Fault Localization on the Transmission Line Using FDOST and RBFNN

Manini Sarkar, Abdul Rahim and Bikash Patel

Abstract This paper presents a fault localization technique based on fast discrete orthogonal Stockwell transform (FDOST) and radial basis function neural network (RBFNN) on the transmission line. A part of the transmission network of WBSETCL, West Bengal is designed and simulated in MATLAB Simulink for the fault investigation. The fault current signals are recorded at one end of the transmission line with a sampling frequency of 50 kHz, and FDOST energy is extracted as fault feature from each of the three fault current signals. These features are fed to the RBFNN for fault localization on the transmission line. The proposed algorithm is found accurate for different types of faults, fault resistances and fault inception angles (FIA) at different locations on the transmission line.

Keywords Fast discrete orthogonal Stockwell transform (FDOST) · FDOST energy · Radial basis function neural network (RBFNN) · Fault inception angle (FIA) · Faults

1 Introduction

The power system protection is very important aspect for uninterrupted quality power supply to the consumers. Fast and accurate detection and localization of faults on the transmission line which is the heart of the power system is very important to restore the power system into normal condition. Different techniques are found in the literature for fault localization on the transmission line. The phasor estimation technique

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using discrete Fourier transform [1] and fast discrete Stockwell transform [2] locates faults on the transmission line accurately, although the travelling wave method [3, 4] is faster than this technique. Wavelet transform has better time–frequency resolution than discrete Fourier transform and is applied for fault localization [5, 6]. The features extracted using signal processing tools are used to train the machine learning tools for the estimation of fault location. Machine learning techniques like support vector machine [4], Fuzzy logic, radial basis function neural network [7, 8], and back propagation neural network [5, 9] are popular for fault localization.

Wavelet packet decomposition (WPD), a generalized form of wavelet transform, has a better time–frequency resolution than the wavelet transform. The drawbacks of WPD are the dilemma of mother wavelet selection and poor noise immunity. The Stockwell transform (ST), which is free from these limitations, can be used as the signal processing tool for fault localization [9–11]. S-transform has high redundancy and computational complexity. The high redundancy of S-transform can be improved by N number of unit length orthogonal basis vector incorporated in discrete orthogonal S-transform (DOST) [11, 12].

The present article proposes a fault localization method using fast discrete orthogonal S-transform (FDOST) and radial basis function neural network (RBFNN). The FDOST coefficients have been extracted from the fault current signals to train radial basis function neural network (RBFNN) for fault localization. The proposed method is tested for different fault resistances and fault inception angles (FIA) at different locations on the transmission line.

2 Fast Discrete Orthogonal Stockwell Transform

The S-Transform (ST), proposed in 1996, represents a signal in the time–frequency domain with a frequency-dependent resolution which is suitable for non-stationary signal analysis.

$$S(\tau, f) = \int_{-\infty}^{+\infty} h(t) \frac{|f|}{\sqrt{2\pi}} \exp\left(-\frac{(\tau - t)^2}{2f^2}\right) \exp(-i2\pi f t) dt \tag{1}$$

where f is the frequency of the signal, and t and τ are the time variables. The discrete S-Transform (DST) can be represented as

$$\begin{aligned} S[j, n] &= \sum_{m=0}^{N-1} H(m+n) \exp\left(-\frac{2\pi^2 m^2}{n^2}\right) \exp\left(\frac{i2\pi m j}{N}\right) \quad \text{for } n \neq 0 \\ &= \frac{1}{N} \sum_{m=0}^{N-1} h[k] \qquad \text{for } n = 0 \end{aligned} \tag{2}$$

where $H[.]$ is the discrete Fourier transform (DFT) of $h[.]$.

