

DG Connection Protection Based on Wavelet and Adaptive Neuro Fuzzy Combination Method

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Abstract:

In recent years, distributed generation has been expanding rapidly. Selection of the capacity and location of DGs has the benefits of improving power quality and reducing losses. In addition, many governments look at this with the aim of attracting private capital. Hence, capital maintaining and security of the investment is important for investors, and it is necessary to minimize the time of diagnosis and troubleshooting when the fault occurs, in order to get the best from the facilities. This paper is used WANFIS, which is presented as a combination of wavelet transform and ANFIS method. It is available to determine a fault in the connecting cable between generator and power supply at the shortest possible time. The proposed method was examined on a prototype network and the results show the accuracy of 94% in the correct diagnosis.

Keywords —Distributed Generation, Protection, Wavelet transform, Fuzzy algorithm, Signal processing

INTRODUCTION

Transmission line protection has always been a topic of major concern in the field of Electrical engineering, as it is a vital power system and is constantly exposed to the environmental conditions. Indeed, the faults due to overhead transmission lines are about 50% as compared to the different types of faults that occur in a power system. Fault analysis is a crucial process following the event of any fault occurrence. It is a direct measure of a system's capability to detect, classify and locate the fault and take preventive measures to protect the remaining equipment of the power system [1,20]. Due to the dynamic nature of fault transients, recent studies show that frequency domain analysis needs to be employed to capture the transient frequency components to accurately detect the occurrence of the fault [2-4].

In [5] Fourier transform is used to extract the fundamental frequency component for fault analysis. The problem of fixed resolution with Fourier

transform is solved by Short Time Fourier transform (STFT) with dynamic window frame size [6,18]. This this technique requires the knowledge of window size Therefore, a more efficient method for fault analysis was required, which overcame these problems, and this led to the design of a dynamic signal processing tool called wavelet.

Artificial Neural Networks (ANN) are recently developed tool in engineering technology, capable of pattern recognition. Fuzzy logic is used in different engineering applications for solving the uncertainty problem. The key benefit of fuzzy logic is that knowledge representation is explicit using simple "if-then" relations [7,19]. So the combination of these tools led to design WANFIS method for cable fault detection.

Magnago et al. [8] have presented an approach for fault location using wavelet MRA technique for calculating Db 4 level 1 and 2 detail wavelet coefficients at a sampling frequency of 100 kHz for the fault signal. Chanda et al. [9] presented a

Wavelet MRA technique for fault location based on the second and third harmonics components of a fault.

Ngaopitakkul et al. [10] have proposed a method combining both wavelet transform and probabilistic neural networks. Db4 is used as the mother wavelet to decompose high frequency components of scales 1 to 5 from the positive sequence phase current waveforms. Pothisarn et al. [11] have presented a fault location algorithm using wavelet transform and fuzzy logic. Positive sequence phase currents are calculated using the Clark's transformation matrix. Db4 is used as the mother wavelet to decompose the high frequency components from these current signals.

The aim of this paper is to investigate the performance of a coupled wavelet-ANFIS (WANFIS) model for detection fault location in the cable of generator feeder.

I. METHODOLOGY

A. Wavelet Transform

Wavelet transform was introduced at the beginning of the 1980s and has attracted much interest in the fields of speech and image processing since then. Wavelet analysis represents a windowing technique with variable-sized regions. This analysis allows the use of long time intervals where we want more precise low frequency information, and shorter regions where we want high frequency information. One major advantage afforded by wavelet is the ability to perform local analysis of a signal. Generally, a wavelet is a waveform of effectively limited duration that has an average value of zero. Compare wavelets with sine waves which are the basis of Fourier analysis, Sinusoids do not have limited duration (they extend from minus to plus infinity) and they are smooth and predictable while wavelets tend to be irregular and asymmetric. Fourier analysis consists of breaking up a signal into sine waves of various frequencies. Similarly, wavelet analysis is the breaking up of a signal into shifted and scaled versions of the original (or mother) wavelet. It is noticeable that sharp changes might be better analyzed with an irregular wavelet than a smooth

sinusoid [12]. Wavelet analysis is based on the decomposition of a signal according to scale, rather than frequency, using mother wavelets. The scale factor is related to the frequency inversely. WT analyzes the signal at different frequency bands with different resolutions by decomposing the signal into approximation and detail coefficients. The ability of the WT to represent different frequency sub-bands makes it appropriate for accurate fault detection, especially at the detail levels of decomposition [13]. The asymmetric DWT decomposes every sampled signal s (s_1, s_2, \dots, s_N) into an approximation signal at a certain decomposition level n ($a_n(t)$) and n detail signals ($d_j(t)$) with j varying from 1 to n .

