

International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)

International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal

Volume 3, Issue 2, June 2023

# **Power Transmission Line Fault: S-Transform based Feature Extraction and ANN-based Classification**

Prof. Vaibhav A. Ghodeswar<sup>1</sup> and Dr. Mirza A. Beg<sup>2</sup>

Assistant Professor, Department of Electrical Engineering<sup>1</sup> Professor and Head, Department of Electrical Engineering<sup>2</sup> MGI College of Engineering and Technology, Shegaon, India ghodeswarvaibhav@gmail.com and ansarbeg@gmail.com

**Abstract:** In this paper a new technique for the identification and discrimination of faults on the transmission line of the power system has been presented. The power system network considered in this study is the two-generator system simulated in a Matrix laboratory i.e., MATLAB milieu. Firstly, captured voltage and current are transformed using S-transform techniques then the various energy of faults has been calculated using Parseval's theorem. Then these energies are given as an input to ANN. The classification results obtained show the effectiveness of this technique.100 percent classification is achieved by using this method.

Keywords: ST(S-transform), Parseval's theorem, ANN, MATLAB.

### I. INTRODUCTION

This paper corresponds to the S-transform and ANN for transmission line fault cataloguing. The S-transform is having good characteristics determination of changes in frequency and period. The fault classification can be done using other various feature extraction techniques such as wavelet transform having a problem of selection of appropriate mother wavelet, FFT cannot be used for non-stationary signal, and Hilbert transforms having high computational complexity. so, ST has a better performance than above mentioned transform.

### **II. POWER SYSTEM MODEL**

The MATLAB-based Simulink of 300KM is used for capturing the raw voltage and current results. Table 1 consists of the actual parameter used during the development of the model). The following system has developed; symmetrical and unsymmetrical faults have been created at different locations such as at 300km,600km, and 900km. The developed system is shown in the following Figure 1 it consists of faults at a 300 KM distance.



Fig. 1. Transmission line faults at 300km distance.

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

Copyright to IJARSCT www.ijarsct.co.in

#### DOI: 10.48175/IJARSCT-11381





International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)

International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal

### Volume 3, Issue 2, June 2023

The various fault created are LL, LG, and LLL in MATLAB Simulink and voltage and current signals were captured. Similarly, faults are created at 600km and 900 km. the raw signals of voltage and current are recorded.

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

Parameter	Specifications
source	
(Vrms)	25e3
F (Hz):	50Hz
R (Ohms)	0.8929
L (H):	16.58e-3
distributed line (Transmission line model)	
Several phases [ N ]:	3
Line length	300km, 600km, 900km
R per unit	[0.01274 0.3865]
L per unit	[0.9339e-3 4.1267e-4]
C per unit	[12.84e-9 7.751e-6]



### Fig. 2. Current waveform 300 KM LL Fault (Phase AB)



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





International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)

International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal

Volume 3, Issue 2, June 2023



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

Similarly, various waveforms for faults between BC, CA, BG, CG, and ABC at 600km and 900km are recorded.

### **III. S-TRANSFORM-BASED FEATURE EXTRACTION**

The time-frequency contour is obtained in the following Figs 5,6 and 7. These contour observations indicate the changes in frequency and period amplitude. Therefore, the calculated energy after this stage can be given as an input for transmission line faults classification. this type of plot is a specialty of S-transform and no other feature extraction technique such as an FFT, or DWT has this advantage.



Fig.5. Contour representation for 300KM LL Fault



Fig.6 Contour representation for 300KM LG Fault





International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)

International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal

Volume 3, Issue 2, June 2023



### Fig. 7 Contour representation for 300KM LLL Fault.

The following figures show the 3D view of Amplitude, Frequency, and Time relation for the various fault situation.



Fig. 8 3D plot for 300KM LL Fault



Fig. 9 3D plot for 300KM LL Fault 3D plot for 300KM LG Fault

DOI: 10.48175/IJARSCT-11381





International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)

International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal

Volume 3, Issue 2, June 2023



Fig. 10 3D plot for 300KM LL Fault.3D plot for 300KM LLL Fault

### **IV. ENERGY LEVELS FOR DIFFERENT FAULTS**

Parseval's energy determination is a key step in this work the voltage and current signals are given as an input to S-Transform for the feature extraction of various contours at the various fault location with different types of faults now Parseval's energy has been calculated using the following formula:

$$\mathbf{E} = \frac{1}{T} \int_0^T (t)^2 dt = \sum_{n=0}^N |V[N]^2| \dots (1)$$

Where T = Periods

N= length of the entire signal

and V[n] = FT of the signal.

The calculated energy is tabulated in the following table.

