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A Novel Approach for Transmission Line Protection Using Wavelet Transform and Neural Network

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Abstract **-** The two most important expected objectives of the transmission line protection are – 1) Differentiating the internal faults from external faults and 2) identifying exactly the fault type using one end data only. In conventional distance protection scheme only 80 percent of line length gets primary protection while for remaining 20 percent of line length a time delay is provided to avoid maloperation due to overreach in case of D.C. offset. In this new scheme a fault generated transients based protection method is introduced by which the whole line length gets primary protection by using the concept of bus capacitance. This scheme implements improved solution based on wavelet transform and self-organized neural network. The measured current and voltage signals are preprocessed first and then decomposed using wavelet multiresolution analysis to obtain the high frequency and low frequency information. The training patterns are formed based on high frequency signal components and the low frequency components of all three phase voltages and current. Zero sequence voltage and current are also used to identify faults involving grounds. The input sets formed based on the high frequency components are arranged as inputs of neural network-1, whose task is to indicate whether the fault is internal or external. The input sets formed based on the low frequency components are arranged as inputs of neural network-2, whose task is indicate the type of fault. The new method uses both low and high frequency information of the fault signal to achieve an advanced transmission line protection scheme.

I. INTRODUCTION

The primary goal of transmission line protection, whatever the principle it uses, is to rapidly and precisely detect the fault and disconnect the faulted area. It should also differentiate the internal faults from external faults so that only the faulted line is removed; provide the exact fault type selection so that advanced tripping and reclosing schemes can be applied; locate the precise fault position on the transmission line so that the line can be repaired and restored quickly.

The conventional line protection schemes based on fundamental frequency components of the fault generated transient voltage and current signals, can be classified into two categories: 1) non-unit protection and 2) unit protection. The non-unit protection schemes use one end transmission line data while the unit protection schemes usually use data from two ends. The non-unit protection such as distance relay, cannot protect the entire length of the primary line because it can not differentiate the internal faults from external occurring around the multizone boundaries. Backup protection approach is then introduced for protecting the entire length of the transmission line. For unit protection such as pilot protection, it usually requires a communication link to transmit the blocking or transfer tripping signals. Therefore, the reliability of the protection scheme highly relies on the reliability of the communication link. The cost of the communication link also needs to be taken into account.

Recently, new techniques using high frequency components of the fault generated transient signals were studied and some useful solutions were obtained [4][5][6][7]. An approach called "boundary protection" for solving the disadvantages of conventional non-unit protection schemes was proposed. Wide-band high frequency signals generated on extra high voltage lines following sudden changes in the system voltage, caused, for example by an arcing fault, are generally outside the bandwidth of receptibility of most conventional voltage transducers. However, it has been recently suggested that these signals, if captured, could be used very effectively to develop new types of protection schemes that would have many advantages over existing power- frequency measurement based methods This approach introduces a possibility of precisely differentiating the internal faults from external using data from one end only. In this case, the relay at one end can protect the entire line length with no intentional time delay. Regarding the fault type classification, the traditional method is based on the fundamental frequency phasors. The feature formed by a nonlinear ratio between voltage and current phasors is compared to the threshold to find out the faulted phase[2].

This paper introduces a new approach based on wavelet transform and a self-organized neural network to realize accurate boundary protection and fault type classification using one end transmission line data. The new method retains both low frequency and high frequency component of the fault signal to achieve high reliability and selectivity of the protection scheme.

II. BOUNDARY PROTECTION

The system shown in Fig. 1 is a typical multiline system. It is supposed that the relay is installed at the bus 2 to protect the line 2-3 shown in the figure. A fault on the lines will generate wideband transient voltage and current signals. The signals will travel in both directions with reflections and refractions at the discontinuity points reflections and refractions at the

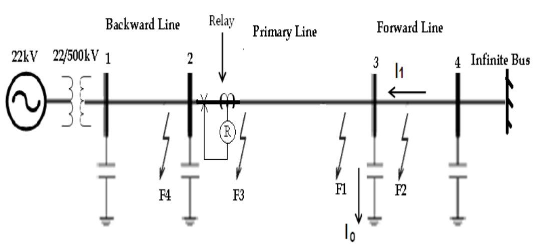

Fig. 1 : Typical Multiline Power System.