$$s(t) = \sum_i \alpha_n(i) \cdot \varphi_{n,i}(t) + \sum_{j=1}^n \sum_i \beta_j(i) \cdot \psi_{j,i}(t) = a_n + d_n + \dots + d_1 \quad (1)$$

Where $\alpha_n(i)$ and $\beta_j(i)$ are the approximation and detail coefficients respectively, $\varphi_n(t)$, $\psi_j(t)$ are the scaling function at level n and wavelet function at level j respectively, and n is the decomposition level. a_n is the approximation signal at level n and d_j is the detail signal at level j [14]. Wavelet theory shows that scaling functions work as low pass filters and extract approximation coefficients while wavelet functions behave as high pass filters and determined detail coefficients. According to [15], each signal in asymmetric DWT definition is the product of the approximation coefficients and scaling function at level n in addition with the product of the detail coefficients and wavelet function at each level j .

If f_s (samples/s) is the sampling rate used for capturing s , then the detail d_j contains the information concerning the signal components whose frequencies are included in the interval $[2^{-(j+1)}f_s, 2^{-j}f_s]$ Hz. The approximation signal a_n includes the low frequency components of the signal, belonging to the interval $[0, 2^{-(n+1)}f_s]$ Hz [16]. Fig. 1 shows the tree algorithm of n -level DWT for a signal.

Fig. 1 The tree algorithm of n-level DWT for a signal

B. ANFIS model

A neuro-fuzzy system is defined as a combination of neural networks and fuzzy inference system. In adaptive neuro-fuzzy inference system (ANFIS) the membership functions (MFs) parameters are fitted to a dataset through a hybrid learning algorithm. ANFIS eliminates the problem of defining the membership function (MF) parameters and design of if-then rules in fuzzy system design by using the learning capability of ANN for automatic fuzzy rule generation and parameter optimization. Besides, ANFIS has the advantage of allowing the extraction of fuzzy rules from numerical data. Adaptive Neuro-Fuzzy Inference System (ANFIS) uses a feed-forward network to optimize parameters of a given FIS to perform well on a given task. The ANFIS proposed here is the Takagi-Sugeno FIS embedded within the structure of the ANN. The ANFIS uses the neural network training process to adjust the membership function and the associated parameter that approach the desired data sets. The learning algorithm for ANFIS is a hybrid algorithm consisting of the use back-propagation learning algorithm and least-squares method together. All these parameters are updated using this hybrid learning algorithm until an acceptable error is reached.

The ANFIS incorporates five-layer network to implement a Takagi-Sugeno-type fuzzy system as described below:

Layer 1 (input nodes): Each node in this layer generates membership grades of an input variable,

Layer 2 (rule nodes): the outputs of this layer, called firing strengths, are the products of the corresponding degrees obtained from the layer 1,

Layer 3 (average nodes): main target is to compute the ratio of firing strength of each i^{th} rule to the sum firing strength of all rules,

Layer 4 (adaptive nodes): the contribution of i^{th} rule towards the total output or the model output,

Layer 5 (output nodes): this layer is called as the output nodes in which the single node computes the overall output by summing all incoming signals.

C. WANFIS model

WANFIS model is obtained by combining two methods, a DWT and ANFIS model. The WANFIS model is ANFIS model, which uses sub-series obtained using DWT on original data.

II. PROPOSED METHOD

The aim of proposed algorithm in this paper is to detect a fault in the cable connection of DG to the power supply; therefore, fault and normal phenomena should be identified correctly. The proposed method uses the WANFIS hybrid algorithm and the performance flowchart of the method is shown in Figure 2.

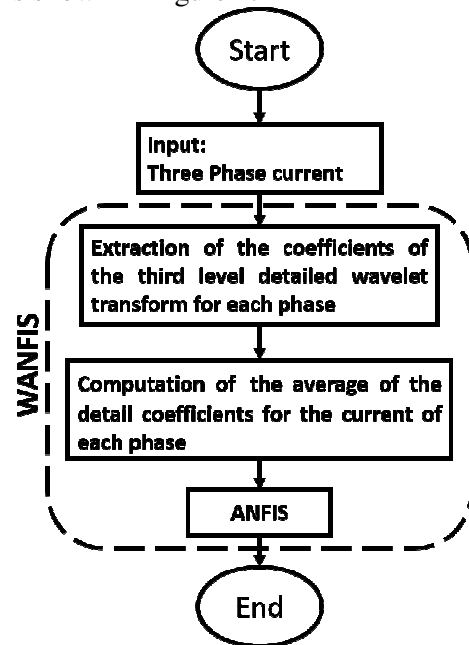


Fig. 1 The performance flowchart of proposed method

In the first phase, the three-phase current pass from the cable is received. In the next step, the coefficients of the third level detailed wavelet transform for each phase are extracted based on the Mexican hat mother wavelet. The mother wavelet is given in the appendix. In the third step, the average of the detail coefficients for the current of each

