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Wavelet-Based ANN Approach For Fault Detection Classification and Location in Transmission line

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Abstract
A new approach of digital relays for transmission line protection is presented. The proposed technique consists of a preprocessing module based on Discrete Wavelet Transforms (DWTs) in combination with an artificial neural network (ANN) for detecting and classifying fault events. The DWT acts as an extractor of distinctive features in the input signals at the relay location. This information is then fed into an ANN for classifying fault conditions. A DWT with quasioptimal performance for the preprocessing stage is also presented.

Keywords
Artificial Neural Networks, Discrete Wavelet Transform, Transmission Line Protection.

I. Introduction
Although traditional digital protective relay algorithms have been proven to be greatly reliable in actual power systems, better performance is required in deregulated power systems due to increased standards of quality of service. Traditional digital protective relays present several drawbacks. For instance, they are usually based on algorithms that estimate the fundamental component of the current and voltage signals neglecting higher frequency transient components. Moreover, has or estimation requires a sliding-window of a cycle that may cause a significant delay. Furthermore, accuracy is not assured. During the last decade, digital protective relaying of transmission lines has greatly benefited from the development of artificial intelligence techniques [1], and more recently, from new signal processing techniques such as the Discrete Wavelet Transform (DWT) [2]. As opposed to conventional techniques, the DWT takes advantage of the valuable information contained in the fast transient components of the voltage and current signals. A combination of these approaches for transformer protection has recently been proposed in [3]. In this letter, a preprocessing module based on DWT in combination with Artificial Neural Networks (ANNs) is used for the detection, analysis, and classification of faults events.

II. Simulation of Faulted Transmission System
A system with two generators and three lines (distributed parameters model) has been simulated (see Fig. 1) using the ATP-EMTP software. The line protected is the central one (Line BC). The location of the relay is at bus B. Extensive series of simulation studies has been carried out to obtain fault transient signals for subsequence analysis. Simulations include ten different type of faults at 20-, 40-, 60-, 80-, and 90-km distances from the beginning of each line, several fault

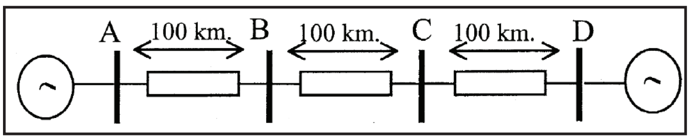

Fig. 1. Simulated Power System

Resistances (0, 10, 20, 30 and 40), and different fault inception angles (0, 20, 40 and 60), and finally steady states. The fundamental frequency is 50 Hz and the sampling frequency is 1600 Hz. This corresponds to 32 samples per cycle. The proposed fault detection scheme is as follows: input signals are preprocessed by a DWT extracting information from the transient signals simultaneously in both time and frequency domains. The output signal of the preprocessing module is then fed into an ANN that classifies the transient. The DWT considerably simplifies the input signal of the ANN; it reduces the Volume of input data of the ANN without loss of information. This dramatically reduces the training stage in the ANN and increases the overall performance of the digital relay

A. DWT Selection
Wavelet transforms are fast and efficient means of analyzing transient voltage and current signals. The wavelet transform not only decomposes a signal into frequency bands, but also, unlike the Fourier transform, provides a no uniform division of the frequency domain (i.e., the wavelet transform uses short windows at high frequencies and long windows for low frequency components). Wavelet analysis deals with expansion of functions in terms of a set of basic functions (wavelets) which are generated from a mother wavelet by operations of dilatations and translations [4]. A wavelet transform is defined by a sequence of functions {h (n)} (low-pass filter) and {g(n)} (high-pass filter).The scaling function φ (t) and wavelet Ψ (t) are defined by the difference equations

$$\varphi(t) = \sqrt{2}\sum_{1}^{n} \mathrm{h(n)}\varphi(2t-n)$$

$$\varphi(t) = \sqrt{2}\sum_{1}^{n} \mathrm{g(n)}\varphi(2t-n)$$

Where $g(n) = (-1)^n h(1-n)$ and n=0……N-1

A sequence defines a wavelet transform. There are many types of wavelets such as Haar, Daubechies, Morlet, etc.For the relay to operate in real time, this work uses wavelets of length six.

