Busbar Protection Using a Wavelet Based ANN

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***Abstract*—This paper presents a new application of wavelet based artificial neural networks to the field of high voltage busbar protection. Any transient event type -whether fault or not- causes high frequency components to be generated and imposed on the fundamental frequency current. Those components propagate from the line causing them through the protected busbar to the other lines connect to the same bus. In this paper it is shown that those components captured at any line connected to the bus can be used not only to detect internal and external faults but also to identify the faulted line in case of external fault. A scheme will be presented that uses the current from any of the lines connected to the bus to detect internal and external bus faults, classify transients on adjacent lines and identify the line that is causing the transient disturbance. Modal transformation is used to transform phase quantities to modal quantities. Discrete Wavelet Transform (DWT) is used to extract high frequency components of the two aerial modes of the current measured. A feature vector consisting of level 3 details coefficients of the two aerial mode currents is used to train a feedforward neural network with one hidden layer. Results show that very accurate classification can be made using one eighth of a cycle of post event data.**

***Index Terms*-- ART neural networks, Classification algorithms, Discrete wavelet transforms, Wavelet coefficients, Modal analysis, Power system faults, Current transformers, lightning.**

I. INTRODUCTION

Power system bus protection has been traditionally accomplished with voltage or current differential schemes [1]. In current differential scheme current, transformers are installed on ongoing and outgoing transmission lines. Currents from CTs are then summed for a fault criterion. If a fault is outside the bus (external fault) then current summation equals to zero, if the currents do not add to zero then the fault is on the bus (internal fault). The major disadvantage of current differential schemes is CT saturation which greatly impairs the method [2]. High impedance current differential schemes have been proposed to counteract CT saturation [2], however they introduce other problems. The problem of CT saturation is eliminated completely at the source by the use of linear couplers with voltage differential principles. Voltages are used instead of currents for fault discrimination. Currents in the feeders are converted to voltages using linear couplers [3] which produce linear input output voltage relation over a very large range of input currents.

Traditional bus protection schemes do not provide backup for incoming and outgoing feeders nor can they discriminate between various transient events occurring on adjacent lines. We seek to provide; fault protection for the bus, back up protection for adjacent lines and classification between transients occurring on adjacent lines identifying the line causing the event.

The application of ANN for classification of faults has been given in [4]. Wavelets applications for power systems have been introduced in [5]. Wavelets have proven to be a very useful tool for transmission line fault detection and classification. Application of wavelets has received much attention for classification of power quality disturbance in [6], [7], [8] and [9]. In these applications and others, energy [10] based methods seem to dominate the application of wavelets in power systems. In energy based methods, the energy of travelling waves can be quantized in time because of the localization property of wavelets which makes it very useful in fault location application [11]. The application of ANN to bus protection is given in [12] where currents are fed to ANN for training and validation. In [13] a wavelet based scheme is presented for busbar protection where currents going in and out of bus zone are analyzed using DWT. DWT [14] produces a series of details coefficients for each level which are used to infer the polarity and the direction of currents thus issuing a trip signal when a fault occurs.

Our paper uses only one of the currents of any of the lines connected to the bus for bus protection and backup protection for lines connected to the bus. We use modal transformation [15] to transform phase signals to modal signals. DWT is used to extract one eighth of a cycle of post fault data. We show that a subset of the modal currents carries enough information for bus protection and providing backup for lines connecting to that bus. We also show that the same subset can be used to classify transient events on the lines connected to the bus and identify the line causing the transient disturbance. The feature vector used to train a feedforward ANN [16] is a vector consisting of level 3 details coefficients of the two aerial modes [11] of currents stacked on top of each other. The transient event types studied in this paper are lightning, faults and line switching. The paper is organized as follows. Methodology is given in section II. EMTP model and ANN training is given in section III. Results are shown in section IV while conclusions are presented in the last section.