phase is computed in the window of 20 ms and in the final stage, by applying the output of the previous stage to the ANFIS network, a fault is detected. It should be noted that the flowchart process is provided as a Shift window for 2 ms online. Therefore, the required hardware for implementation must have the ability to perform the calculation. In the figure 3 the sampling process of the phase signal is shown.

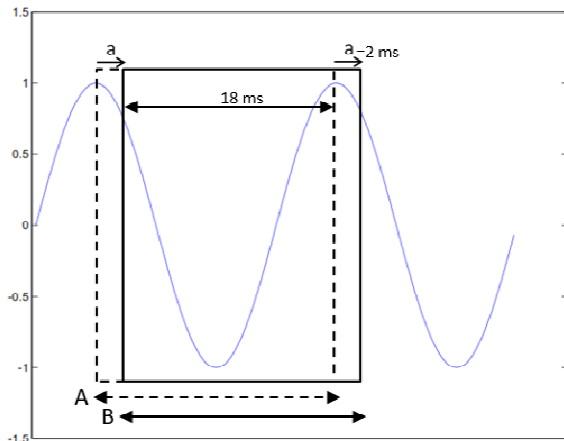


Fig. 2 Sample signal for processing

In Figure 3, the signal in the window A is processed and then, with a 2ms window shift, a processing will be performed again for Window B. As shown in this Figure, 18ms is shared between two windows A and B, so this subscription can be used to accelerate the computation process.

III. SIMULATION

In this section, the proposed algorithm is used for the cable feeder. For this purpose, ESUSCON power grid has been used [17] That its single line diagram It has been shown in figure 4.

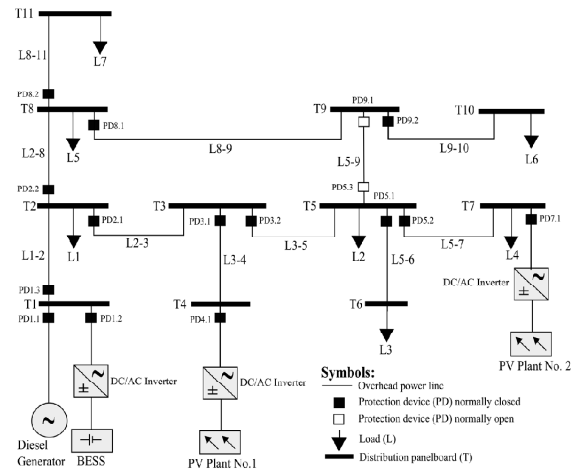


Fig. 4 Single line diagram of the ESUSCON network

The proposed algorithm has been implemented on the cable L1-2 in single line diagram. DigSILENT software is used for all simulations. Simulation has been performed for various conditions, including normal conditions, switching and fault.

Figures 5, 6 and 7 show the current of phase A for different modes. As it is obvious, the changes in the signal are light under normal and switching conditions, but in the case of fault, these changes are severe.

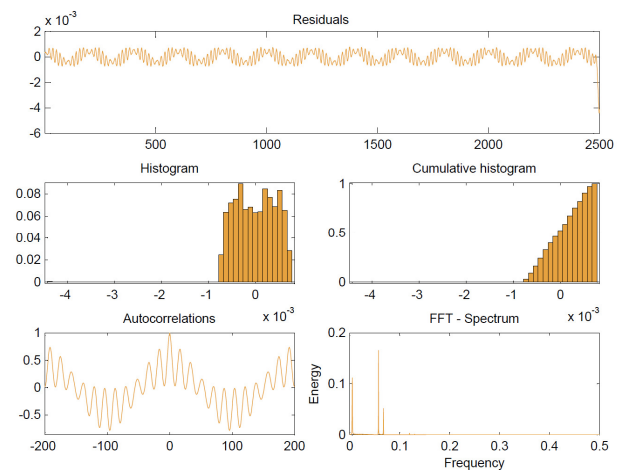


Fig. 5 Simulation results in normal mode

The simulation results shown that, in the normal operating conditions, the average of the details components for each phase in different windows is in the range of 4.4×10^{-7} to 5.1×10^{-7} . The standard

variance in this situation is also in the range of 0.00045 to 0.00049.

