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# Identification of Short-circuit Fault Conditions in a Single Circuit Power Transmission Network using DOST and ANN

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Abstract **The present paper demonstrates how Discrete Orthonormal S-Transform (DOST) can be implemented for fault recognition in a power system network. A single circuit 3 -phase power transmission network has been considered for study. The simulated Voltage signal of each phase at the sending end of the network has been used for obtaining features by DOST under different fault conditions. The output matrix of DOST is a row vector of complex elements in which the number of elements is equal to the number of samples of the signal. 3 features have been obtained from the absolute value of the output matrix: Variance, Standard Deviation and Peak value of the row vector. Out of these features, only Standard Deviation has been selected as input parameter for training the PNN to identify the type of fault as the classification accuracy obtained with the other two types of features is unacceptable. The PNN architecture is also tested with the features obtained from the voltage signals in presence of noise. The noisy voltage signals have been generated by impregnating them with Gaussian White Noise of 10 DB by programming in MATLAB. The faults have been successfully classified even in presence of noise with only one set of feature reducing the size of the input vector of PNN. The runtime of both the programmes of DOST and PNN is around 27 sec. which is quite low.**

***Keywords —Artificial Neural Network (ANN), Discrete Orthonormal S-Transform (DOST), Fault, Fault Classification, Feature, Signal Processing, Probabilistic Neural Network (PNN)***

## I. INTRODUCTION

With the expansion of power industry to meet the growing need of mankind and industry, its protection system has to be reliable and accurate. Fault detection in overhead transmission lines is a challenging task since the beginning. Different conventional techniques based on numerical methods are available which have been substituted by soft computational techniques. The methods based on soft computation involve extraction of features from voltage/current signals obtained at different points of a network. The features are obtained from the signals by application of different signal processing techniques such as Fast Fourier Transform (FFT), Wavelet Transform and Stockwell Transform (S-Transform). Subsequently, these features are trained /supervised by any of the algorithm such as Artificial Neural Network (ANN), Support Vector Machine (SVM), Decision Tree method to identify a particular fault condition and its location. These methods provide accurate results within minimum time and do not require large calculations. The results are independent of the system parameters such fault impedance, sequence impedance, fault inception angle which are otherwise inaccessible to the user.

ANN has been always a powerful tool in detection of faults in overhead transmission lines as described in [1] , but in this paper the current signals have been directly used for training the network without involving any signal processing. The results in that case would contain errors as the practical signals contain noise. S-Transform on the other hand has been used for obtaining features from the voltage and current signals in a IEEE 14 bus system in [2]. Energy levels on the basis of parseval's theorem have been calculated to distinguish the different types of faults but no training algorithm/classifier has been used for fault identification. Discrete Wavelet Transform (DWT) is another powerful signal processing tool that has been used in [3] for feature extraction from the current signals of a three phase transmission network . But in this paper, the

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faults have been classified without involving any neural classifier /svm and the presence of noise has not been considered. A comprehensive survey on the applications of signal processing techniques in smart grids has been presented in [4]. A detailed survey of the various signal processing techniques, impedance-based measurement method, travelling wave phenomenon-based method, artificial intelligence-based method and some special technique for the detection, location and classification of various faults in a transmission network is provided in [5] till August 2017.

Discrete Orthonormal S-Transform (DOST) has been recently used as signal processing tool for feature extraction from voltage signals in [6]. Other than DOST, several other transformation tools have been used in this paper to make comparative analysis. A similar type of research has been conducted in [7] in which DOST has been used to obtain features from the current signals of the same network. However, in both these papers, the method of feature extraction presented is quite complicated and no expert classifier like ANN/SVM has been used for fault detection.

In the present work, DOST has been only used for feature extraction from the voltage signals of a single terminal of a three phase power transmission network. The layout of the paper is as follows. Section II describes the system used for the study and the conditions of simulations. The feature extraction and its selection has been explained in detail in section III . The architecture of PNN used for the method of fault classification has been discussed in section IV. The effect of noise in fault classification has been presented in section V. The conclusion is given in section VI.

