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# **Electrical Signal Driven Transmission Line Protection Using Signal Processing Techniques**

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**ABSTRACT:** This paper presents a new protection for an electrical signal driven system that has been created for transmission lines. Using electrical signals like current and voltage waveforms to identify and categorise faults improves the reliability of this protection scheme. The transmission lines are important links in the power system; they carry a large amount of power from a remote distance, sending end to the distribution substation. During this time, there is a chance of various faults arising from it. So, early-stage fault identification is essential for a reliable power transfer. This paper implements signal processing techniques such as the Stockwell transform and Hilbert transform the signals of various fault conditions such as LG, LL, LLG, LLL, and LLL along with NOFAULT are captured and statistical parameters are calculated, from these signal features extracted using Stockwell transform and Hilbert transform and Hilbert voltage index are given as input to ANN for the detection and classification of fault type. The neural network-based approaches have been quite successful in determining the correct fault type. The ANN-based classification achieves more accuracy with the Hilbert transform-based fault detection technique, and the Stockwell transform fault detection and classification technique is confirmed on MATLAB Simulink.

**KEYWORDS**: signal processing technique; Stockwell transform; Hilbert transform; Fault Index; transmission line; protection scheme; artificial neural network (ANN)

#### I. INTRODUCTION

The protection of transmission lines is a critical aspect of power system stability and reliability, particularly as electrical grids become increasingly complex and interconnected. Traditional protection schemes, primarily dependent on distance relays, often come across challenges such as mal-operation during power swings, load encroachment, and high impedance faults (HIFs). As a result, there is a growing need for innovative fault detection and classification methods that can enhance the awareness and accuracy of protection mechanisms.

Recent advancements in signal processing have shown potential in addressing these challenges. For instance, conventional methods have been improved with fuzzy logic algorithms that effectively classify different fault types on transmission lines. Furthermore, techniques including wavelet transforms have been explored for power line fault identification, leveraging their capacity to analyze varying frequency components within current waveforms [7] [8].

Such methodologies are vital as they provide greater reliability by enabling fault detection in diverse scenarios, including different fault locations and occurrence angles [13].

Moreover, hybrid approaches combining multiple signal processing techniques have met research interest, as they allow for improved fault recognition by processing both current and voltage signals simultaneously. The integration of these methodologies not only enhances fault detection accuracy but also minimizes misinterpretations that may arise from relying on conventional single-domain analysis Similar hybrid protective schemes have contributed significantly to the development of further robust power systems, able to accept the addition of saturation of renewable energy sources and the complications they bring [9] [10].





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In response to these developments, this paper aims to propose an advanced electrical signal driven protection scheme for transmission lines that employs a signal processing approach. The proposed system aims to enhance the detection and classification of faults using an Artificial Neural Network (ANN), ensuring the dependable operation of power transmission networks facing momentary problems. Also, the methodology addresses critical factors such as fault inception angles, varying fault resistances, and the different fault distances. Through detailed testing on a two-terminal transmission line model simulated in MATLAB. The paper is organised as follows:

- Section 2 describes the test transmission line.
- Section 3 offers the proposed methodology.
- Section 4 provides a summary of the Stockwell and Hilbert transforms.
- Section 5 involved a fault classifier such as an Artificial neural network.
- Section 6 presents the results of simulations for identifying and classifying faults.
- Section 7 reviews the conclusions of the paper.

#### **II. TEST TRANSMISSION LINE**

Figure 1 describes the test system for the two-terminal transmission lines employed in the proposed study [4]. Between buses 1 and 2, the transmission line is under consideration for the proposed scheme. Large utility grids are represented by sources 1 and 2. CB-1 and CB-2 are the circuit breakers. Bus 2 is regarded as the receiving end of the transmission line, whereas bus 1 is regarded as the sending end. The per-unit calculations for both buses are based on a reference voltage of 500 kv (Vrms, phase-to-phase) and a base apparent power of 100 MVA. The suggested technique is evaluated under reverse power flow conditions as well, though, because the transmission line is bidirectional. The system parameters used in the study are provided in Table 1 [4]. Under the line loading scenario, an inductive load of 50 MW and 10 MVAR is applied.



