Neural Network and Daubechies Wavelet in Power System Protection

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Abstract. Wavelet theory is a mathematical tool which has been developed independently for various signal processing applications: multiresolution signal processing, subband coding and wavelet expansion. The Wavelet Transform (WT) has become an important tool for power engineering, because it is an alternative to classical methods (the Fourier Transform). This form of signal analysis is far more efficient than Fourier in cases where a signal is dominated by transient behaviour or discontinuities. Neural networks are appropiate and especially powerfull when they are used to find such relationships that are difficult to describe explicity. This work explains a neural network-wavelet based protection relay.

Keywords

Wavelet Transform, Neural Network, Power System Relay.

1. Introduction

Traditionally the way for analysing many signals was the Fourier method, but such an algorithm is limited in its performance because of its limitation in the presence of non-stationary signals. The wavelet expansion of a signal has appeared to overcome these limitations. On the other hand a multilayer feedforward neural network can be thought as a multiplier where each unit has the function of a weighted sum. This advantage is used to design a neural network which calculates the wavelet decomposition by using the Daubechies wavelet.

2. Wavelet Theory

The basic principles of this signal analysis is that a wavelet is generated through a scaling function defined as:

$$\phi(x) = c_0 \cdot \phi(2x) + .. + c_N \cdot \phi(2x - N) \quad (1)$$

where N is the number of coefficients. The analyzing wavelet is created from the scaling function:

$$W(x) = \sum_{k-1}^{N-2} (-1)^k c_{k+1} \cdot \phi(2x - k) \quad (2)$$

and the wavelet expansion is expressed as:

$$f(x) = a_0 + a_1 \cdot W(x) + .. + a_{2^j + k} \cdot \phi(2^j x - k) \quad (3)$$

This breaks down the signal into different scales, each of which represents a band of frequencies centered about f_c, where

$$f_c = \frac{f_s}{2^n} \cdot 2^l \quad l = 0, 1, ..., n-1 \quad (4)$$

and l is the scale and f_s the sample frequency.

In the wavelet decomposition a signal is compared with the basic wavelet function, or mother wavelet $\psi(t)$, which is translated and scaled (Figure 1).
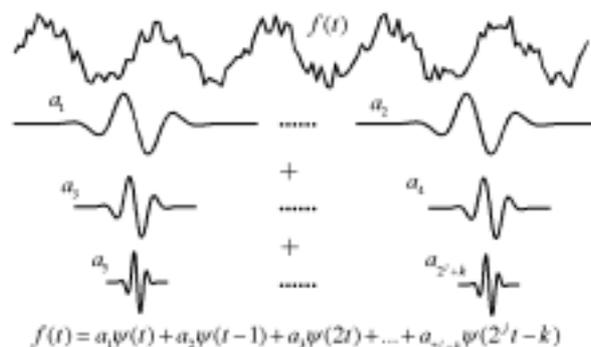

Fig. 1. Wavelet Transform

The similarity between the analyzing signal and the wavelets is computed, which allow us to break down the original signal in the respective levels.

A. Wavelet Analysis

The basics of wavelet theory and signal analysis are thoroughly explained with mathematical precision in the bibliography [1-3] [16-19]. The main charasteristic of the wavelet transform is to break down into different scales with different levels of resolution by dilating a single prototype function (mother wavelet). The effectiveness of such a breakdown depends on three basic "parameters":

1) Mother Wavelet.

Many types of wavelet families exist and they have several applications. Choosing the right one plays an important role in detecting and localizing various types of power quality disturbances. There is no agreement in the selected family: for short and fast transient disturbances, it is said that there are better wavelets localized in time, like Daubechies of 4 coeffcients- called "D4". Nevertheless, for slow transients, D8 and D10 are good, although in [5] both D4 and D10 detect fault ocurrences.

In [6], the arc furnace current from the secondary of the transformer is recorded, and the wavelet analysis is carried out using D20. In [7] high-order Feaveau wavelets were found to meet the best characteristics for analyzing power disturbances. In [10] the Morlet wavelet is proposed for the analysis of high-impedance fault-generated signals.

2) Sample Frequency (f_s) and Number of points (N)

It is possible to observe the same lack of concurrence in the various authors' opinions regarding sample frequency. In order to avoid tedious explanations, we have summarized the results in Table I, with requisite references and characteristics indicated.