discontinuity points, which are usually the buses and faults. The bus of the power system is always connected to many power system apparatus. And at higher frequencies the total impedance at bus tends to be more capacitive. This fact could be effectively used to develop a non-communication protection scheme in which the busbar at both ends of a protected line can be used as the boundary of the protected zone. This effect is shown in Fig.1. For an external fault close to the bus 3, the high frequency portion of the fault current signal (Io) will be shunted to earth significantly due to the bus capacitance. The higher the frequency, the more significant portion of the current signal will be shunted. From the viewpoint of the relay, the magnitude of high frequency portion of the fault current signal is reduced. In contrast, for the internal fault F2 close to the bus 3, the fault current of the entire frequency band can be seen by the relay. That means, if other fault conditions (fault type, fault resistance, fault angle) are identical, it will be possible to differentiate the internal fault F2 from the external fault F3 by comparing the high frequency portions of their signals.

Similarly, the same method can be used to differentiate the faults at F3 and F4. Using the voltage signals, we can still differentiate faults at F1 and F2 but cannot differentiate faults at F3and F4 because the voltage measurements of the relay are obtained from bus 2. The feature differences of the faults on different line sections seen by the relay at bus 2 in Fig.1 can be summarized as follows.

- For faults on the primary line, the energy of the high frequency portion of the voltage and current signals will be seen as “big” values.
- For faults on the backward line, the energy of high frequency portion of the voltage signals will be seen as “big” values while the energy of high frequency portion of the current signals will be seen as “small” values.
- For faults on the forward line, the energy of high frequency portion of the voltage and current signals will be seen as “small” values.

It should be noted that the above statements are based on the assumption that all other fault parameters are the same and the “big” and “small” value are indicating relative numbers. The absolute values are dependent on fault type, fault resistance, fault angle, etc.

III. WAVELET TRANSFORM

Wavelet analysis is a relatively new signal processing tool and is applied recently by many researchers in power systems due to its strong capability of time and frequency domain analysis. The two areas with most applications are power quality analysis and power system protection.

The definition of continuous wavelet transform (CWT) for a given signal x(t) with respect to a mother wavelet ψ(t) is:

$$\mathrm{CWT}(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} x(t)\, \psi\left(\frac{t-b}{a}\right) dt \qquad (1)$$

where a is the scale factor and b is the translation factor. For CWT, t, a, b are all continuous. Unlike Fourier transform, the wavelet transform requires selection of a mother wavelet for different applications. One of the most popular mother wavelets for power system transient analysis found in the literature is Daubechies’s wavelet family. In the new scheme, the db5 wavelet is selected as the mother wavelet for detecting the short duration, fast decaying fault generated transient signals. Mother wavelet is also called as the analyzing wavelet.

The term wavelet means a small wave. The smallness refers to the condition that this (window) function is of finite length (compactly supported). The wave refers to the condition that this function is oscillatory. The term mother implies that the functions with different region of support that are used in the transformation process are derived from one main function, or the mother wavelet. The term translation is related to the location of the window, as the window is shifted through the signal. It corresponds to time information in the transform domain.

The application of wavelet transform in engineering areas usually requires discrete wavelet transform (DWT), which implies the discrete form of t, a, b in (3.1). The representation of DWT can be written as:

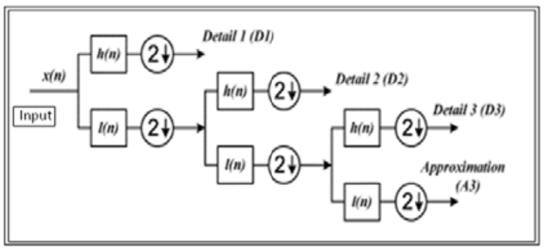

Fig. 2 : Wavelet Multiresolution Analysis

$$DWT(m,n) = \frac{1}{\sqrt{a_o{}^m}} \sum_k x(k)\ \psi\left(\frac{k - nb_o a_o^m}{a_o^m}\right) \qquad (2)$$

where original a and b parameters in (1) are changed to be the functions of integers m, n. k is an integer variable and it refers to a sample number in an input signal.