Table 2: Calculated Energy values for different faults such as LL, LG, and LLL at different locations Line A-B.

KM and Fault	EAIA	EAIB	EAIC	EAVA	EAVB	EAVC
300KM LG	19.62324	19.47912	26.03786	90.76439	90.4864	92.6652
300KM LL	91.06198	11.25217	91.14425	19.40605	19.40605	19.5429
300KM LLL	14.74992	27.33527	28.68186	11.61259	2.68E+02	2.88E+0
600KM LG	1.27E+02	1.41E+02	73.60312	27.56991	27.12089	30.2425
600KM LL	36.08655	11.48016	33.8067	35.35378	11.86862	35.130
600KM LLL	12.96985	59.48306	63.54803	14.39028	70.16776	80.2531
900KM LG	6.57E+01	4.91E+01	5.27E+01	19.69894	19.85441	32.7095
900KM LL	41.1927	11.12013	37.99804	31.87283	11.72898	31.6114
900KM LLL	22.53765	67.17354	73.7722	19.61247	54.11459	66.0155

Similarly, energy calculated for phase B-C and phase C-A line

#### V. CLASSIFICATION NETWORK USED

In this research work, Artificial Neural [13] Network is used and trained with supervised learning. The neural network is provided with 3 input layers, 3 hidden layers, and 3 output layers during the fault classification process. The energy of the current signal in the feature extracted data-sheet is fed to the neural network in MATLAB and several iterations are varied and decided by the trial-and-error method. In the ANN transfer function 'tension', the learning rule, 'learngdm', momentum 0.7, and maximum epochs1500 iterations are used to train that network.the ANN architecture which is shown in Fig. 11 is chosen as the final NN for the given input and output.

DOI: 10.48175/IJARSCT-11381





International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)

International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal

Volume 3, Issue 2, June 2023

Neural Network				
			Hidden Laye	Output Layer Output Layer 3
Algorithms				
Data Division: Random (divide	erand)			
Training: Levenberg-Marq	juardt (trainlm)			
Performance: Mean Squared Er	rror (mse)			
Calculations: MEX				
Progress				
Epoch: 0	6 iterations	1000		
Time:	0:00:00			
Performance: 2.69e+04	5.04e-27	1.00e-15		
Gradient: 8.70e+04	3.48e-11	1.00e-15		
Mu: 1.00e-05	1.00e-10	1.00e+20		
Validation Checks: 0	0	6		
Plots				
Performance (plotnerfor	rm)			
(piotperior				
Training State (plottrains	tate)			
Regression (plotregres	ssion)			
			Plot Interval:	1 epochs
Performance goal met.				

Fig. 11 ANN architecture used for fault classification

It can be seen in Fig. 12 the chosen neural network has 100 percent accuracy in fault classification.

		Confusio	on Matrix	
1	1	<b>0</b>	0	100%
	33.3%	0.0%	0.0%	0.0%
Class 5	<b>0</b>	1	<b>0</b>	100%
	0.0%	33.3%	0.0%	0.0%
Output	<b>0</b>	<b>0</b>	1	100%
	0.0%	0.0%	33.3%	0.0%
	100%	100%	100%	100%
	0.0%	0.0%	0.0%	0.0%
	1	2 Target	3 Class	

Fig. 12 ANN classification matrix

### VI. CONCLUSION

The proposed algorithm is a fast, reliable algorithm for transmission line fault identification and discrimination This technique uses ST for the feature extraction then the extracted features are fetched to ANN. The ST-based ANN classifier gives 100 percent classification, the results show the effectiveness of this technique, which is more suitable than Wavelet and FFT.

### REFERENCES

[1] S. Assous and B. Boashash, "Evaluation of the modified S-transform for time-frequency synchrony analysis and source localization," EURASIP J. Adv. Signal Process., vol. 49, no. 1, pp. 1–18, 2012.

Copyright to IJARSCT www.ijarsct.co.in DOI: 10.48175/IJARSCT-11381





International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)

International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal

#### Volume 3, Issue 2, June 2023

[2] S. Zhang, P. Li, L. Zhang, H. Li, W. Jiang, and Y. Hu, "Modified S transform and ELM algorithms and their applications in power quality analysis," Neurocomputing, vol. 185, pp. 231–241, Apr. 2016.

[3] N. Huang, D. Xu, X. Liu, and L. Lin, "Power quality disturbances classification based on S-transform and probabilistic neural network," Neurocomputing, vol. 98, pp. 12–23, Dec. 2012.