Figure 1. Proposed test system of transmission line





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

S. No.	Parameter	Magnitude of parameter
1	Total Line Length	150km
2	Voltage of Source-1	500∠ 20°kV
3	Voltage of Source-2	500∠0°kV
4	Equivalent Impedance of Source-1	17.177+j45.529Ω
5	Equivalent Impedance of Source-2	15.31+j45.925Ω
6	Positive Sequence Impedance of Transmission Line	4.983+j117.83Ω
7	Zero Sequence Impedance of Transmission Line	12.682+j364.196Ω
8	Positive Sequence Admittance of Transmission Line	j1.486m℧
9	Zero Sequence Admittance of Transmission Line	j1.099m℧
10	Rated Apparent Power of Transmission Line	433.63+j294.52MVA

Five fault types, LG, LL, LLG, LLL, and LLLG, were created. These fault types were simulated using the test transmission system shown in Fig. 1. Cases per 10 km for different fault types, along with the no-fault condition, were analyzed. The inception angle varies as  $0^{\circ}$ ,  $30^{\circ}$ ,  $60^{\circ}$ ,  $90^{\circ}$ ,  $120^{\circ}$ ,  $150^{\circ}$ , and  $180^{\circ}$  in each case, while the fault resistance varies as  $0 \Omega$ ,  $2 \Omega$ ,  $4 \Omega$ ,  $6 \Omega$ ,  $8 \Omega$ ,  $10 \Omega$ , and  $50 \Omega$ . This data processing is performed by the Stockwell and Hilbert transforms. The mathematical formulations are being used to identify fault events that happened on a transmission line. The faults created in MATLAB Simulink are LG, LL, LLG, LLL, and LLLG, and the voltage and current signals are captured. Faults are created as the total line length is 150km.





# **III. PROPOSED METHODOLOGY**

To detect and classify transmission line faults, the Stockwell transform approach is proposed:

- 1. Simulate the test system under both normal and faulty conditions.
- 2. Record the line current and voltage signals.
- 3. Apply the S-transform to the recorded signals.
- 4. Compute the median and variance of the Stockwell transform, defining it as the Stockwell Fault Index (SFI).
- 5. The Stockwell Fault Index (SFI) for each phase and input it into an artificial neural network (ANN) for fault detection and classification.

To detect and classify transmission line faults, the Hilbert transform approach is proposed:

1. Simulate the test system under both normal and faulty conditions.

Т

- 2. Record the line current and voltage signals.
- 3. Apply the H-transform to the recorded signals.
- 4. Compute the absolute value of the Hilbert transform, defining it as the Hilbert Current Index (HCI) and Hilbert Voltage Index (HVI).
- 5. The Hilbert Current Index (HCI) and Hilbert Voltage Index (HVI). For each phase and input it into an artificial neural network (ANN) for fault detection and classification.

The method to apply the transmission line protection scheme is given in Figure 12, which shows the proposed scheme of this paper to apply for detection and classification of various types of faults such as LG, LL, LLG, LLL and LLLG.





## **IV. SIGNAL PROCESSING TECHNIQUES**

4.1. Stockwell fault index. The ST is computed from continuous wavelet transform (WT) to represent a signal in time frequency form this time frequency representation gives higher frequency resolution than wavelet transform corresponding to all frequency spectra associated with the signal the Gaussian function utilized as a window for ST and The Gaussian window is updated by multiplying a phase correction factor, which is an oscillatory exponential function [14]. The decomposition of a current signal (i(t)) using ST is expressed by the following mathematical formulation

$$S(\tau, f) = \int_{-\infty}^{+\infty} i(t) g(\tau - t) e^{-j2\pi f t} dt$$
(1)

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Where  $g(\tau)$  is the Gaussian modulation function and is defined by the following mathematical formulation,  $\tau$  and f represent time for spectral localization and Fourier frequency in the same order.

$$g(t) = \frac{|f|}{\sqrt{2\pi}} e^{-\frac{f^2 t^2}{2}}$$
(2)

Then ST is defined as

$$S(\tau, f) = \int_{-\infty}^{+\infty} i(t) \frac{|f|}{\sqrt{2\pi}} e^{-\frac{f^2 t^2}{2}} e^{-j2\pi f t} dt$$
(3)