An implementation of DWT called Multiresolution Analysis (MRA) is as shown in Fig 2. MRA as implied by its name, analyzes the signal at different frequencies with different resolutions. MRA is designed to give good time resolution and poor frequency resolution at high frequencies and good frequency resolution and poor time resolution at low frequencies. This approach makes sense especially when the signal at hand has high frequency components for short durations and low frequency components for long durations. The signals that are encountered in practical applications are often of this type.

IV. NEURAL NETWORK

The application of artificial intelligent techniques in protection attracted researchers since 1990s [9][14][15]. As an example, neural networks can be used for different applications in transmission line protection including fault detection, fault location, distance and direction detection, autoreclosing, etc. The neural networks based protection scheme arranges the voltage and current signal samples as a pattern. The fault detection issues then become the pattern recognition issues. The advantage of neural network based protection scheme is its "intelligence" to find the internal similarity of different types of disturbances. The only concern is that is one must train the network with a large data set, and one must select enough relevant training scenarios.

There are several types of neural networks used for power system protection. In this paper, a type of self-organized, adaptive resonance theory (ART) neural network and Learning Vector Quantisation is used. Learning process is the most important step when applying neural networks. The learning techniques for most neural networks can be classified into two broad categories: *supervised learning* (or learning with a teacher) and *unsupervised learning* (or learning without a teacher). In supervised learning, each input signal is associated with the labeled output. The task is the input-output mapping by adjusting the synaptic weights to minimize the overall error between the entire output set and their corresponding input data set. In unsupervised learning, the categories of the outputs are not known in advance. The network is self-organized by some sort of clustering techniques to identify the mutual similarity of the input patterns. The task is to adjust the network weights until the similar inputs can produce similar outputs.

V. PROPOSED METHODOLOGY

The three-phase secondary voltage and current signals are obtained at the sampling frequency of Fs = 200 kHz. The zero-sequence voltage and current are computed by adding up the corresponding phase values. Through the signal preprocessing stage, the prefault steady state component is removed from each signal. Then the wavelet multiresolution analysis (MRA) is used for decomposing each signal into low frequency approximation and high frequency details. The information is used for feature extraction stage and forming the patterns for neural-networks. Two neural networks are so trained so that to achieve the aim of boundary protection and fault classification respectively. The final conclusion can be made by simultaneously combining the outputs of the two neural networks and then appropriate signal should be issued by the relay to its associated circuit breaker.

A. Signal Preprocessing Stage

In order to reduce the impact of prefault load conditions and other non-fault disturbances, a simple signal preprocessing stage is implemented. The signal are preprocessed using the following equations:

$$i(k) = i(k) - i(k\text{-}n)$$

$$v(k) = v(k) - v(k\text{-}n) \qquad (3)$$

where represents the sample number at the current measuring point and represents the number of samples in one cycle. By this approach, the prefault steady state components are removed from the observed measurements. When there is no fault, the obtained voltage and current samples from (3) are close to zero (normal state), or small values (under power swing).

The preprocessed signals are then sent to the wavelet transform stage. Using the scheme shown in Fig. 2, the signals are decomposed using db5 wavelet upto level 5. Since the sampling rate is 200 kHz, the obtained coefficients A5, D5, D4, D3, D2 and D1correspond to the frequency band of 0–3.125 kHz, 3.125–6.25 kHz, 6.25–12.5 kHz, 12.5–25 kHz, 25–50 kHz, and 50–100 kHz, respectively. Those values are used for feature extraction in the neural networks.

