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Hilbert transform and Ann-based power transmission line faults identification and classification

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ABSTRACT
The transmission lines are important links in the power system. it carries a large amount of power from a remote distance sending the end to the distribution substation. During this, there are chances of various faults on it. So, early-stage fault identification is essential for a reliable power transfer. this paper implements a high-impedance fault identification technique based on the Hilbert-Huang transform (HHT). The signals of various fault conditions such as LL, LG, and LLL are captured and fourteen statistical parameters are calculated, from these signal features extracted using HT are given as input to ANN for the determination of fault type. The highest result of 96.3 per cent was obtained after changing the training and testing data, various Epochs, and percentage validations. The proposed HHT-based fault detection technique is confirmed on MATLAB Simulink.
Keywords: *MATLAB Simulink, HHT, Statistical Parameters, ANN.*

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I. INTRODUCTION

Power transmission line fault identification and discrimination are very difficult tasks. Power reliability is the most essential factor in the power sector as transmission lines are a concern due to their large geographical area fault identification in the early stages is essential, so researchers always trying to develop fault identification and discrimination algorithm with fast detection features in that different ways have been implemented for fault classification such as the approaches depends on travelling waves [1-2], adaptive Kalman filtering [3], fuzzy logic, neural networks [4], and the combination 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, hyperbolic-s [5], H-Transform, and Parks transform. These all transforms have some drawbacks such as high convergence time, not being suitable for nonlinear signals, complexity, etc. In this work The Hilbert Transform is used due to its important features i.e., it can able to extract the features of the non-stationary and non-linear signal. The calculated 14 statistical parameters are given as input to ANN for the discrimination of various faults. the neural-network-based approaches have been quite successful in determining the correct fault type.

II.PROPOSED FAULT DETECTION METHODOLOGY

The two-generator model created in MATLAB Simulink then creates a fault on the transmission line at various locations such as 300KM,600KM, and 9900Km. the term fault means any abnormal condition and situation cause or in simple words when current diverted to its intended path is called a fault [10]. Two types of faults are symmetrical and unsymmetrical LLL, LL, and LLG, respectively. The developed system is shown in the following Figure 1 .in this figure fault was created at 300 km[8,9].

