown in Fig. 5. Ten types of faults are coded decimally as 1, 2, 3, 4, 5, 6, 7, 8, 9 and 10 for aG, bG, cG, ab, bc, ca, abG, bcG, caG and abcG respectively and no- fault is coded as 0. The output of RBF neural network for faults at different test locations for FIA 90^0, fault resistance 0 Ohm and loading angle 10^0 is shown in Table II. The values of the output are rounded to match these faults with their coding.

TABLE I.SAMPLE FEATURES FOR SLG, LL, LLG AND THREEPHASE FAULTS

Fault Description	**For Current**	**Wavelet Packet Energy**			
		AAA_3	DAA_3	ADA_3	DDA_3
SLG Fault at 36 km, FIA=0^0, R_f =20 Ω, δ =10^0	I_1	6243.5	0.0905	0.0226	1.86×10^{-5}
	I_2	532.15	0.0244	0.0061	7.55×10^{-6}
	I_3	369.66	0.0178	0.0045	7.36×10^{-6}
LL Fault at 110 km, FIA=225^0, R_f=0 Ω, δ =10^0	I_1	478.21	0.0378	0.0093	0.0004
	I_2	1868.9	0.2981	0.0734	0.0034
	I_3	3984.8	0.2955	0.0725	0.0036
LLG Fault at 80 km, FIA=0^0, R_f =0 Ω, δ =20^0	I_1	434.65	0.0212	0.0053	2.76×10^{-5}
	I_2	4301.8	0.1441	0.0358	0.0011
	I_3	1102.1	0.1271	0.0315	0.0009
LLLG Fault at 80 km, FIA=0^0, R_f=150 Ω, δ =10^0	I_1	1453.3	0.0383	0.0096	1.09×10^{-5}
	I_2	1252.6	0.061	0.0153	0.0002
	I_3	1089.8	0.0486	0.0122	0.0002

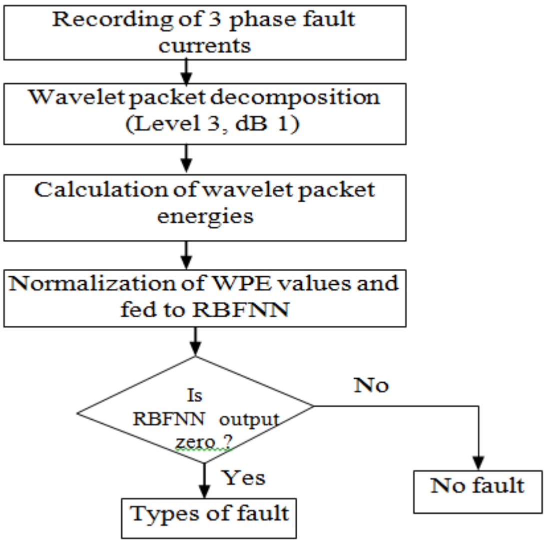

Fig. 5. Flowchart of the proposed fault detection and classification algorithm

TABLE II. RBFNN OUTPUT FOR FIA 90^0, FAULT RESISTANCE 0 OHM AND LOADING ANGLE 10^0

Distance										
5	0.9988	2.0079	2.9758	4.0042	4.9989	6.0030	7.0073	8.0206	9.0102	10.0093
16	1.0000	1.9987	3.0014	3.9997	5.0004	5.9998	6.9995	7.9983	8.9995	9.9995
23	1.0007	1.9997	2.9997	4.0001	4.9996	6.0001	7.0004	8.0012	9.0002	10.0003
36	1.0004	1.9999	3.0002	4.0000	5.0014	5.9999	6.9999	7.9979	9.0000	10.0003
43	1.0004	2.0011	2.9996	3.9998	5.0001	5.9999	6.9999	7.9997	8.9999	9.9998
53	0.9997	1.9988	3.0003	3.9998	5.0002	6.0000	7.0000	7.9997	9.0000	10.0001
67	0.9997	1.9997	3.0004	3.9994	5.0000	5.9999	6.9999	8.0000	9.0000	10.0002
76	0.9999	1.9996	3.0001	3.9999	4.9998	6.0000	6.9999	8.0002	9.0000	10.0000
87	1.0003	2.0003	3.0003	4.0004	5.0001	6.0000	7.0003	8.0000	9.0000	9.9998
92	1.0000	2.0002	3.0000	3.9999	4.9999	6.0000	6.9998	8.0000	9.0000	10.0001
107	1.0003	2.0002	2.9999	3.9999	5.0000	5.9999	7.0000	8.0000	9.0000	10.0000
113	1.0002	1.9992	3.0001	3.9999	5.0000	6.0000	6.9999	8.0000	9.0000	10.0000
119	1.0004	2.0002	2.9997	4.0000	5.0001	6.0000	7.0000	8.0001	9.0000	10.0000
122	0.9997	1.9994	3.0000	3.9995	5.0001	6.0000	6.9997	8.0002	9.0000	10.0000
128	0.9996	2.0001	2.9999	3.9998	5.0001	5.9999	6.9998	7.9998	9.0000	10.0000
133	0.9996	1.9996	3.0001	3.9999	5.0000	6.0000	7.0000	8.0002	9.0001	9.9997
138	1.0014	1.9996	3.0004	4.0000	5.0001	5.9996	7.0003	8.0001	9.0000	10.0012