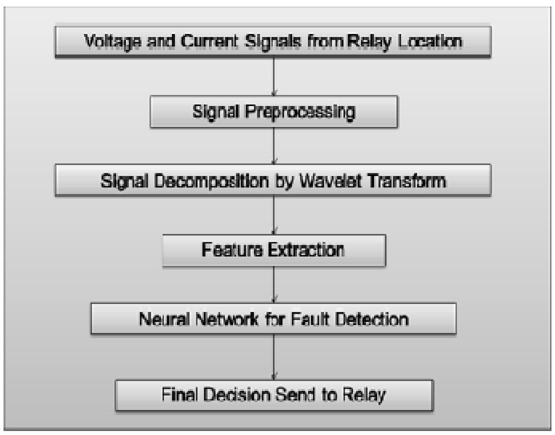

Fig. 4 : Overview of the New Protection Scheme

B. Signal Decomposition using Wavelet Transformation

Fig 5(a) shows a post fault one cycle waveform of a current signal. Using the MRA technique this signal is decomposed into various bands as shown in Fig 5(b).

C. Feature Extraction

Next stage is the feature extraction where useful information is obtained from the wavelet decompositions i.e detail and approximation coefficients. The energy spectra of the all the detail and approximation of the three phase currents and voltages are obtained as below:

$$E(D_i) = \sum_{k=1}^{m} I_{p-Di}^{2}(k).\Delta t \qquad (4)$$

Where p is the phase a, b, c

E(Di) is energy of Detail coefficient at level i

Δt is time step for samples.

m is total samples in a data window.

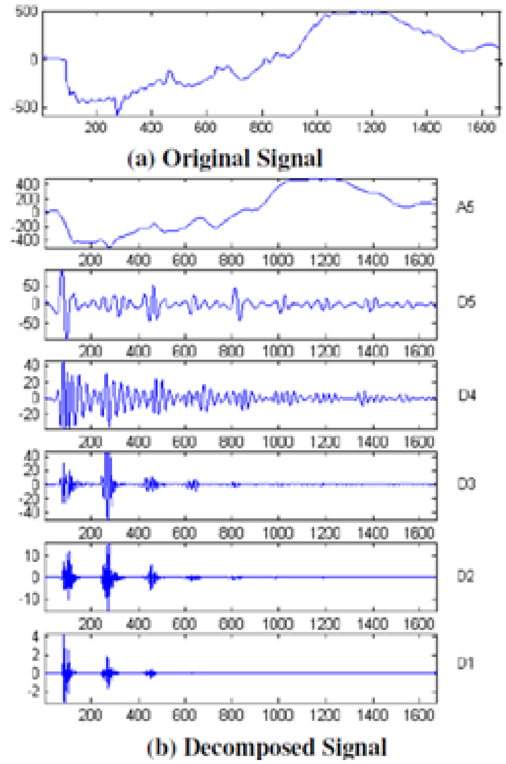

Fig.5: Signal Decomposition by Wavelet Transformation.(Vertical Axes: Magnitudes, Horizontal Axes: Samples)

The pattern arranged for boundary protection is shown in Fig 6(a). For that pattern, there are four features obtained for all of the phase voltages and currents. Therefore the pattern dimension is 24 × 1. The four features in each phase are defined as follows:

$$x_1 = \log\frac{E(D_1)}{E(D_5)} \qquad x_2 = \log\frac{E(D_1)}{E(D_4)}$$

$$x_3 = \log\frac{E(D_2)}{E(D_3)} \qquad x_4 = \log\frac{E(D_2)}{E(D_4)}$$

where is the energy spectrum at detail and the definition is the same as in (4).

The pattern arranged for fault classification is shown in Fig 6(b). For that pattern, there are 16 features per phase obtained in one cycle of voltage or current signals. The zero-sequence voltage and current are also taken into account for indicating whether the ground is involved during the fault. The entire input pattern dimension is 128×1. The features are the samples decimated through the approximation coefficients.