The Stockwell fault index (SFI) is derived from the output matrix of the Stockwell Transform, S ( $\tau$ , f). The median Stockwell Transform index (MSTI) is obtained by calculating the median value for each column in the matrix S ( $\tau$ , f), as explained below.

$$MSTI = median(S(\tau, f))$$
(4)

The variance Stockwell Transform index (VSTI) is determined by calculating the variance of the Stockwell transform matrix S ( $\tau$ , f), as explained below.

$$VSTI = var(S(\tau, f))$$
(5)

The Stockwell fault index (SFI) is derived by the multiplication of MSTI and VSTI elements by element, as detailed below:

$$SFI = MSTI \times VSTI$$
 (6)



Figure 13. Current waveform of SFI for LG Fault (Phase AG)



Figure 14. Voltage waveform of SFI for LG Fault (Phase AG)

Figures 13 and 14 show the current and voltage waveform of the (SFI) Stockwell fault index, which is computed by processing the captured signal of current and voltage.

4.2. Hilbert Current and Voltage Index. 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 singular integral that takes a function of a real variable and generates another real-variable function. In the frequency domain, it has a straightforward representation, introducing a phase shift of  $\pm 90^{\circ}$  ( $\pi$ /2 radians) to each frequency component of the function. The sign of the shift is dependent on the sign of the frequency. It applies the Hilbert Transform (HT) to the electrical signals of all three phases and computes an HT output matrix by extracting the absolute magnitudes of the transformed data, which is designated as Hilbert voltage index (HVI) and Hilbert Current index (HCI) using the following expression:

$$HVI = HCI = abs\left(\frac{1}{\pi}p.v\int_{-\infty}^{\infty}\frac{u(t)}{t-\tau}d\tau\right)$$
(7)



Figure 15. Current waveform of HCI LG Fault (Phase AG)



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Figure 16. Voltage waveform of HVI LG Fault (Phase AG)

Figure 15 and 16 shows the current and voltage waveform of the (HCI) Hilbert current index and (HVI) Hilbert voltage index, which is computed by processing the captured signal of current and voltage.

## V. FAULT CLASSIFIER

One of the advanced computational approaches employed is Artificial Neural Network (ANN), which is frequently used for function approximation problems, such as fault detection and classification in power systems. In this study, an Artificial Neural Network is used for the detection and classification of various fault categories. The neural network consists of 6 input and 10 hidden layers. The fault index of the Stockwell transform have been calculated and given as input to the ANN, and the Hilbert current and voltage indices have been calculated and given as input to the ANN uses the transfer function, the learning rule 'leamgdm'. The maximum epoch is 1000, along with 52 iterations for Stockwell-based and 25 iterations for Hilbert-based. The training percentage is 30%, the validation percentage is 35%, and the testing percentage is 35%, which shows that the data required for classification is less. For this, the number of iterations is varied the testing data is then given as input to the Function Fitting Neural Network.

The architecture shown in Figs. 17 and 18 show Neural network training, which gives Important performance indicators are examined, including regression (R) values, error histogram, and mean squared error (MSE). The neural network's strong accuracy and dependability are indicated by a low MSE and an R value near 1. The trained ANN's ability to anticipate outputs and suitability for use in fault detection or classification applications are both confirmed by these measures.

The testing data, which is not utilised during training, is given as input to the ANN Architecture, which is then identify and classify the faults into binary 0 and 1 accurately. The output in binary form we seen in the blocks of Fig. 25 and 26, ANN Architecture. Five types of faults are LG, LL, LLG, LLL, and LLLG. Identify and classify along with NOFAULT.