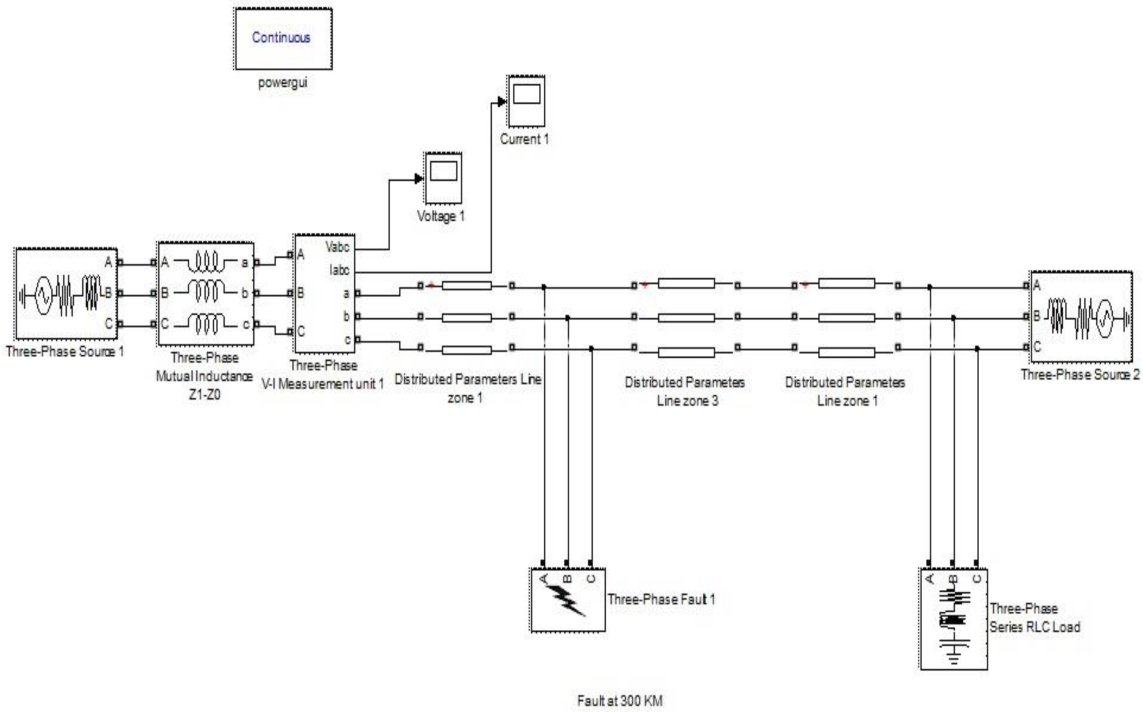

Figure. 1**:** MATLAB Simulation Model of Transmission line faults at 300KM distance

The following parameters are used to create the simulation model of transmission line faults.

Table 1: Parameters used for a simulation model of transmission line faults

Parameter	Specifications
1. Source	
Ph-ph voltage (Vrms)	25e3
F (Hz):	50Hz
R(Ohms)	0.8929
L (H):	16.58e-3
2. Three-phase Mutual Inductance	
+ve- sequence parameters: [R1 (Ohms) L1 (H)]	[2 50e-3]
0-sequence parameters: [R0 (Ohms) L0 (H)]	[4 100e-3]
2. Distributed line (Transmission line model)	
Several phases [N]:	3
Transmission Line length	300km, 600km, 900km
R per unit length (Ohms/km) [NxN matrix] or [r1 r0 r0m]:	[0.01274 0.3865]
L per unit length (H/km) [NxN matrix] or [l1 l0 l0m]:	[0.9338e-3 4.1364e-3]
C per unit length (F/km) [NxN matrix] or [c1 c0 c0m]:	[12.84e-9 8.751e-8]

The faults created in MATLAB Simulink are LL, LG, and LLL and the voltage and current signals are captured. Similarly,faults are created at 600km and 900 km.

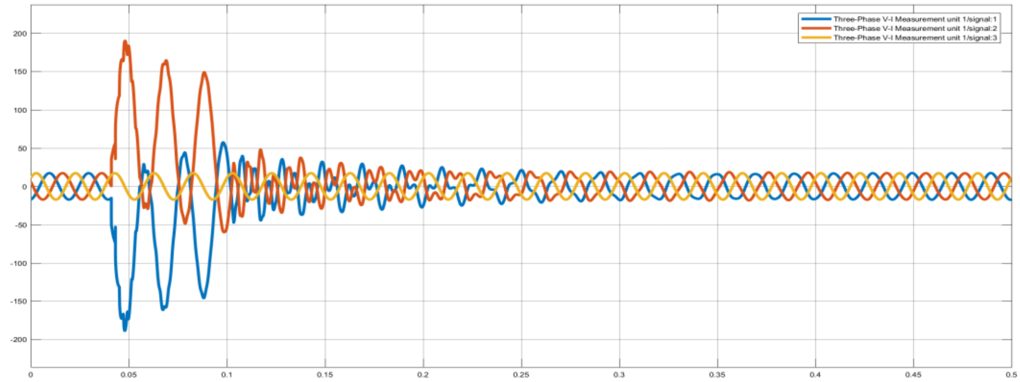

Figure:2. Current waveform 300KM LL Fault (Phase AB)