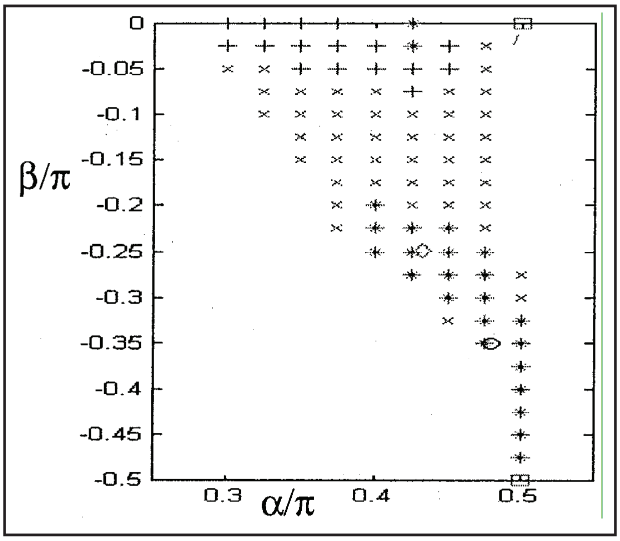

Fig. 2: Length-6 Wavelets. Continuous (+). Derivable (X). Good performance (*). Haar (□). Daubechies (◊_). Selected wavelet (o)

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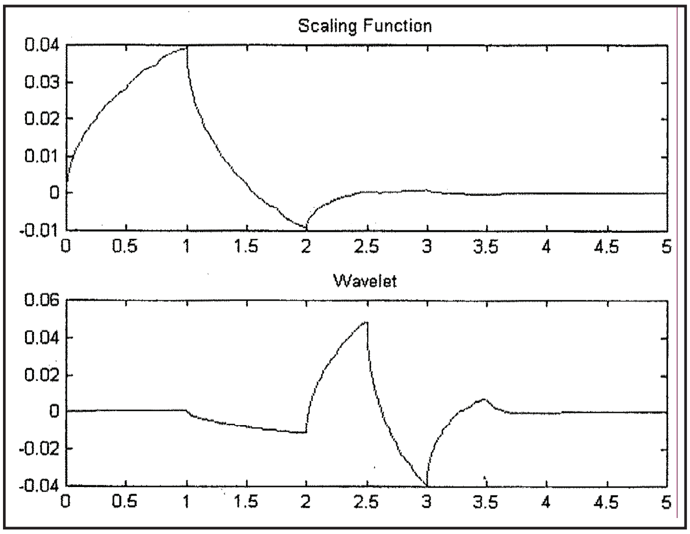

Fig. 3: Scaling Function and Wavelet for α = 0:48π and β = -0:35π

These wavelets can be expressed as functions of two parameters α and β [4]

$$h(0) = 1/(4\sqrt{2})[(1 + cos\alpha + sin\alpha) \times (1 - cos\beta - sin\beta + 2sin\beta cos\alpha$$

$$h(1) = \frac{1}{4\sqrt{2}}[(1 - cos\alpha + sin\alpha) \times (1 + cos\beta - sin\beta - 2sin\beta cos\beta)$$

$$h(2) = \frac{1}{2\sqrt{2}}(1 - \cos(\alpha - \beta) + \sin(\alpha - \beta))$$

$$h(3) = \frac{1}{2\sqrt{2}}(1 - \cos(\alpha - \beta) - \sin(\alpha - \beta))$$

$$h(4) = \frac{1}{\sqrt{2}} - h(0) - h(2)$$

$$h(5) = \frac{1}{\sqrt{2}} - h(1) - h(3)$$

The choice of a suitable wavelet plays an important role in analyzing fault transients. By varying parameters α and β in the above equations, a family of length-6 wavelets can be generated. In Fig. 1, and for certain range of variation of these parameters, the generated wavelets are classified according to their performance for this particular application. For instance, wavelets with good characteristics of continuity or derivability are marked with “ ” or “ ,” respectively. Haar(□) and Daubechies(◊) wavelets are also identified in fig. 2.