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Neural Network	aining (nn	traintool) —			
	Hidden + /	Output	Output		
Algorithms					
Data Division: Rand	om (divid	derand)			
Training: Lever Performance: Mear Calculations: MEX	nberg-Ma Squared	rquardt (trainIm) Error (mse)			
Progress					
Epoch:	0	52 iterations	1000		
Time:		0:00:01			
Performance:	1.30	0.00901	0.00		
Gradient:	1.38	0.000644	1.00e-07		
Mu: C	0.00100	0.000100	1.00e+10		
Validation Checks:	0	6	6		
Plots					
Performance	(plotpe	rform)			
Training State (plottrainstate)					
Error Histogram	m (ploterrhist)				
Regression	Regression (plotregression)				
Plot Interval:		1 ep	pochs		
Validation ston					
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		Stop Trainin	g Cancel		

# Figure 17. Neural network training for Stockwell-based



Figure 19. Performance plot for Stockwell-based

Hide	den	Output b		Output 4
Algorithms Data Division: Random Training: Levenbe Performance: Mean So Calculations: MEX	dividera rg-Marqua quared Erro	and) ardt (trainlm) or (mse)		
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Mu: 0.00 Validation Checks:	0	1.00e-15 0		1.00e+10 6
Plots Performance ( Training State ( Error Histogram ( Pageserion (	plotperfor plottrainst ploterrhist plotregres	m) ate) ) sion)		
Regression				

## Figure 18. Neural network training for Hilbert based



Figure 20. Performance plot for Hilbert-based





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# Figure 21. Error Histogram for Stockwellbased



Figure 23. Regression plot for Stockwell based

Figure 22. Error Histogram for Hilbertbased



Figure 24. Regression plot for Hilbertbased





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Figure 25. ANN Architecture (SFI\_current and voltage as input)



Figure 26. ANN Architecture (HCI\_current and HVI\_voltage as input)

## VI. RESULTS AND DISCUSSION

6.1 Stockwell Transform-Based Result. This section describes the simulation findings using the Stockwell fault index with a combination of ANN. Table 2 shows the detection and classification of the fault, which gives output in binary. Figure 27 shows the confusion matrix with the accuracy obtained by the Stockwell transform-based method.

÷						
	Sr.	Type of fault		Fault de	tection	
	No					
			L	L	L	G
	1	Line-Ground	1	0	0	1
	2	Line-Line	1	1	0	0
	3	Line-Line-Ground	1	1	0	1
	4	Line-Line-Line	1	1	1	0
	5	Line-Line-Ground	1	1	1	1
	6	No Fault	0	0	0	0

Table 2: Fault detection for Stockwell-based





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6.2 Hilbert Transform-Based Result. This section describes the simulation findings using the Hilbert current and voltage index with a combination of ANN. Table 3 shows the detection and classification of the fault, which gives output in binary. Figure 28 shows the confusion matrix with the accuracy obtained by the Hilbert transform-based method.

Sr. No	Type of fault	Fault detection			
1.0		L	L	L	G
1	Line-Ground	1	0	0	1
2	Line-Line	1	1	0	0
3	Line-Line-Ground	1	1	0	1
4	Line-Line-Line	1	1	1	0
5	Line-Line-Line-Ground	1	1	1	1
6	No Fault	0	0	0	0

Table 3: Fault detection	for Hilbert-based
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Figure 28. Confusion matrix for Hilbert-based

## VII. CONCLUSION

In this paper, the Stockwell transform and ANN, as well as the Hilbert transform and ANN combination, are used for transmission line fault detection and classification. Hilbert transform is beneficial in the analysis of complex and non-stationary signals, while the Stockwell Transform offers better adaptability for time-frequency decomposition, yielding highly detailed signal features. A simple power system network is trained and tested for evaluating faults. From the results, it has been identified that the signal processing in combination with ANN is producing good results in fault detection classification. Hence, the proposed scheme is expected to work for complicated transmission line networks accordingly. The combination of Stockwell Transform and ANN gives a classification accuracy of 96.94%, and the combination of Hilbert Transform and ANN gives a high classification accuracy of 99.72%, which is far better than other feature extraction and classification techniques. The ANN-based classification achieves more accuracy with Hilbert Transform and Stockwell Transform, giving similar superior performance.

## ABBREVIATIONS

ANN: Artificial Neural Network HCI: Hilbert current index HIF: High impedance faults HVI: Hilbert voltage index H-Transform: Hilbert transform LG: Line-to-Ground LL: Line-to-Line LLG: Line-to-Line-Ground LLL: Line-to-Line-Ground LLL: Line-to-Line-to-Line-ground MSTI: Median of Stockwell transform index SFI: Stockwell fault index S-Transform: Stockwell transform index





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