(y1, y2. . . . . . .,y16) = Decimated (Coef(A5))

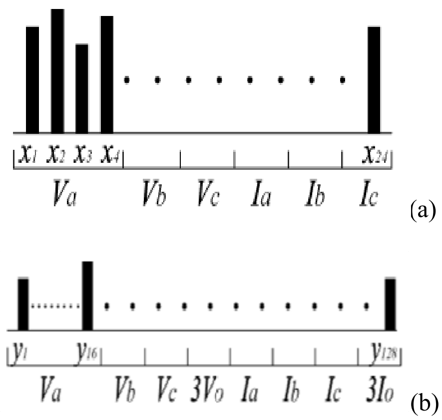

Fig. 6 : Pattern arrangement for (a)Neural Network 1 (b) Neural Network 2

D. Neural Network Training

The final stage is mow to train the neural networks with the input datasets obtained. Thousands of fault scenarios were generated taking into account the different fault types, fault locations and fault resistances. It should be noted that training the neural networks with the raw input dataset is not a desirable approach. The patterns shown in Fig. 5.6(a) and (b) need to be normalized into the range of [1, -1] before the training and testing process. This was achieved by using the mapminmax() function in MATLAB. After normalizing the dataset, both the neural networks were trained.

In this paper the neural networks were created using two different techniques. They are: ART and LVQ neural network.

VI. PERFORMANCE STUDIES

A. Power System Model

The performance studies for the paper are based on a 500kV power system model as shown in fig 7. The system is modeled using the MATLAB 7.8. The lengths of the three transmission lines are identical and set to 300km. The bus capacitances are set to 0.1µF which is the typical value from literature.

B. Feature Comparison

For the boundary protection, six fault points are selected for comparison, as shown in Fig 7. Those fault points are located 1km away from the nearest bus. We randomly selected an ABG fault, with fault resistance of 20Ω for all six fault points. The features obtained and the input patterns for boundary protection (neural network #1) as shown in Fig. 9.

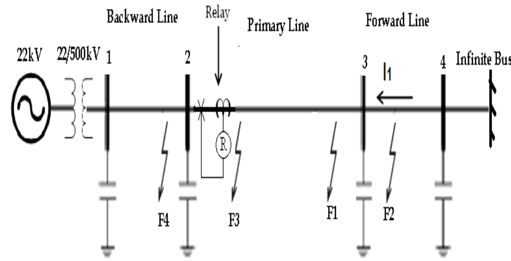

Fig. 7 : Power System Model

C. Neural Network Training

During the training stage, the performance of the neural networks was studied. It was found that in order to train the neural network accurately a large dataset is required. Larger the dataset, the better is the training of the neural networks. Also the performance of the neural networks increases if proper value of the bus capacitance is selected. Increasing the value

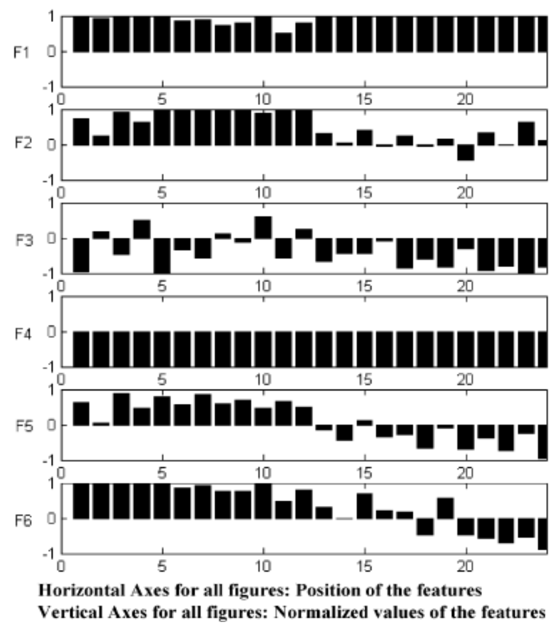

Fig. 9 : Pattern comparison for boundary protection (neural network - 1)

of the bus capacitances lead to well defined and differentiable input patterns. Hence the new scheme works more efficiently.

For neural network #1, all 3259 cases are used as inputs for training. The outputs of the neural network are “Primary line fault,” “Forward line fault,” and “Backward line fault.”

For neural network #2, only 1210 fault cases on the primary line are used as the inputs for training since only the events on the primary line are of concern in this case. The outputs of neural network #2 indicate the fault type directly.