The parameters for the length-6 wavelet with quasioptimal performance are α=0.48π and β=-0.35π. For these values, the following sequence is obtained: h(1)=0.4886, h(2)=0.8262,h(3)=0.2445, h(4)= -0.1344, h(5)= -0.026. The scaling function and wavelet are displayed in fig. 3.

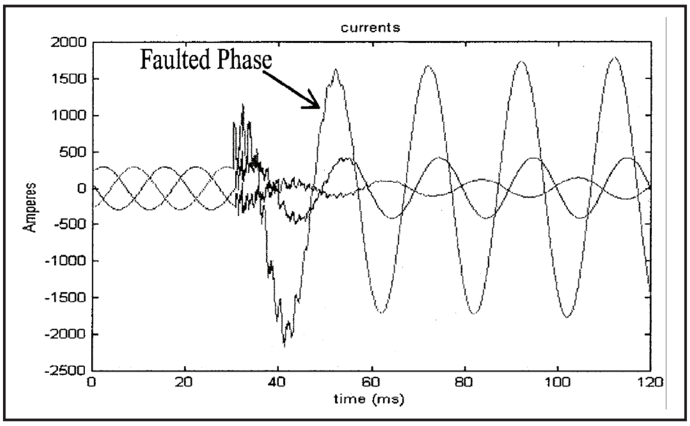

Fig. 4: Three Phase Currents at Point B Under Fault Conditions

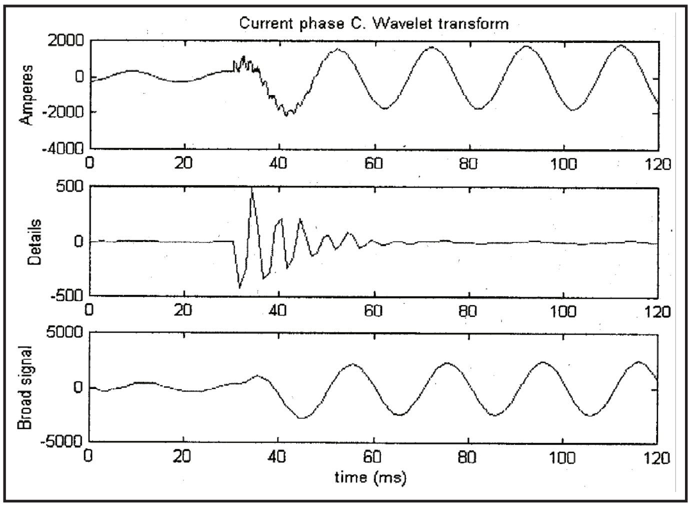

Fig. 5: Current at Phase C and Wavelet Transform

B. Artificial Neural Network

Three independent multilayer (two hidden-layers), feed-forward neural networks have been used for detection, classification, and location of fault transients. Number of neurons has been optimized by neglecting very low coefficients. The input data of the ANN are organized in a sliding-window of a quarter of cycle (5 ms, eight samples of currents and voltages). The DWT splits the signal in details and broad signals, each with 16 coefficients per cycle. Therefore, a detail signal sliding-window has four coefficients. The ANNs are fed with the six detail signals (three currents and three voltages); thus, the input vector has 24 elements. The detection ANN has one output neuron which indicates the existence of a fault. The location net has one neuron that indicates if the fault has occurred in the protected zone. The classification ANN output layer has four neurons indicating which phases (A, B, C) or grounds are involved in the fault event. An error back propagation algorithm has been used for training the ANN. A total of 3800 simulations were generated, half of them were used for training, and the other half for testing. In Fig. 4, it is shown the evolution of the three phase currents of a single phase to ground fault at 20 km of point B. The current signal of the faulted phase, the detail, and the broad signal are displayed in Fig. 5. It can be observed that the detail signal clearly shows distinctive features of the transient (i.e., immediately after the fault occurrence, several sharp spikes appear in the detail signal indicating the occurrence of a fault). Regarding the ANN performance, a 100% success was obtained within the detection ANN; the errors in the classification and location ANN were under 1%.

