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A systematic fuzzy rule based approach for fault classification in transmission lines

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ABSTRACT

The paper presents a new approach for fault classification in transmission line using a systematic fuzzy rule based approach. Fault classification is one of the important requirements in distance relaying for identifying the accurate phases involved in the fault process. The proposed technique starts with pre-processing the fault current signal using advanced time–frequency transform such as S-transform to compute various statistical features. After the required features are extracted, the Decision Tree (DT), a knowledge representation method, is used for initial classification. From the DT classification boundaries, the fuzzy membership functions (MFs) and corresponding fuzzy rule-base is developed for final classification. Thus a systematic fuzzy rule base is developed for fault classification, reducing the redundancies and complexities involved compared to Heuristic fuzzy rule-based approach. Also a qualitative comparison is made between S-transform and Wavelet transform, where S-transform based DT-fuzzy provides highly improved results compared to the later during simulation as well as experimental tests.

1. Introduction

FAULTS on transmission lines need to be detected, classified, and cleared as fast as possible. In power transmission line protection, fault detection and faulty phase fault classification [1,2] are the two most important items which need to be addressed in a reliable and accurate manner. Distance relaying techniques based on the measurement of the impedance at the fundamental frequency between the fault location and the relaying point have attracted wide spread attention. The sampled voltage and current data at the relaying point are used to detect and classify the fault involving the line with or without fault resistance present in the fault path.

The proposed scheme works on the assumption that the fault detection has been done. The pre-fault and post-fault boundary is detected by using the phase space based fault detector [3] with response time of 4 ms (within 1/4th cycle). Thus, this paper focuses on effective fault classification in transmission lines for different types of faults. This provides information regarding the involvement of corresponding phase and ground in the fault process. There are 10 types of shunt fault occur on the power system such as a-g, b-g, c-g, a-b-g, b-c-g, c-a-g, a-b, b-c, c-a, a-b-c (a, b, c and g are the corresponding phases and ground, respectively of the transmission lines). Conventional approaches for fault classification are based on power frequency measurements and suffer from deficiencies due to fault resistance, fault distance, influence of mutual coupling from adjacent lines, reactance effect, incomplete knowledge of system parameters etc. In this regard, some new techniques have been adopted. Approaches using traveling wave theory have been proposed to perform fault classification task. A method based on initial current traveling waves is presented in [4,5]. However, these approaches lead to increased hardware requirement. Traveling waves, being high frequency signals, are difficult to separate from interference noise.

In recent years, techniques using artificial neural networks (ANN) and fuzzy logic have been employed for fault classification [6–9] due to their superior ability to learn and generalize from training patterns. However, in the fault classification tasks [6,7], the neural networks cannot produce accurate results due to the inaccuracies in the input phasor data and the requirement of a large number of neural networks for different categories of fault. The networks generate the trip or block signals using a data window of voltages and currents at the relaying point. However, the above approaches are sensitive to system frequency-changes, training time and a large number of neurons.

The combined Wavelet transform and fuzzy rule base [8,9] has been found very effective in fault classification and suitable for on-line implementation. To obtain more satisfactory results, however, wavelet filters having longer length and more levels of wavelet decomposition must be employed. Although wavelets provide a variable window for low and high frequency components in the corresponding signal, their capabilities are often significantly

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degraded owing to the existence of noises riding high on the signal [10]. Also the Heuristic fuzzy logic system [8,9] includes redundancies and complexities which increase the computational burden and reduce transparency. Thus, there is a strong motivation to design a more transparent and simple fuzzy logic system with improved accuracy to ensure reliable fault classification (faulty phase identification) in transmission lines. This research work aims at closing this gap by developing a more systematic approach for developing the fuzzy-logic based fault classifier while improving the classification performance. The advantage of the proposed scheme is that it exploits the time–frequency pattern of the faulted signal using S-transform (better time–frequency transform compared to Wavelet transform) followed by a transparent fuzzy classifier for final decision making. More the transparent is the classifier, implementation becomes easier for commercial relay module.

The proposed technique uses S-transform for preprocessing one cycle post fault current signal after fault detection to derive the sensitive statistical features. The S-transform [11–14] is an invertible time–frequency spectral localization technique that combines elements of wavelet transforms and short-time Fourier transform. The S-transform uses an analysis window whose width is decreasing with frequency providing a frequency dependent resolution. S-Transform is continuous wavelet transform with a phase correction. It produces a constant relative bandwidth analysis like wavelets while it maintains a direct link with Fourier spectrum. The S-transform has an advantage in that it provides multi resolution analysis while retaining the absolute phase of each frequency.