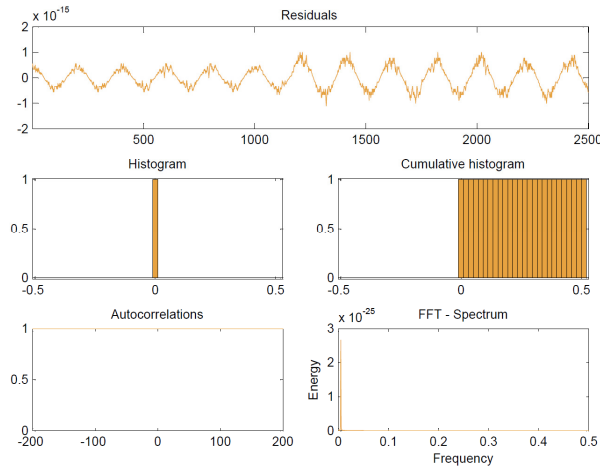


Fig. 6 Simulation results in switching mode

The simulation results shown that, in the switching conditions, the average of the details components for each phase in different windows is in the range of 3.7×10^{-5} to 4.5×10^{-5} . The standard variance in this situation is also in the range of 0.0072 to 0.0094.

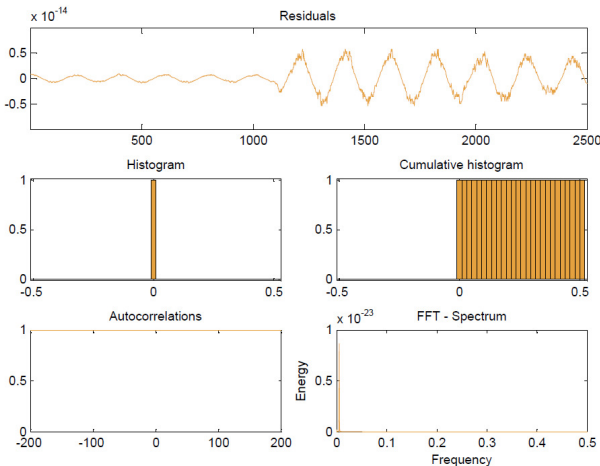


Fig. 7 Simulation results in fault mode

The simulation results shown that, in the fault conditions, the average of the details components for each phase in different windows is in the range of 0.065 to 0.082. The standard variance in this situation is also in the range of 0.053 to 0.061.

Of the 64 simulation modes, 48 were used for WANFIS training and 16 were used to test the

proposed algorithm. Table 2 presents simulation results. The results show that the algorithm has been able to correctly identify all the modes used for training in the test phase. Of the 16 non-training tests that were considered as a completely new one for the algorithm, only one item was not correctly identified, which means the accuracy of the proposed method is 94%.

TABLE I
 THE RESULT OF FAULT DETECTING LOCATION BY THE PROPOSED ALGORITHM

	Training stage	Test phase
Number of data	48	16
Number of correct diagnosis	48	15
Accuracy(%)	100	94

IV. CONCLUSIONS

In this paper, an algorithm was developed to protect the cable feeders of the generator, using WANFIS-based wavelet transform and improved fuzzy algorithm (ANFIS). To implement the proposed algorithm, the power grid was simulated in DigSILENT software and coding algorithm was performed in MATLAB software. The experiments were carried out for 65 modes including normal conditions, switching and fault. The simulation results showed 94% accuracy of the algorithm in determining the correct location of the fault.

V. INDEX

The figure 8 Shows the mother wavelet curve of the Mexican hat.

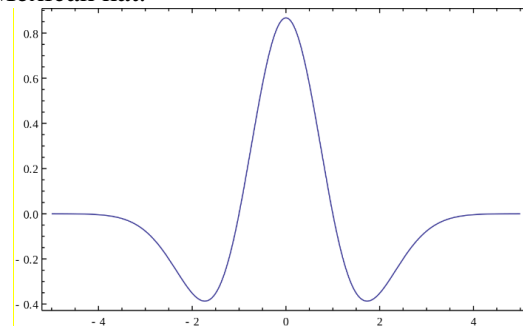


Fig. 8 the mother wavelet curve of the Mexican hat

ACKNOWLEDGMENT

We would like to thank Khorramshahr University of marine science and technology for supporting this work under research grant contract No.138.

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