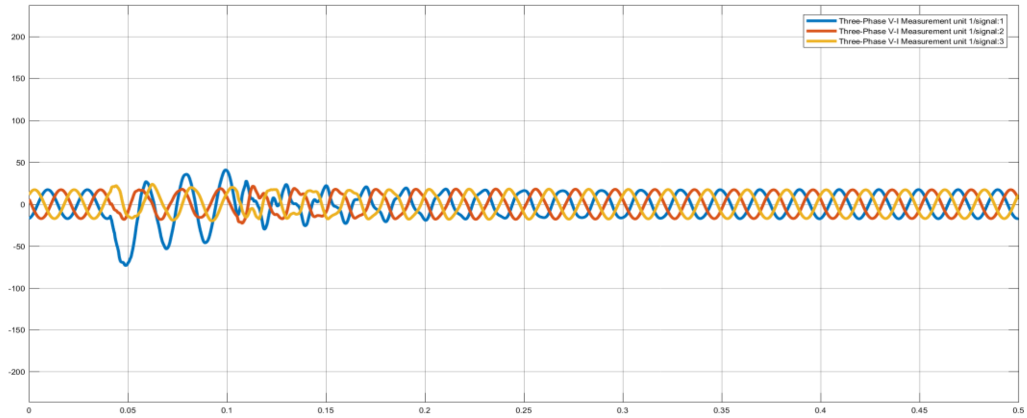

Figure: 3. Current waveform 300 KM
LG Fault (Phase AG)

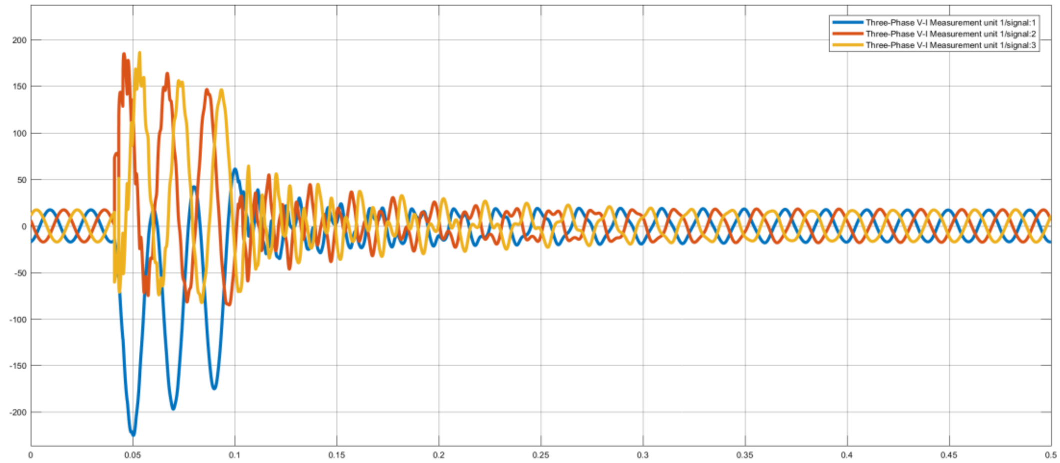

Figure:4. Current waveform 300KM
LLL Fault (Phase ABC)

Similarly, various waveforms for faults between BC, CA, BG, CG, and ABC phases have been created at 600km and 900 km [23].

III. HILBERT TRANSFORM

The Hilbert transform was first introduced by David Hilbert to solve a special case of the Riemann–Hilbert problem for analytic functions The Hilbert transform is a specific singular integral that uses a function(t) of a real variable and produces another function of a real variable H(U)(t). The Hilbert transform has a particularly simple representation in the frequency domain: It reports a phase shift of ±90° ($\pi/2$ radians) to every frequency component of a function, the sign of the shift dependent on the sign of the frequency. The Hilbert transform [25] is significant in signal processing, where it is a component of the analytic illustration of a real-valued signal u(t).

the Hilbert transform of a function (or signal) $u(t)$ is given by

$$H(u)(t) = 1/\pi \, \text{p.v} \int_{-\infty}^{\infty} \frac{u(\tau)}{t-\tau} \, d\tau$$