VI. RESULTS AND ANALYSIS

Features obtained using WPD are fed to the RBF neural network after normalization for training as well as for testing. The proposed algorithm has been tested on a hybrid transmission line consisting of 100 km over head line and 40 km underground cable for SLG, LL, LLG and LLLG (three phase) fault with different fault resistances (0 Ω, 20 Ω & 150 Ω), fault inception angles (0^0 & 90^0) and different loading angles (δ) of 10^0 and 20^0. The algorithm has been tested for faults created at 17 different locations on both overhead section and underground cable section. The nature of fault transients may change depending on fault inception angle, fault impedance and loading angle of the alternators. In the present work, variation of all these parameters have been considered as discussed below.

Effect of Fault Inception Angle

Fault inception angle depends on the time of fault initiation and mostly unpredictable. Thus the nature of fault transients changes with the time of fault inception, although the proposed algorithm is independent of FIA. In the presentwork 0^0 and 90^0 FIA has been considered for testing.

Effect of Fault Impedance

Low value of fault resistance produces large transients in fault signals, whereas high value of fault resistance damps out these transients. Hence the wavelet packet energies are also different for high and low resistance faults. The normalized values of these features fed to RBFNN diminish the impact of fault resistance on detection and classification of faults on transmission line. Although the fault impedance is mostly resistive, sometimes non ideal fault involving fault reactance may occur. This paper also considers a fault impedance of (1 + j5) Ω along with fault resistances of 0 Ω, 20 Ω and 150 Ω to justify the ability of proposed algorithm for different fault impedances.

Effect of Loading Angle (δ) of alternator

The loading angle of alternators determines the load share by the alternators. With the change in the loading angle the current through the transmission line changes which leads to vary the fault transients. The proposed algorithm has been tested for two loading angles of 10^0 and 20^0 and it has been observed that the accuracy of detection and classification of faults immunes to the variation of loading angle.

The results of fault classification at different conditions are shown in Table III. From this table, it is clear that accuracy of the algorithm is very high irrespective of fault resistance, fault type, fault inception angles and loading angles. The accuracy is calculated with respect to total number of faults tested as given in (6).

$$\text{Percentage Accuracy} = \frac{\text{Number of correct predoctions}}{\text{Total faults tested}} \times 100\% \qquad (6)$$

VII. CONCLUSION

In the present work, Wavelet packet decomposition up to 3rd level with mother wavelet db1 is applied for feature extraction from fault current signals. The normalized wavelet packet energies of fault currents are then fed to RBFNN for detection and classification of faults on the hybrid transmission line. From the result, it can be concluded that that combination of wavelet packet decomposition and RBFNN can classify faults with an acceptable accuracy irrespective of fault resistance, FIA and loading angles. The proposed algorithm is fast as it utilizes on only half cycle of post-fault current and requires lesser memory to store only current signals recorded at the local end of the transmission line. The major advantage of this proposed algorithm is that this method is independent of identification of fault section for classification of faults on the hybrid transmission line.

TABLE III. RESULTS OF FAULT CLASSIFICATION USING RBFNN

Fault Condition	**FaultType**	**No of Faults Tested**	**No of Correct Prediction**	**% Accuracy**
FIA = 0^0, Rf = 0 Ω, δ = 10^0	SLG	51	51	100
	LL	51	50	98.03
	LLG	51	50	98.03
	LLLG	51	51	100
FIA = 0^0, Rf = 20 Ω, δ = 10^0	SLG	51	51	100
	LL	51	50	98.03
	LLG	51	50	98.03
	LLLG	51	51	100
FIA = 0^0, Rf =150 Ω, δ = 10^0	SLG	51	51	100
	LL	51	50	98.03
	LLG	51	51	100
	LLLG	51	51	100
FIA = 0^0, Rf = 0 Ω, δ = 20^0	SLG	51	51	100
	LL	51	50	98.03
	LLG	51	50	98.03
	LLLG	51	51	100
FIA = 90^0, Rf = 0 Ω, δ = 10^0	SLG	51	51	100
	LL	51	50	98.03
	LLG	51	50	98.03

	LLLG	51	51	100
FIA = 0^0, Zf =(1+j5) Ω, δ = 10^0	SLG	51	51	100
	LL	51	50	98.03
	LLG	51	51	100
	LLLG	51	51	100
	Overall	1224	1214	99.18

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