Towards a New Paradigm for Ultrafast Transmission Line Relaying

Abstract –Digital impedance protection of transmission lines suffers from known shortcomings not only as a principle but also as an application as well. This necessitates developing a new relaying principle that overcomes those shortcomings. Such a principle is offered in this paper and is currently being field validated. The principle is a new application of wavelet based neural networks. The application uses high frequency content of a subset of local currents of one end of a protected line to classify transients on the line protected and its adjacent lines. The scheme can classify transients –including faults- occurring on a protected line, categorize transients on adjacent lines and pinpoint the line causing the transient event. It is shown that the feature vector of the event can be determined from a subset of local currents without using any voltages altogether. The subset of local currents consists of the two aerial modes of the local current. Modal transformation is used to transform phase currents to modal quantities. Discrete Wavelet Transform (DWT) is used to extract high frequency components of the two aerial modal currents. A feature vector is built using the wavelets details coefficients of a one level of the aerial modes and used to train a neural network. Results show that the classes corresponding to each transient event type on the protected line and its adjacent lines are almost linearly separable from each other. Results demonstrate that very accurate classification within one eighth of a cycle is possible.

I. Introduction

Protection of a transmission line involves installing relays at both ends of the line that constantly monitor voltages and currents and act when a fault occurs on a line. Traditional protection uses phasor estimation to estimate the fundamental component of voltages and currents and take a decision when certain criteria corresponding to certain fault conditions are met. Distance protection is the most widely used method for transmission line protection. CVTs are generally used to measure the voltages making them available to the relay. It is known that due to the interaction between the capacitive voltage divider and the transformer inductance, oscillations are imposed on the fundamental frequency measured [1]. Additionally, distance relay can only protect up to 85% of the line instantaneously. This necessitates the use of a communication link between the relays at the two ends of the line to achieve fast tripping from both ends. With communication links utilizing the internet, a cyber-threat is unavoidable. With all limitations mentioned above, a new relaying principle is needed. This principle has to be using currents only, fast, and finally doesn't need any communication link for its operation. Such a principle is theoretically tested in this paper and is currently being validated using field data.

With the advent of wavelets, the power system community has seen a surge in application of wavelets based methods for various power system problems notably in the area of power system protection- mainly in transient based protection schemes, transients' classification and fault location. The use of Artificial Neural Networks (ANN) for fault classification and detection has been given in [2, 3, 4]. In [5] and [6] DWT is applied to voltages and currents and entropy (energy) of the signal is then captured and fed to the ANN to make fault type classification. In [7], [8] and [9], DWT is applied to voltage and current signals at a relay location resulting in series of details coefficients that are used to train ANN for fault detection and type classification.

Existing classification techniques as the ones in [8] and [9] do not take transients on adjacent lines into account which could mislead these schemes. In this paper, the wavelets details coefficients are directly used to train the ANN without using any entropy based method.

This paper proposes a novel application for wavelet based ANN. In this paper we show that using the details coefficients of a subset local currents only, we can distinguish between fault and non-fault conditions on a protected transmission line without using any voltage signals at all. We can also distinguish between faults on the protected line and faults on adjacent lines. The algorithm provided can not only tell the difference between forward and reverse faults but also can determine which adjacent line is faulted. We also show that the same apply for lightning strikes and line switching cases i.e., the algorithm can tell which line is causing which transient event. DWT is used to extract useful oscillatory information about the signal. Oscillatory information is manifested in the wavelets details coefficients at various levels. We argue and show that any transient event on a specific transmission line causes currents to oscillate in a unique way and these oscillations can be detected in the wavelets details coefficients themselves at various levels. The use of these wavelets details coefficients show the possibility of building ultra-high speed relays.