TABLE I. – Summary of chatacteristics

Reference	Family	(fs) kHz	(N)
5	D4,D10	2.56	128
6	D20	10.24	2048
7	Feaveau	10	256
8	D4	8.192	4096
9	D20	2.4	512
10	Morlet	4.096	512

Because of this lack of concurrence it was first necessary to carry out a previous study involving these "wavelet parameters" including :

1) *Wavelet family.* Daubechies wavelet from 4 to 20 coefficients.
2) *Sample frequency.* Ranging from 2.5 kHz to 12.8 kHz.
3) *Number of sampled points.* 128 and 256 points cases were studied.

It can be said that when more coefficients are used it increase the computation and memory requirements and higher sample frequency and sample points do not necessarily lead to better results [14]. So, in this work, the sample frequency and wavelet family were 1.6 kHz and Daubechies 4 respectively.

3. Feedforward Neural Network

The basic unit of a neural net is the neuron, which realizes a function of weighted summation, as is depicted in Figure 2.
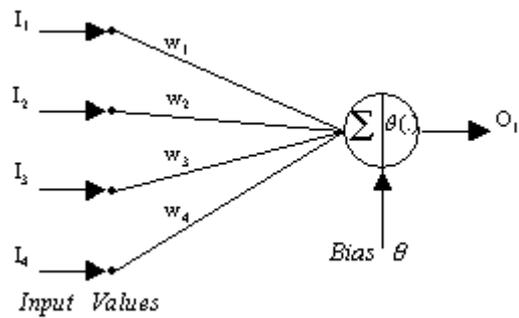

Fig. 2. Model of the neuron

A multilayer feedforward neural net, showed in Figure 3, can be considered as an algebraic operator, such as weighted summation and multiplication. So, it is possible to reconstruct a wide class of algorithms by using a multiplier module [11-13].
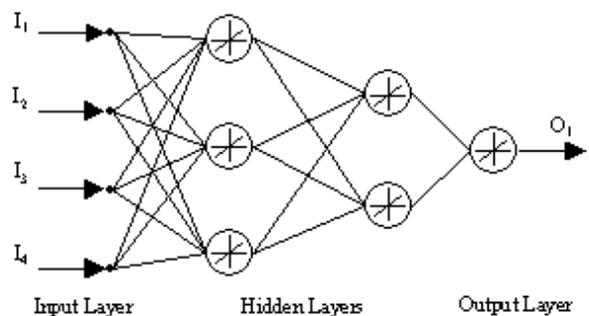

Fig. 3. Multilayer Feedforward Neural Network

4. Neural Network & Wavelet Transform

The proposed neural network consists of two parts. One is the traditional Multilayer Feedforward (MLF) network, and the other realizes the discrete wavelet transform (DWT), resulting a MLF-DWT relay, Figure 4. Input values to the network are voltages and currents, and there are four outputs: A,B,C which indicate the faulted phase (high level) or correct phase (low level); DIR shows the fault direction.
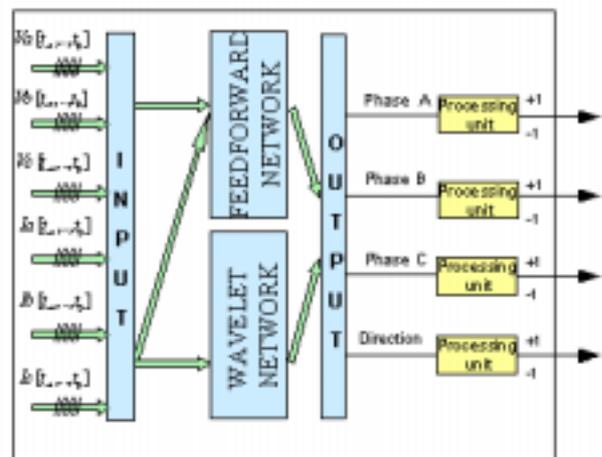

Fig. 4. MLF-DWT relay

The wavelet transform is carried out by employing the current values. With this neural network it is not necessary to calculate the WT in a previous step with specific software.