For a discrete signal with the length N, DST has N^2 number of coefficients and large computational complexity of $O(N^3)$. The computational complexity can be reduced by introducing N number of orthogonal basis vectors of unit length. This DST is known as discrete orthogonal S-transform (DOST), and it generates N numbers of coefficients with a computational complexity of $O(N^2)$. By introducing FFT, the computational complexity of DOST reduces to O(N log N). The basis function used in this algorithm is defined in a fixed window. A generalized window-dependent basis function is developed for more efficient time–frequency representation of S-transform using FDOST algorithm. The FDOST coefficients are calculated by inner product of the signal $h(k)$ and the basis function $E^{\varphi}_{[p,\tau]}(k)$ as given in (3).

$$S^{\varphi}_{[p,\tau]} = \left\langle h(k), E^{\varphi}_{[p,\tau]}(k) \right\rangle = \left\langle F^{-1} R^{\varphi} H, D[k]_{[p,\tau]} \right\rangle = \left\langle F^{-1} R^{\varphi} H, D[k]_{[p,\tau]} \right\rangle \quad (3)$$

where H is the DFT of $h(k)$ and R^{φ} is a sequence function and

$$E^{\varphi}_{[p,\tau]}(k) = \frac{1}{\sqrt{\beta(p)}} \sum_{j=0}^{\beta(p)-1} \left[C^{\varphi}_{[p,j]}(\nu(p)) \right]^{-1} \exp\left(2\pi i(\beta(p)+j)\left(\frac{k}{N} - \frac{\tau}{\beta(p)} \right) \right) \quad (4)$$

$$D[k]_{[p,\tau]} = \frac{1}{\sqrt{\beta(p)}} \sum_{j=0}^{\beta(p)-1} \exp\left(i2\pi(\beta(p)+j)\frac{k}{N} \right) \exp\left(-i\frac{2\pi\tau j}{\beta(p)} \right) \quad (5)$$

The computational complexity remains same as O(N log N) but only N numbers coefficients are generated. These coefficients are localized in both time and frequency domains. Each FDOST coefficient measures a specific feature of a signal in different window-dependent bases. The energy of FDOST coefficients of a signal can be used to represent the feature of the signal and it is defined as the sum of square of absolute values of the coefficients.

$$E = \sum_{k=1}^{N} \left| S^{\varphi}_{k[p,\tau]} \right|^2 \quad (6)$$

3 Radial Basis Function Neural Network (RBFNN)

The radial basis function neural network consists of three layers: input layer, hidden layer and output layer. The hidden layers consist of radial basis function and receive input vector via unit connection weight. The hidden layer calculates the Euclidean distance between centre and input vector, and it maps the input vector into output space by nonlinear transformation. The output layer uses linear combiner with adjustable weight parameter. Here, the parameters can be determined using least square method. If the input space is p dimensional and output space is m dimensional, the complete transformation can be written as

$$\mathrm{d_i} = \omega_{0\mathrm{i}} + \sum_{j=1}^{h} \omega_{ij} \varnothing\left(\left\|\mathrm{x} - \mathrm{c_j}\right\|, \beta_j\right) \tag{7}$$

where $\mathrm{d_i} \rightarrow i$th output, $\mathrm{x} \in \mathrm{R}^p \rightarrow$ input vector, $\omega_{0\mathrm{i}} \rightarrow$ biasing term, $\omega_{ij} \rightarrow$ weight between ith hidden node and jth output node, $c_j \in R^p \rightarrow$ centre of jth hidden node, $\beta_j \rightarrow$ real constant (spread factor), $\varnothing(\cdot) \rightarrow$ Nonlinear function and $i = 1, \ldots, m$ (number of output layer) and $j = 1, \ldots, h$ (number of hidden layer).

4 System Description and Fault Simulation

A part of West Bengal State Electricity Transmission Company Limited (WBSETCL) is designed in MATLAB Simulink for the fault investigation as shown in Fig. 1. The transmission lines are modelled using positive, negative and zero sequence components of resistance, inductance and capacitance. Total amount of load is 400 MW including 150 MW at Bus-3 and 250 MW at Bus-2. The specifications of the transmission lines are given in Table 1.