## II. Simulation of Power System Network and Fault Conditions

The voltage data of the sending end of the power system network have been considered for obtaining features. The system specifications , given in Table I , and the single line diagram of the power system network, shown in Fig. 1, are available in [8]. The system parameters used for generation of fault conditions for training and testing of PNN are provided in Table II.

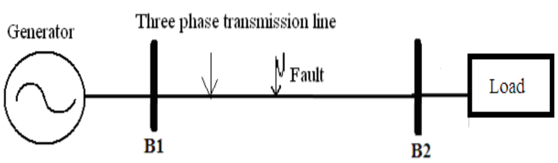


Figure 1. Single Line diagram of 400 kV, 50 Hz, 3-phase power system network

Table I: Specifications of the Power System network for the Study

| System Components | Specifications |
|---|---|
| Generator | Impedance = (0.2+j4.49) Ω, X/R ratio = 22.45. |
| Transmission Line | Length: 300 Km, R1 = 0.02336Ω/km, R2 = 0.02336Ω/km, R0 = 0.38848Ω/km, L1 = 0.95106mH/km, L2 = 0.95106mH/km, L0 = 3.25083mH/km, C1 = 12.37nF/km, C2 = 12.37nF/km, C0 = 8.45 nF/km |
| Balanced Load | Load Impedance = (720+j11) Ω, p.f.= 0.9, MVA rating = 200 |

The following 10 types of faults have been simulated in steps of 10km from the sending end of the network.

- Single Line-Ground fault for phase A, B and C respectively,(i.e. AG, BG and CG).
- Double Line fault (i.e. AB, BC and CA).
- Double Line-Ground fault (i.e. ABG, BCG and CAG).
- Three phase fault, i.e. LLL

Table II: Line and System Parameters used for generation of training and testing patterns

| Parameters of Fault conditions | Training dataset | Testing dataset |
|---|---|---|
| No. of types of faults | 10 | 10 |
| Fault resistance ($R_F$, Ω) | 0 | 20, 40, 60, 80, 100 |
| Fault location from sending end (D, in km) | 10 -290 km in steps of 10 km | 10 -290 km in steps of 10 km |
| Total number of patterns | 29×10 = 290 | 29×5×10=1450 |

## III. Feature Extraction and Selection

The mathematical functions of DOST are available in details in the literatures [9]. The coefficients of DOST have been obtained in a similar framework as Discrete S-Transform (DST) but there are some major differences as explained in the algorithm provided in the literature [10-14].

In the present work, DOST has been employed for obtaining features from the voltage signal of each phase. The output matrix of DOST is a row vector of complex elements. The absolute value of the output matrix has been obtained. From the elements of the row vector, Standard Deviation has been calculated for each phase for all the types fault conditions. From the elements of the row vector, the following three features have been calculated for each phase from the output matrix of DOST:

Variance, Standard Deviation and Peak/Maximum value.

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Profiles of the set of features have been shown in Figs. [2-4] for a particular fault condition for different fault locations. It is observed from the Figs. [2-4] that the magnitudes of the three features (Variance, Standard Deviation and Peak/Maximum value) for the faulty phase are quite low compared to the healthy phases in all cases of fault location.

The Probabilistic Neural Network (PNN), discussed in the next section, has been tested with the 3 sets of features individually. With Variance and Peak, the classification error has been obtained to be 84% which is unacceptable. Hence, the magnitudes of standard deviation have been used as the input features of a Probabilistic Neural Network. The results of fault classification have been shown in Table III. DOST has been implemented in MATLAB and the total run time of the programme is 1.537 sec.