C. Preprocessing

Preprocessing is a useful method to reduce the dimensionality of the input data set to neural networks. The preprocessing stage can significantly reduce the size of the neural networks based classifiers, which in turn improves the performance and speed of training process [14]. Three phase voltage and current input signals were processed by 2nd-order low-pass Butterworth filters. The anti-aliasing filters had a cut-off frequency of 400 Hz. In addition, 2-sample FIR digital filters were used to remove the dc component. Magnitudes of the voltage and current signals have been obtained by the full cycle discrete Fourier transform (DFT) filter using voltage and current samples. Patterns were then generated using the processed amplitudes voltages and currents. Obtained patterns are scaled appropriately. The preprocessing configuration of the proposed algorithm is shown in fig. 6.

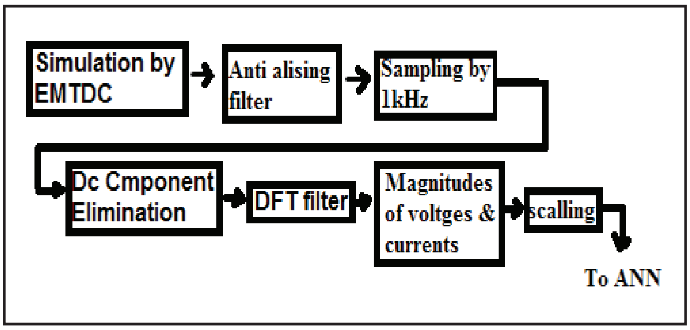

Fig. 6: Pre-Processing Structure

D. Proposed ANN For Fault Classification

Multilayer feed forward networks were chosen to process the prepared input data. A few different networks were selected initially. For designing the fault classifier based neural network, different networks with four inputs and four outputs were considered. Four different A, B, C and N outputs were considered to determine whether each of the three phases A, B, C and neutral are present in the fault loop.

The e networks' architecture were decided empirically which involved training and testing different number of networks. Three layer networks were found to be appropriate for the fault selector application. For all the networks, hyperbolic tangent function was used as the activation function of the hidden layer neurons. Saturated linear function was used for the output layer [14].

Various networks with different number of neurons in their hidden layer were trained with Marquardt-Levenberg (ML) algorithms [15]. The ML algorithm is a nonlinear least square algorithm applied to learning of the multiplayer perceptions. Once trained, the networks performance was tested using a validation data set. The suitable network, which showed satisfactory results were finally selected. The selected network structure is shown in Fig. 3. The network has 4 normalized inputs and 4 outputs. The number of neurons for the hidden layer is chosen to be 8 neurons. Based on the fault type, which occurs on the system, output neurons should be 0 or 1. Outputs which are greater than 0.9 are considered to be active and outputs which are smaller than 0.1 are considered to be inactive. Neural network desired outputs for different types of faults are shown in Table 1.