The data set to train the net uses 30 samples of voltage and current (five consecutive sample points of current and voltage are used). The architecture of this net consists of 30 input nodes, 25 neuron in the first hidden layer, 20 in the second hidden layer and 4 outputs. Threshold functions in all neurons were hyperbolic. The training set consists of 8960 patterns, including phase to ground, phase to phase faults, arcing faults, etc

5. Example

The electric power system depicted in Fig. 5 and Fig. 6 was used to carry out the simulations by employing the EMTDC/PSCAD program. The sample frequency is 1.6 kHz. A three phase arcing fault to ground (143 km from bar X) is selected to analyze the behaviour of the neural relay. In the middle of both figures is depicted the topology of the electric network. There are five lines and ten relays, each of them at the start and end of the line to protect it. Fault is simulated during three periods to observe the behaviour of the neural relay.

Line TL4 with relays 40-42 is out of service. Each relay has four outputs (A,B,C, and DIR): low level in A,B, and C, indicates healthy phase and high level faulted phase. The DIR output indicates the fault direction. Its value is positive (high level) or negative (low level) depending on the current flow before faults inits, due to the polarization of relay. If fault causes current to increase indicate a forward fault, and DIR output maintain the reference.

On the other hand, if current flow decreases, the DIR output changes, and indicate a backward fault.

Figure 5 shows the output from a single MLF neural relay, when a three phase arcing fault occurs in TL3. The ten relays show the measure of voltages and currents in the point of the line where they are located. Relays 10, 12, and 20 suffer an increase of current because the fault is in front of them (high level in DIR output). Nevertheless, relays 32, 50 and 52 suffer a dramatic fall of voltage and current due to the loss of power supply; fault is backward and DIR output change to low level. However, in both previous situations, outputs A, B, C detect perfectly the fault and change to high level. Line TL 2, detect a slight decrease in both voltage and current values, but still is in service. In this case, as both the voltage and current waves are symmetrical, it is difficult to distinguish between a fault or load change, therefore the relay remains blind, and the output oscillates, which is a obstacle when a quick and reliable decision in the first stage of the fault is required. DIR output changes to high level, because the fault is backward. After three periods, the fault is cleared, and the outputs of relays 10, 12, 20 and 22 in line TL1 and TL2 change to low level because the system is working correctly again.

When applying the joined MLF-DWT neural relay, Figure 6, these oscillations in relays 20 and 22 are attenuated, especially in the first 10 ms from the fault start, which is the most important as a rapid decision is required.
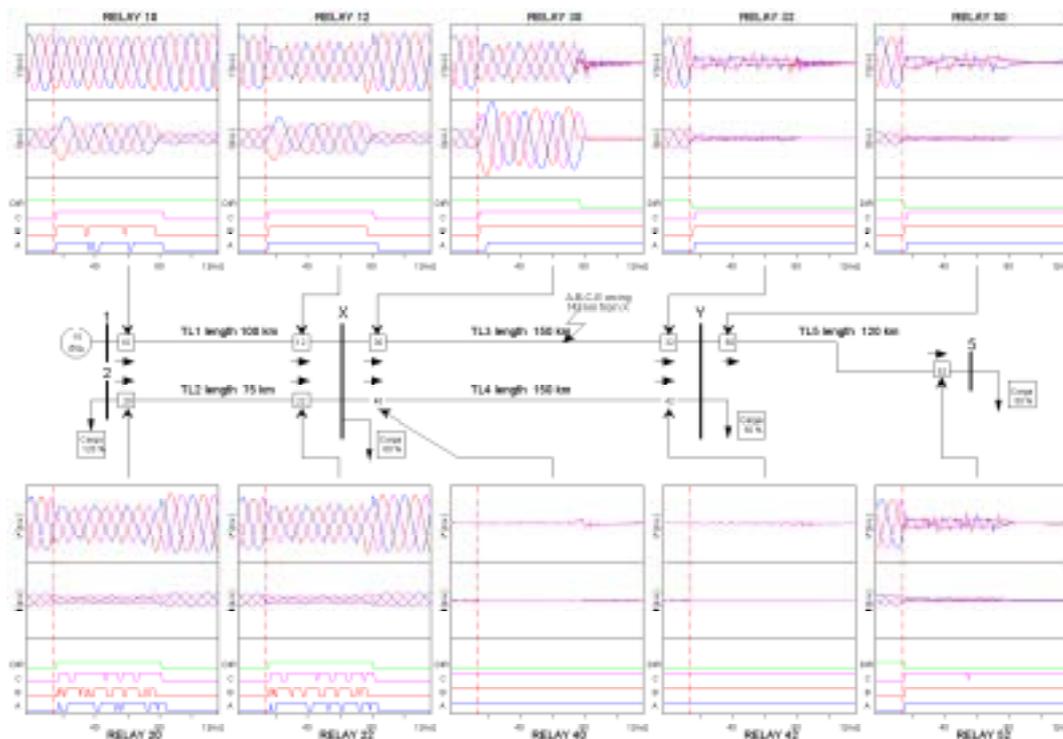