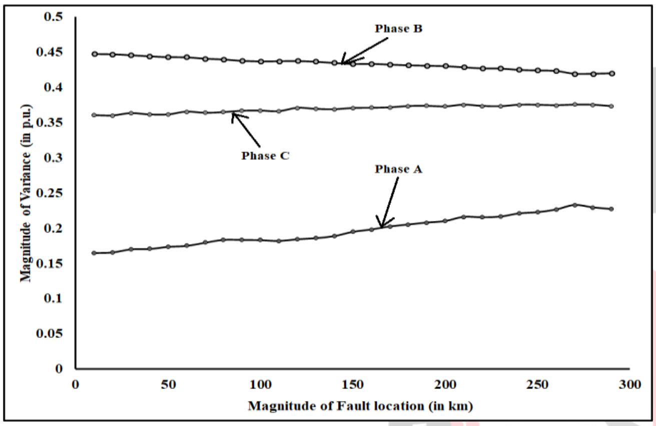


Fig.2 Profile of the magnitude of Variance calculated from the output matrix of DOST for each phase during AG fault occuring at different locations with $R_F$ = 0 ohm

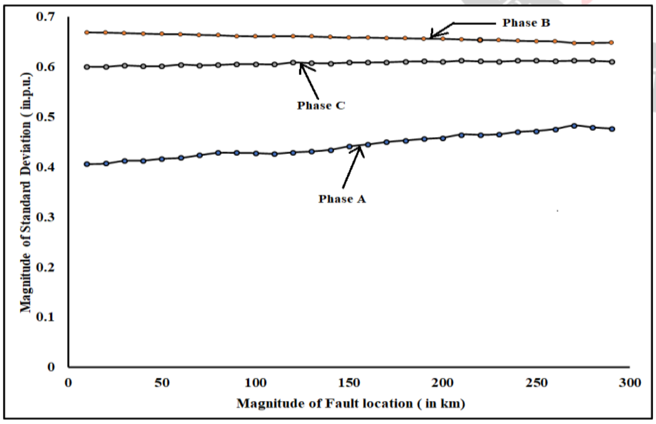


Fig.3 Profile of the magnitude of Standard Deviation calculated from the output matrix of DOST for each phase during AG fault occuring at different locations with $R_F$ = 0 ohm

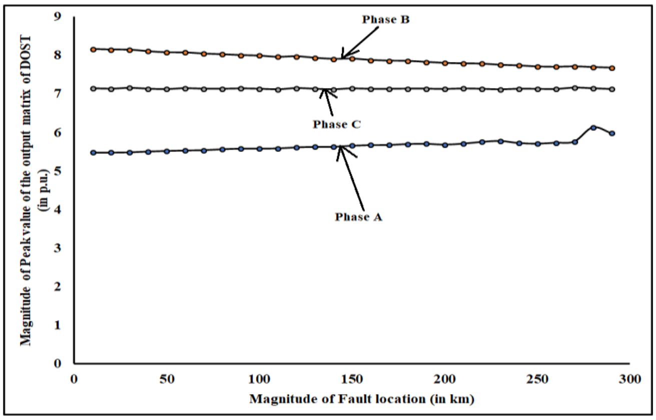


Fig.4 Profile of the magnitude of Peak value of the output matrix of DOST for each phase during AG fault occuring at different locations with $R_F$ = 0 ohm

## IV. Fault Classification by PNN

Standard deviation has been chosen as the characteristic feature which is to be used as training and testing parameter of PNN network. The advantage of using PNN is that the input parameters can be modified conveniently without involvement of rigorous training. The total time taken in obtaining the output results from PNN by running the programme in MATLAB is 25.715 seconds which is quite fast. The ten types of fault have been categorized integral values from 1 to 10. For example, AG fault has been categorized as 1, BG as 2 and so on.