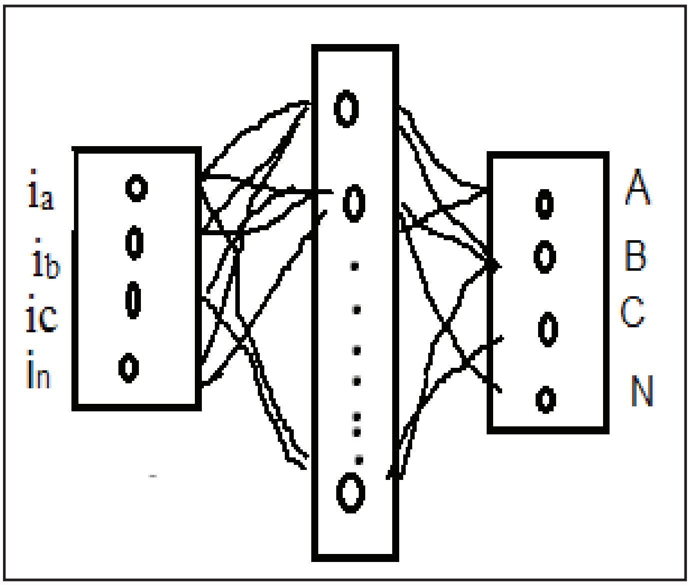

Fig. 3: The Proposed Network Structure

Table 1: Neural Network Desired Outputs

Fault Type	A	B	C	N
AG	1	0	0	1
BG	0	1	0	1
CG	0	0	1	1
AB	1	1	0	0
BC	0	1	1	0
AC	1	0	1	0
ABG	1	1	0	1
ACG	0	0	1	1
BCG	0	0	1	1
ABC	1	1	1	0

The proposed network outputs for a single phase CG fault are shown in Fig. 4. For this case, a fault is applied to the system at the time 20 ms and the network outputs are shown for about the first 40 ms after the fault inception, which is of interest. The fault location was 35 km from the relay location. As shown in this figure, the proposed ANN is able to respond to the fault correctly in a timely fashion. The fault is identified just in a few ms, which shows that the ANN is able to detect and classify the fault quit fast. The ANN outputs remain stable after identifying the fault.

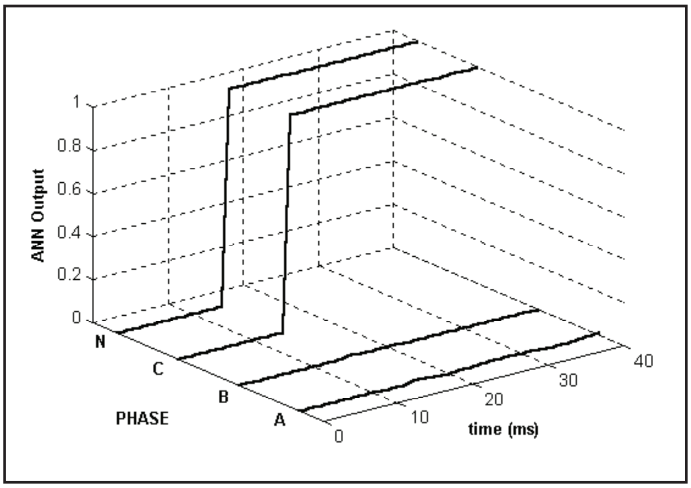

Fig. 4: Outputs of ANN for a Fault CG at 35 km

III. Conclusion

The ability of wavelets to decompose the signal into frequency bands (multi resolution) in both time and frequency allows accurate fault detection. The proposed wavelet has proved optimal performance within the tested faults. The ANNs correctly classify the fault with advantages in accuracy and speed upon classical algorithms. A faster response is obtained since only a quarter of cycle from the occurrence of The fault is required. In this paper an accurate fault classifier and locator Algorithm is designed. Neural networks capabilities in pattern recognition and classification are used and two neural network-based modules are designed. Simulation studies are performed and the modules' performance with different system parameters and conditions is investigated. A common problem using conventional fault locator schemes is the distance estimation error. As it is shown by different examples in the paper the proposed fault locator module is more immune to this problem. Different types of faults could be located on the cable with high accuracy using the proposed on-line scheme. Neural networks could be used as a part of a new generation of high speed advanced fault locators.

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