The transmission line 1 between Bakreswar and Arambag is considered to test the proposed algorithm. Four types of faults like line to ground fault (LG), line to line fault (LL), line to line to ground fault (LLG) and three-phase fault (LLLG) are generated at 12 locations for training purpose and another 7 locations for testing purpose. All these faults are simulated for fault resistances (R_f) of 10 and 100 Ω as well as for fault inception angles (FIA) of 0^0 and 90^0. Three-phase fault current

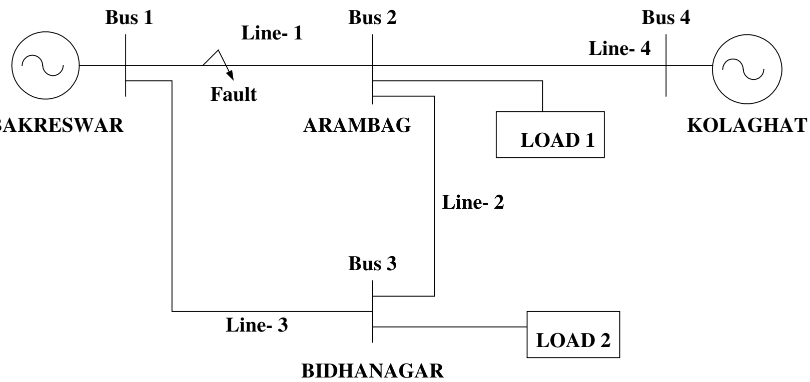

Fig. 1 The single-line diagram of the practical power system under investigation

Table 1 Specifications of the transmission lines

Line	Description	Length of the line (km)	Voltage (KV)
Line-1	Bakreswar to Arambagh	130	400
Line-2	Arambagh to Bidhannagar	114	400
Line-3	Bakreswar to Bidhannagar	40	220
Line-4	Kolaghat to Arambagh	64	400

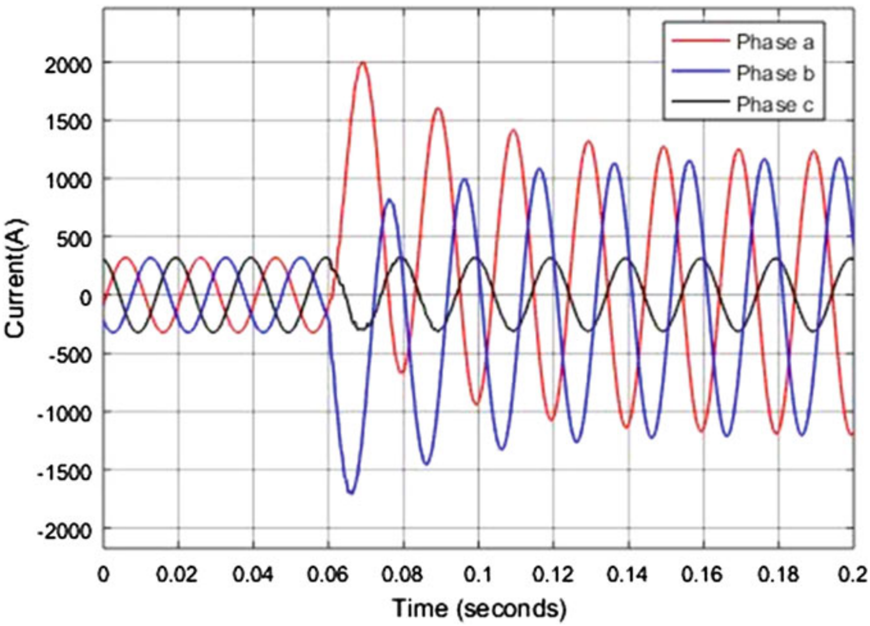

Fig. 2 Three-phase current signals for LLG fault at 70 km with fault resistance 10 Ω, FIA 0°

signals are recorded at Bus-1 with sampling frequency of 50 kHz. Fault current signals for three-phase fault at 70 km are shown in Fig. 2.

5 Feature Extraction and Fault Localization

The FDOST energy is calculated from half-cycle post-fault three-phase current signals, recorded for different conditions using Eq. (6). The FDOST energy is used as the fault feature. The extracted features are fed to RBFNN after normalization.