[4] S. R. Samantaray, L. Tripathy, and P. K. Dash, "Sparse S-transform for the location of faults on transmission lines operating with unified power flow controller," IET Generat.,

[5] M. Abdel-Akher and K. Mohamed Nor, Fault analysis of Multiphase Distribution Systems Using Symmetrical Components, IEEE Trans. On Power Delivery, vol. 25, No. 4, pp. 2931-2939, Oct. 2010.

[6] Francisco Martín, and José A. Aguado, Wavelet-Based ANN Approach for Transmission Line Protection, IEEE Trans. On Power Delivery, vol. 18, No. 4, pp. 1572-1574, Oct. 2003.

[7] J. Upendra, C.P.Gupta, G.K.Singh, Discrete Wavelet Transform and Genetic Algorithm based Fault Classification of Transmission Systems, 15th National Power Systems

[8] V.S. Kale, S.R. Bhide, P.P.Bedekar and G.V.K.Mohan, Detection, and classification of Faults on Parallel transmission Lines using Wavelet Transform and Neural Network, International Journal of Electrical and Electronics Engineering, pp. 364-368, 2008.

[9] P.S.Bhowmik, P.Purkait, K.Bhattacharya, A novel wavelet transform aided neural network based transmission line fault analysis method, International Journal of Electrical Power and Energy Systems, Vol. 31, No. 5, pp. 21-19, June 2009.

[10] K.H.Kashyap,U.J.Shenoy, Classification of Power System Faults using Wavelet Transforms and Probabilistic Neural Networks, Proceedings of International Symposium on Circuits and Systems, 25-28th May 2003, Vol.3, pp. III-423-III-426.

[11] O.A.S. Youssef, Combined fuzzy-logic wavelet-based fault classification technique for power system relaying, IEEE Trans. On Power Delivery, vol. 19, No. 2, pp. 582-589, Apr. 2004.

[12]H. Wang and W. W. L. Keerthipala, Fuzzy-neuro approach to fault classification for transmission line protection, IEEE Trans. On Power Delivery, vol. 13, No. 4, pp. 1093-1104, Oct. 1998.

[13] B. Das and J. V. Reddy, Fuzzy-logic-based fault classification scheme for digital distance protection, IEEE Trans. On Power Delivery, vol. 20, No. 2, pp. 609-616, Apr. 2005.

[14] Ali-Reza Sedighi, Mahmood-Reza Haghifam, O. P. Malik, and Mohammad-Hassan Ghassemian, High Impedance Fault Detection Based on WaveletTransform and Statistical Pattern Recognition, IEEE Trans. On Power Delivery, vol. 20, No. 4, pp. 2414-2421, Oct 2005.

[15] Y. Sheng and S. M. Rovnyak, Decision tree-based methodology for high impedance fault detection, IEEE Trans. On Power Delivery, vol. 19, No. 2, pp. 533-536, Apr. 2004.

[16] A. Jamehbozorg and S.M.Shahrtash, A Decision-Tree-Based Method for Fault Classification in Single-Circuit Transmission Lines, IEEE Trans. On Power Delivery, vol. 25, No. 4, pp. 2190-2195, Oct 2010.

[17] P. K. Dash, B. K. Panigrahi, and G. Panda, Power Quality Analysis using S-Transform, IEEE Trans. On Power Delivery, vol. 18, No. 2, pp. 406- 411, April 2003.

[18] M. V. Chilukuri and P. K. Dash, Multiresolution S-Transform-Based Fuzzy Recognition System for Power Quality Events, IEEE Trans. On Power Delivery, vol. 19, No. 1, pp. 323-330, Jan 2004.

[19] F. Zhao and R. Yang, Power-Quality Disturbance Recognition using STransform, IEEE Trans. On Power Delivery, vol. 22, No. 2, pp. 944-950, April 2007

[20] S. Mishra, C. N. Bhende, and B. K. Panigrahi, Detection and Classification of Power Quality Disturbances Using S-Transform and Probabilistic Neural Network, IEEE Trans. On Power Delivery, vol. 23, No. 1, pp. 280-287, Jan 2008.

[21] Ameen M. Gargoom, Nesimi Ertugrul, and Wen. L. Soong, Automatic classification and characterization of Power Quality Events, IEEE Trans. On Power Delivery, vol. 23, No. 4, pp. 2417-2425, Oct 2008.

[22] Navid Eghtedarpour, Ebrahim Farjah, and Alireza Khayatian, Effective Voltage Flicker Calculation Based on Multiresolution S-Transform, IEEE Trans. On Power Delivery, vol. 27, No. 2, pp. 512-530, April 2012.

[23] S.R.Samantaray, P.K.Dash, G. Panda, Fault classification and location using HS-transform and radial basis function neural network, Electric Power Systems Research, 2006, pp. 897-905

DOI: 10.48175/IJARSCT-11381