Cauchy principal value (denoted here by p.v.) Alternatively, by changing variables, the principal value integral can be written explicitly as

$$H(u)(t) = 2/\pi \lim_{\epsilon \to 0} \int_{\epsilon}^{\infty} \frac{u(t-\tau)-u(t+\tau)}{2\tau} \, d\tau$$

When the Hilbert transform is applied twice in succession to a function u, the result is:

$$H(H(u))(t) = -u(t)$$

IV.STATISTICAL PARAMETERS

The various statistical parameters [10] used are sum, absolute, minimum, maximum, mean, median sum, standard deviation, variance rms value, energy, kurtosis, crest factor shape factor, and skewness of captured stator current signals [12,13]. They are given by the following formula.

$$\bar{X} = \frac{\sum_{i=1}^{n} x_i}{n} \quad (4.1)$$ where xi is the data value.

The median is the middle value of data arranged according to size. The variance is given by deviation from the mean $\bar{x}$ and is defined by the equation (4.2).

$$S^2 = \frac{\sum_{i=1}^{n} \left(x_i - \bar{x} \right)^2}{n-1} \quad (4.2)$$

Standard deviation is the square root of the variance and can be obtained by equation (4.3).

$$S = \sqrt{\frac{\sum_{i=1}^{n} \left(x_i - \bar{x} \right)^2}{n-1}} \quad (4.3)$$

The addition of all sample values is also one of the statistical parameters used to differentiate the abnormal and normal conditions. RMS value and absolute sum of all samples are the other useful parameters that give useful information about the signals to differentiate amongst each other. The kurtosis can be obtained by equation (4.4).

$$K = \frac{1}{N} \sum_{i=0}^{N-1} \frac{\left(xi - \bar{x} \right)^4}{\sigma^4} \quad (4.4)$$ where σ is the standard deviation

The energy of the signal can be calculated using equation (4.5)

$$Ex = \sum_{n=-\infty}^{\infty} \left| x(n) \right|^2 \quad (4.5)$$

The crest factor is given by .

$$C.F = \frac{x_{peak}}{x_{rms}} \quad (46)$$

The Skewness of any perfectly symmetric data is zero.

$$Skewness = \frac{\sum_{i=1}^{N} xi - \bar{x}}{(N-1)\sigma^3} \quad (4.7)$$

$\bar{x}$ is mean, S is standard deviation, N is several samples in a given signal.

V.RESULT AND DISCUSSION

` The current signals are not sufficient to classify the transmission line faults so its Hilbert transform has been taken and 14 statistical parameters [14] have been calculated for the classification of faults [7]. the following figures show the different HT results for various types of faults.