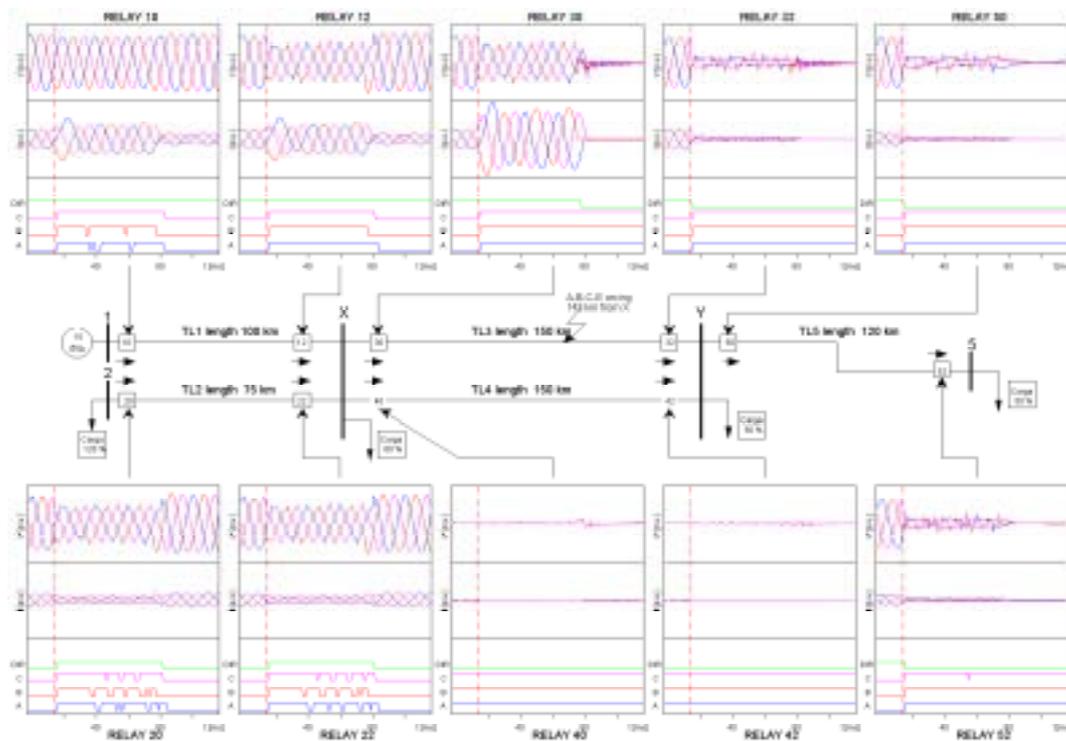Fig. 5. Test circuit and MLF Neural Relay Output

Fig. 6. Test circuit and MLF-DWT Neural Relay Output

The ability of the wavelet transform to detect changes in the waveform [21-22] is employed to help the relay to make a correct and rapid decision in the first stage of the fault.

4. Conclusion

The advantages of such a network are the following.

1. The neural net implement a general purpose relay, which is able to detect a fault in any part of the electrical net, selecting the phaulted phases and direction
2. The wavelet decomposition is obtained with linear functions, which are easy to program by using a single feedforward net
3. The net which calculated the DWT uses fixed weights, and there is no necessity to train them
4. This configuration allows th integration of DWT as a part of the whole neural network and there is no necessity to design another special hardware or software preprocessing module
5. The WT helps the neural relay making its response faster and reliable

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