The size of the input vector of PNN is 290 × 3 and that of the target vector is 290 × 1. The input vector consists of the magnitudes of standard deviation of the three phases for ten types of faults with Fault resistance 0 ohm. The target vector consists of the integral values from 1 to 10. The network has been tested with the rest of the data as shown in Table II and the results of classification are shown in Table III. It is observed in Table III that the mean error of classification for different values of fault resistances is 6.76%.

Table III: Results of Fault Classification

| Fault Resistance (ohm) | Classification Performance of PNN obtained from MATLAB toolbox | Absolute value Percentage error in classification | Absolute Mean error |
|---|---|---|---|
| 20 | 0.9034 | 7.66% | 6.76% |
| 40 | 0.9034 | 7.15% | |
| 60 | 0.9034 | 7.66% | |
| 80 | 0.9034 | 6.08% | |
| 100 | 0.9034 | 5.27% | |

## V. Impact of Noise

The practical voltage/current signals are corrupted The same PNN architecture as discussed in section IV has been once again tested with noisy signals. The training data set remains unchanged. The Testing dataset has been

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generated by impregnating the voltage signals with 10DB Gaussian white noise. DOST has once again been implemented on the noisy voltage signals and Standard Deviation has been calculated from the output matrix of DOST in a similar way as explained in section III. The resultant set of data has been used to test the PNN. The quantity of training and testing parameters that has been used is shown in Table IV. The results of classification have been provided in Table V from which it is observed that the mean error of classification for different values of fault resistances is 6.42%.

TABLE IV: LINE AND SYSTEM PARAMETERS USED FOR GENERATION OF TRAINING AND TESTING PATTERNS

| **Parameters of Fault conditions** | **Training dataset** | **Testing dataset generated with noise of 10 DB** |
|---|---|---|
| No. of types of faults | 10 | 10 |
| Fault resistance ($R_F$, Ω) | 0 | 0, 20, 40, 60, 80,100 |
| Fault location from sending end (D, in km) | 10 -290 km in steps of 10 km | 10 -290 km in steps of 10 km |
| Total number of patterns | 29×10 = 290 | 29×6×10=1740 |

TABLE V: RESULTS OF FAULT CLASSIFICATION WITH NOISE

| **Fault Resistance (ohm)** | **Classification Performance of PNN obtained from MATLAB toolbox** | **Absolute value Percentage error in classification** | **Absolute Mean error** |
|---|---|---|---|
| 0 | 0.9034 | 2.54% | 6.42% |
| 20 | 0.9034 | 5.89% | |
| 40 | 0.9034 | 8.99% | |
| 60 | 0.9034 | 7.26% | |
| 80 | 0.9034 | 7.76% | |
| 100 | 0.9034 | 6.08% | |

The difference of the mean error of classification between Table III and Table V is 5.11 % which is acceptable. The result indicates that the output matrix of DOST remains almost unaffected in presence of noise. Hence, the proposed method of fault classification works efficiently in presence of noise.

## VI. CONCLUSION

The present paper represents a method on Fault classification in overhead transmission lines of power system network using signal processing and neural network. Selection of feature is a challenging task for which three sets of features have been initially computed from DOST. Out of the three sets classification accuracy has been achieved with one set. Hence, size of the input vector of PNN reduces significantly. In this work, only the single circuit transmission network has been considered. The faults have been simulated under all possible conditions by changing the values of fault location and fault resistance. Hence, the maximum possible fault conditions have been rigorously investigated and they have been classified satisfactorily with the average percentage of error being 6.76%. The effect of noise has been studied by injecting synthetic noise in all the voltage signals. The sane PNN architecture has been tested with the noisy signals with the training set remaining unchanged. The average percentage error of classification obtained with noisy signals is 6.42%. The absolute value of the difference in the mean error of classification is 5.11%. Thus, it can be concluded that the proposed method identifies the type of fault and the faulty phases with acceptable accuracy even in presence of noise. Both the programmes of DOST and PNN work quite fast with the total time taken to be 27.252 sec. in a standard PC.

In the next part of this work, fault location would be obtained.

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