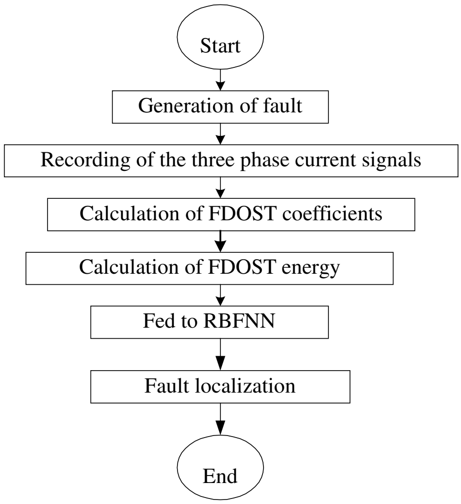

Fig. 3 Flowchart of the proposed fault localization algorithm

The RBFNN is trained with 12 sets of features for faults at 12 locations, and then it is tested for 7 fault locations on transmission line. The RBFNN is designed with three input vectors (features for three-phase currents) with a spread factor of 0.8. The complete flowchart is shown in Fig. 3.

6 Result and Analysis

Applying the proposed algorithm, the fault locations are estimated on transmission lines and the percentage error is calculated with respect to total length of the transmission line.

$$\text{Percentage Error} = \frac{\text{Estimated Location} - \text{Actual Location}}{\text{Total Length of Transmission Line}} \times 100 \qquad (8)$$

The results of fault localizations for different types of faults, fault resistances (R_f) and fault inception angles (FIA) are tabulated in Table 2. From this table, it is clear that the proposed algorithm is accurate to locate faults at different conditions. 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 accuracy of the proposed algorithm is independent of FIA as shown in Table 2. The nature of fault transients also depends on the fault resistances but the normalized values of FDOST-based fault features diminish the impact of fault resistance on fault localization on the transmission line.

Table 2 Result for fault localization for different conditions

Fault condition	Fault type	Actual fault location (km)	Estimated fault location (km)	% Error
$R_f = 10\ \Omega$ and FIA $= 0^o$	LG	7	7.0509	0.0391
		25	24.9870	−0.01
		85	85.0064	0.0049
	LLG	47	46.9764	−0.018
		103	103.1240	0.095
		122	121.9142	0.066
	LL	85	84.9936	−0.005
		103	103.1118	0.086
		122	122.0298	0.023
	LLLG	64	64.0064	0.005
		85	85.0094	0.007
		103	102.9802	−0.015
$R_f = 10\ \Omega$ and FIA $= 90^o$	LG	7	7.271	0.208
		25	24.814	−0.143
		85	85.546	0.420
	LLG	47	46.655	−0.265
		103	102.743	−0.198
		122	122.392	0.302
	LL	85	85.421	0.324
		103	102.964	−0.028
		122	122.149	0.115
	LLLG	64	63.823	−0.136
		85	84.694	−0.235
		103	102.951	−0.038
$R_f = 100\ \Omega$ and FIA $= 0^o$	LG	7	6.8356	−0.126
		25	25.0873	0.067
		85	85.0539	0.041
	LLG	47	46.4955	−0.388
		103	103.189	0.145
		122	122.194	0.149
	LL	85	85.0143	0.011
		103	103.0632	0.049
		122	121.8884	−0.086
	LLLG	64	63.9334	−0.051
		85	85.0387	0.030
		103	103.0615	0.047

7 Conclusion

This paper presents a fault localization technique based on fast discrete orthogonal S-transform (FDOST) and radial basis function neural network (RBFNN) on transmission line. A part of WBSETCL, West Bengal is designed in MATLAB Simulink for the fault investigation. FDOST energy is extracted as fault feature from each of the three fault current signals. The normalized values of these features are fed to the RBF neural network for fault localization at different distances on the transmission line. The accuracy of the proposed algorithm is very high for different types of faults, fault resistances and fault inception angles (FIA).

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