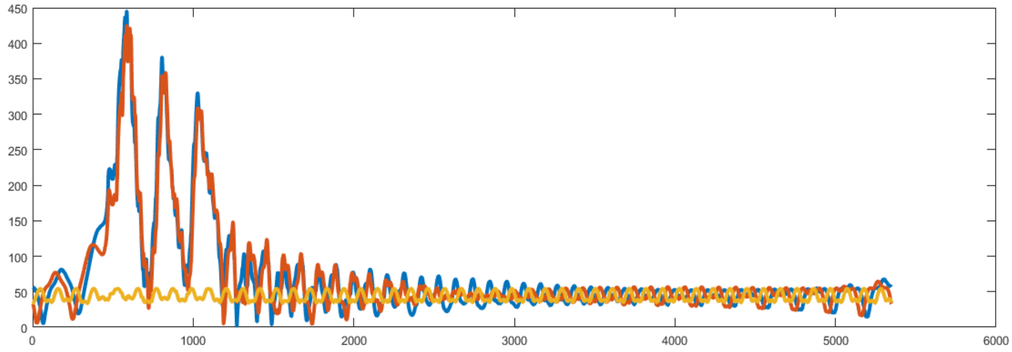

Figure:5. HT of current signal for L-L (A-B) fault 300KM

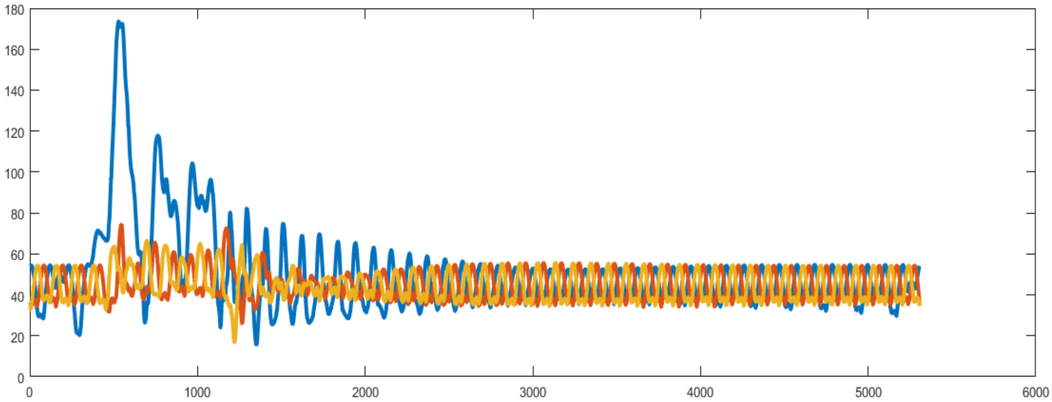

Figure:6. HT of current signal for L-G (A-B) fault 300KM

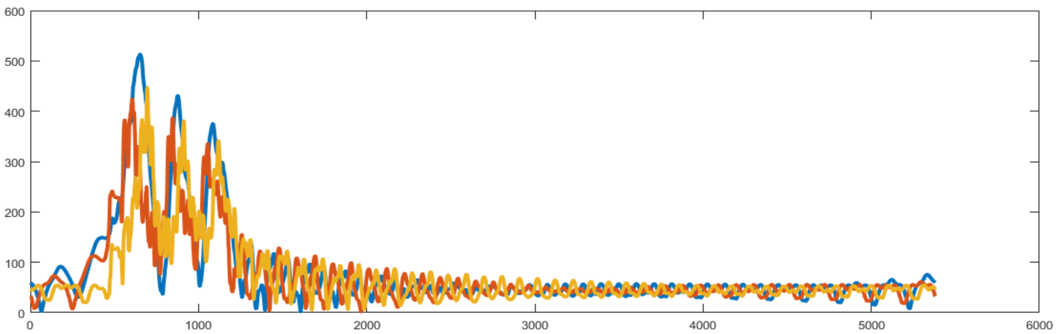

Figure:7. Hilbert Transform of current signal for L-L-L (A-B-C) fault 300KM

Similarly, currents for faults between BC, CA, BG, CG, and ABC at 600km and 900km are recorded. Hilbert Transform [16] is suitable for accurate time-frequency analysis. After Hilbert transform 14 Statistical parameters are calculated [19] and shown for phase AB in tabulated form.

Table 2: Statistical parameter Calculation for phase AB

	absum	add	cf	E	kurtosis
300KM LL AB	3.86E+05	3.86E+05	4.409876916	5.45E+07	11.34813631
300KM LG AG	2.65E+05	2.65E+05	3.195294252	1.57E+07	13.3580134
300KM LLL ABC	4.33E+05	4.33E+05	4.265863737	7.79E+07	10.78333365
	max	mean	median	min	Sf
300KM LL AB	4.45E+02	72.247078	50.475579	1.4984609	4.33E+05
300KM LG AG	1.74E+02	49.882607	44.360784	15.588873	1.57E+07
300KM LLL ABC	5.13E+02	80.395486	50.258491	1.7001074	4.23E+09
	skewness	std	var	Rms	
300KM LL AB	2.8514313	70.501191	4.97E+03	1.01E+02	
300KM LG AG	2.7789162	21.513706	4.63E+02	54.323354	
300KM LLL ABC	2.839917	89.516925	8.01E+03	1.20E+02	

Similar calculation has been done for phase B and phase C, these calculated 14 statistical parameters are given as input to the ANN along with the different hidden layer, epoch, and training and testing for getting the maximum accuracy of the transmission line fault classification [19,20].