II. EMTP Model

A snapshot of the area under study is shown in figure. 1. We use IEEE 118 bus [10] as a test system. The line under study is the line connecting buses 23 and 25 (line 23-25). All power transformers have been modeled by ATP Hybrid Transformer Model according to [11] with typical parameters provided by ATPDraw. Synchronous machines are modeled using ATP SM-59 type generator except for excitation and governor controls. This is because we only use one eighth of a cycle of post event data which is a period much shorter than modern exciters' and governors' time constants. In our simulations we used very general tower configurations for the line under study and its adjacent lines. All towers have been taken from [12] and will be shown in the full paper. All lines in the study area have been modeled as lines with frequency dependent parameters with ground return. All other lines have been modeled as symmetrical (fully transposed) lines with frequency dependent parameters with no ground wire. It should be pointed out that surge arresters and bus capacitance have been also used in our simulations.

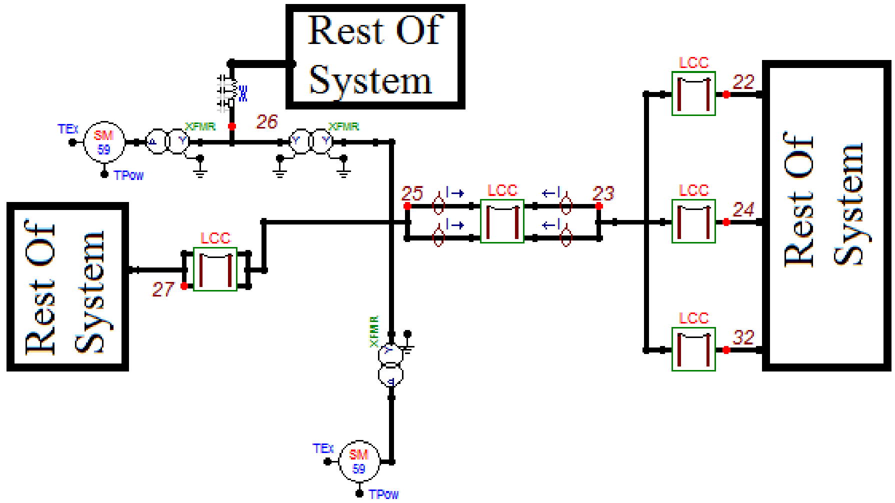

Figure 1. System configuration under study

III. Creation of Transient Cases

For the purpose of analysis and ANN training, we have created fault cases, lightning cases and line switching cases.

For faults, a total of 8066 cases per line have been created which gives a total of 48396 cases because line 25-27 is double circuit line, i.e., we create two batches of faults for line 25-27: one for each circuit.

For line switching, we created 360 cases per line, giving a total of 2160 cases.

For lightning, a total of 3780 cases has been created, i.e., 630 cases per line.

IV. Feature Vector for ANN Training

We decouple the phase quantities using the modal matrix [13] calculated at 10 kHz even though the matrix is frequency dependent. We tried different modal frequencies for decoupling the modal matrix but this didn't affect the classification results at all. The two aerial modes are the only ones used for training.

Once the modal quantities are available, we run DWT for 4 levels, starting from level 1 to level 4. The outcome of DWT is a series of coefficients for each level and for each mode. Since we are only interested in the first one eighth of a cycle following the transient event, we only obtain those details coefficients corresponding to that period. We stack the details coefficients of any level of one of the aerial modes on top of the other mode. It should be emphasized that building the n-dimensional vector this way doesn't change the temporal content of the feature vector, as long as all other n-dimensional vectors are built consistently this way, i.e. we have to preserve the order of the modes in the feature vector and the vector has to be built using one level only. If we change the order of modes in the feature vector this amounts to a rotation of n-dimensional space but shouldn't change the results of classification, again as long as we build all vectors consistently.

Having created n-dimensional vectors, the input for the ANN is ready. We proceed to train the neural network. We randomly divide the cases into the following categories: 70% of all cases for training, 15% for validation and another 15% for testing.

V. Results

In case all transients were faults, the faulted line was 100% correctly identified using a trained ANN using the fault cases in section III. In case all transients were switching operations, the line being switched was 100% correctly classified via another ANN trained with the switching cases mentioned in section III. In case all transients were lightning strikes, the line being hit by a strike was 100% identified using a third ANN trained by the strikes created in section III. In case transients were faults, line switching and lightning strikes, the event type was 99.2% correctly classified using a forth ANN trained with all cases in section III. A detailed look at the results will be offered in the full paper.

VI. References

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