After the features are extracted using S-transform, the important issue is to design a classifier for classifying all the ten types of shunt faults. The method includes building a simplified and robust fuzzy classifier initialized by Decision Tree (DT) [15–19] for fault classification. As a result of the increasing complexity and dimensionality of classification problems, it becomes necessary to deal with structural issues of the identification of classifier systems. Important aspects are the selection of the relevant features and determination of effective initial partition of the input domain. Moreover, when the classifier is identified as part of an expert system, the linguistic interpretability is also an important aspect which must be taken into account. The first two aspects are often approached by an exhaustive search or educated guesses, while the interpretability aspect is often neglected. Now the importance of all these aspects is recognized, which makes the automatic data-based identification of classification systems that are compact, interpretable and accurate.

Compared to Heuristic fuzzy logic system [8,9], the proposed fuzzy rule base is optimal with respect to rule base formulation and complexity reduction. The DT provides the optimal tree for initial classification and from the initial classification boundaries, the fuzzy MFs and corresponding fuzzy rule-base [20–22] is developed for fault classification. Further the rule base simplification and fuzzy MFs tuning are performed using real coded GA. Thus the proposed technique is highly systematic compared to Heuristic fuzzy logic system.

2. System studied

The power system model shown in Fig. 1 is simulated using MATLAB (SIMULINK) software package. The relaying point is as shown in Fig. 1, where fault current signal samples (per unit) are retrieved for different fault conditions. The power system network consists of two areas of 400 kV generation capacities and connected by 300 km long transmission line (distributed model). The transmission line parameters are as given as; Zero sequence impedance $Z_{L0} = 96.45 + j\,335.26\,\Omega$, Positive sequence impedance $Z_{L1} = 9.78 + j\,110.23\,\Omega$, Source impedance $Z_S = 6 + j\,28.5\,\Omega$ and $Z_R = 1.2 + j\,11.5\,\Omega$, Source voltage $E_S = 400\angle\delta$ kV and $E_R = 400$ kV, where δ = load angle in degrees.

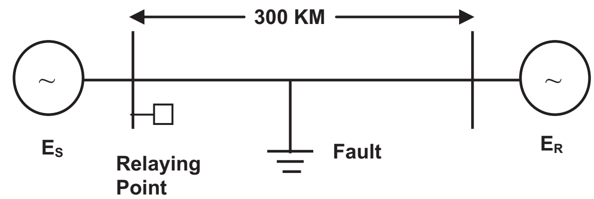

Fig. 1. Transmission line model.

The power system model is simulated at 1.0 kHz sampling frequency (20 samples per cycle) on a base frequency of 50 Hz. The current signals for different fault conditions are retrieved at the relaying point and preprocessed through S-transform to derive different features prior to develop DT-fuzzy rule base for fault classification.

The fault conditions are simulated under various operating conditions of the power system network as follows.

- Variations in fault resistance from 0 ohm to 200 ohm (0, 50,100, 200 Ω).
- Variations in source impedance by 30% from normal value (−30%, 0, +30%).
- Variations in fault location: 10, 30, 50, 70, 90% of the line (5 locations).
- Variations in inception angle: 0°, 30°, 45°, 60°, 90° (5 inception angles).
- Different types of fault: a-g, b-g, c-g, a-b-g, b-c-g, c-a-g, a-b, b-c, c-a, a-b-c (10 types).
- Reverse power flow (2 cases)

3. Feature extraction using S-transform

The S-transform [11–14] is an extension to the Gabor Transform and wavelet transform, and is based on a moving and scalable localizing Gaussian window. The interesting phenomena in the S-transform are that it is fully convertible both forward and inverse from time domain to frequency domain. This property is due to the fact that the modulating sinusoids are fixed with respect to the time axis while the localizing scalable Gaussian window dilates and translates. The S-transform falls within the broad range of multi-resolution spectral analysis, where the standard deviation is an inverse function of the frequency, thus reducing the dimension of the transform. The expression for S-transform of a continuous signal $x(t)$ is given as

$$s(t,f) = \int_{-\infty}^{\infty} x(t)w(t-\tau,f)e^{-2\pi i f\tau}d\tau \quad (1)$$

The window function can be expanded and the S-transform is given as follows

$$s(t,f) = \int_{-\infty}^{\infty} x(t)\frac{1}{\sigma(f)\sqrt{2\pi}}e^{((t-\tau)^2)/(2\sigma f^2)}e^{-i2\pi i f\tau}d\tau \quad (2)$$

Here f is the frequency, t is the time and τ is a parameter that controls the position of the gaussian window on the t-axis. The standard deviation $\sigma(f)$ of the gaussian window is related to frequency f as

$$\sigma(f) = \frac{1}{|f|} \quad (3)$$