V.a. Classification network used

In this study, Artificial Neural Network [17] is used for the discrimination of various fault categories. The neural network consists of 3 input and 3 output hidden layers. the 14 statistical parameters of the Hilbert transform have been calculated and given as input to ANN. The ANN uses the transfer function 'tansig', the learning rule 'learngdm'and momentum 0.7, The maximum epoch is 1000 along with the 226 iterations. The training percentage is 50% and the testing percentage is 50% which shows the data required for classification is less. for this the number of iterations is varied and the performance of the network is evaluated [13,15]. The architecture which is shown in Fig. 8 is chosen as the final for given input and output.

Figure: 8**.** Neural network training

Fig. 9 shows the confusion matrix for the three phases of training, testing and validation. It can be seen in Fig. 9 the chosen neural network has 96.3 per cent accuracy in fault classification [24].

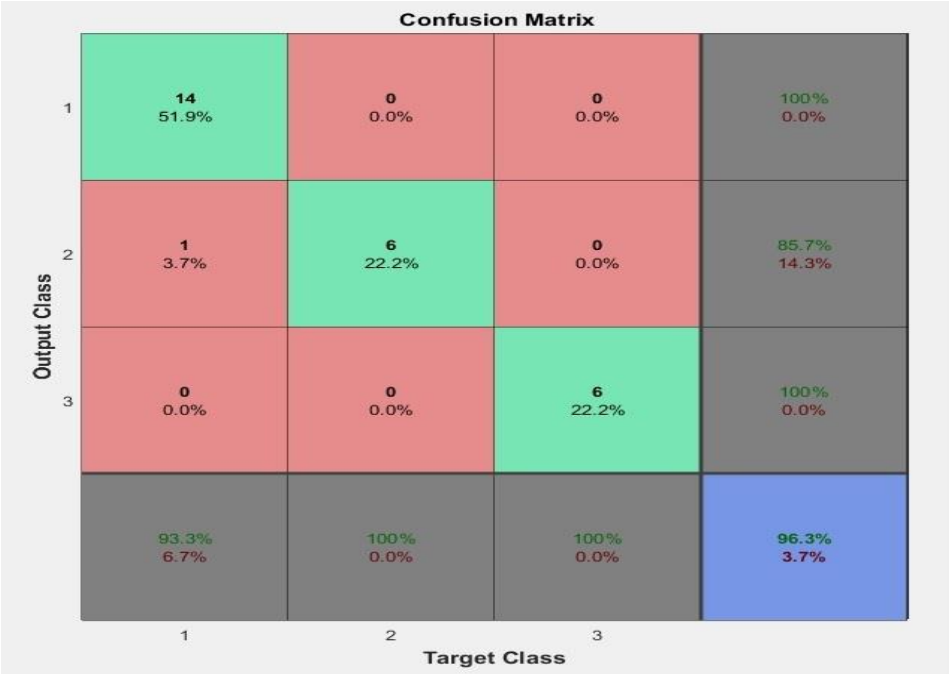

Figure:9**.** Confusion matrix for percentage accuracy of fault classification

VI.CONCLUSION

In this paper, the Hilbert transform and ANN combination is used for transmission line fault detection and classification. Hilbert transform is very useful in the analysis of the complex and non-stationary signals. a simple power system network is trained and tested for evaluating the algorithm. from the results, it has been identified that the algorithm is producing good results in fault classification. Hence the proposed algorithm is expected to work for complicated transmission line networks accordingly. The classification efficiency does not depend upon fault resistance, the location of the fault or the load value. The combination of Hilbert transform-based feature extraction, 14 statistical parameters, and ANN gives a classification accuracy of 96.3 % which is far better than other feature extraction and classification techniques.

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