VII. CONCLUSION

This paper implements a new protection scheme which is aimed at solving the problem of differentiating the internal faults from external ones using local-end data and providing the exact fault type at the same time using the concept of bus capacitance. The scheme uses advanced signal processing and artificial intelligence techniques to achieve that objective. The highlights of the new scheme are:

- The wavelet transform provides an efficient way to extract signal components at different frequency bands.
- The neural network provides an intelligent method and a "soft" criterion for feature comparison.
- The protection tasks are distributed into two neural networks so that each neural network has a different task.
- Both neural networks take a post-fault one cycle data of the voltage and current waveforms; therefore, the protection speed is improved.

The new boundary protection scheme accuracy is improved over the accuracy of traditional non-unit protection. It can work as a unit protection scheme to protect the entire length of transmission line while it does not have to use the communication link. This will not only increase the efficiency of the protection system but also reduce the economic costs of misjudgments.

REFERENCES

[1] G. Phadke and J. S. Thorp, 'Computer Relaying for Power Systems', Taunton, U.K.: Wiley, 1988.

[2] S.N.Sivanandam, S.Sumati and S.N.Deepa, 'Introduction to Neural networks using MATLAB 6.0', Tata McGraw Hill Publishing Company Limited', New Delhi, 2008.

[3] Nan Zhang and Mladen Kezunovic, Transmission Line Boundary Protection Using Wavelet Transform and Neural Network', in IEEE Transactions On Power Delivery, Vol. 22, No. 2, April 2007,pp. 859-869

[4] Z. Q. Bo, F. Jiang, Z. Chen, X. Dong, G. Weller, and M. A. Redfern, 'Transient based protection for power transmission systems', in Proc. IEEE Power Eng. Soc. Winter Meeting, Singapore, Jan. 2000, vol. 3, pp. 1832–1837.

[5] Z. Q. Bo, "A new non-communication protection technique for transmission lines," IEEE Trans. Power Del., Oct. 1998,vol. 13, no. 3, pp. 1073–1078.

[6] A. T. Johns and P. Agrawal, "New approach to power line protection based upon the detection of fault induced high frequency signals," Proc. Inst. Elect. Eng., Gen., Transm. Distrib., vol. 137, no. 4, pp. 307–313, Jul. 1990.

[7] Z Q Bo, B H Zhang, J H He, X Z Dong, B R J Caunce, A Klimek, 'An Integrated Boundary Protection Scheme for Power Transmission Line Systems', The 8th International Power Engineering Conference (IPEC 2007).

[8] A. G. Phadke and S. H. Horowitz, "Adaptive relaying," IEEE Computer Applications in Power, vol. 3, no. 3, pp. 47–51, July 1990.

[9] T. Kakagi, J. Bab, K. Uemura, and T. Sakaguchi, "Fault protection based on traveling wave theory – Part 1: Theory," in Proc. IEEE PES Summer Meeting, Mexico City, Mexico, July 1977, vol. 3, pp. 750–753.

[10] H. W. Dommel and J. M. Michels, "High speed relaying using traveling wave transient analysis," in Proc. IEEE PES Winter Meeting, New York, Jan./Feb 1978, vol. 3, pp. 214–219.

[11] P. A. Crossely and P. G. McLaren, "Distance protection based on traveling waves," IEEE Trans. Power Apparatus and Systems, vol. 102, pp. 2971–2983, 1983.

[12] A. H. Osman and O. P. Malik, "Transmission line distance protection based on wavelet transform," IEEE Trans. Power Del., vol. 19, no. 2, pp. 515–523, Apr. 2004

[13] T. S. Sidhu, H. Singh, and M. S. Sachdev, "Design, implementation and testing of an artificial neural network based fault direction discriminator for protecting transmission lines," IEEE Trans. Power Delivery, vol. 10, no. 2, pp. 697–706, Apr. 1995.

[14] M. Kezunovic and I. Rikalo, "Detect and classify faults using neural nets," IEEE Computer Applications in Power, vol. 9, no. 4, pp. 42–47, Oct. 1996.

[15] Wavelet Toolbox User's Guide The MathWorks Inc.,Natick, MA, 2005 [Online]. Available: http://www.mathworks.com