II. METHODOLOGY

In this paper we show that the information present in the transient current available at a local substation caused by sudden network topology changes contains sufficient information for classification not only between internal and external bus faults but also between transients on adjacent lines which effectively provides back up for lines terminating on the bus. Any change of system topology – caused by faults for example- causes a traveling wave to be generated travelling from the point of change towards the ends of the line. In the simplest case this wave will be just a step but in reality will be accompanied by a lot of oscillating components. Those high frequency transients are a function of the initial and boundary conditions at the location of the event causing the change of topology. Fourier analysis is not suitable for analyzing such waveforms because the oscillations will be distorted and attenuated as they arrive at the line terminals. However, applying discrete wavelet transform will enable us to see both the spectral and temporal variations of those high frequency components.

We extract the information from the high frequency components using DWT at level 3. Level 3 is used for computational efficiency as the feature vector -under the sampling frequency we used- with level 1 or 2 will have a lot of coefficients that will make ANN training impossible with modern day PCs because of the high RAM needed. For example, training an ANN with MATLAB neural network toolbox needs 30 GB of RAM with Level 2 coefficients. Before we apply DWT we decouple phase currents from each other using modal analysis [15]. The modal matrix is calculated at 10 kHz even though it is frequency dependent. The author has tried different frequencies for the modal matrix and has not seen any effect on classification. Since current transformer has a bandwidth of 100 kHz [17] which could go up to 400 kHz [18] or even 500 kHz [19], we choose to be on the conservative side and select our sampling rate such that the maximum frequency available in the signal is 100 kHz. The time step used in our EMTP simulations is 1μs which should theoretically give a maximum frequency of 500 kHz in sampled output according to Nyquist theory. However, it is given in [20] that the maximum frequency in the EMTP simulations is only one fifth of that, so the maximum frequency is 100 KHz.

After decoupling phase quantities, DWT is applied to the transmission line currents chosen to convert them from modal currents to a series of coefficients that will be used for training of the neural networks. The event is detected once a change of level 3 coefficients is detected. Once the event is detected, a window of one eight of a cycle of post event information is used for neural network training. The outcome of the DWT is a series of coefficients for each mode. We stack the coefficients of the two aerial current modes on top of each other to build one vector that will be used to train the network. A neural network of an appropriate size is selected for classification. The neural network is then trained using various scenarios for transients on lines. If we run internal and external fault simulations on the bus and its adjacent lines then using the feature vector built above, we can tell whether the bus is faulted or we can identify the faulted line. If we only run line switching cases on the lines terminating on the bus then using the feature vector above, we can tell which line is being switched. If we run only lightning cases, then using the same feature vector, we can identify the line being hit by a strike. Finally, the aggregate of all transient event types can be distinguished from each other: this means if we train ANN using all transient events, then we can have three ANN output classes each of which corresponds to fault, line switching and lightning. In summary, the procedure is as follows:

1. Currents are decoupled using modal analysis.
2. Apply DWT to the two aerial modes of one eighth of a cycle of post event information.
3. Build feature vector consisting of details coefficients of level 3 of the two aerial modes on top of each other to train the neural network.
4. A neural network of suitable size is selected for training.

Training is accomplished using transient scenarios. Those scenarios include: faults, line switching and lightning.

III. SIMULATION PLATFORM

This section describes the EMTP model used and the cases used to train the neural network and how the data was prepared as input for ANN.

A. ATP/EMTP Model Description

We present the topology of the system under study in fig. 1. This topology is part of IEEE 118 bus case [21]. Current is being measured from bus 23 to bus 25. Any current can be used but we only choose to report on this current due to paper length requirement. Our selection for bus 23 for study is because it has almost all power system components around it. Bus 23 has three incoming feeders into it, namely line connecting bus 23 to bus 22 (line 23-22), line 23-32 and line 23-24. The outgoing feeder is line 23-25. Bus 25 has a generator connected to it through a step up transformer and power transformer connecting it to bus 26. Bus 26 has another generator connected to it via a step up transformer.

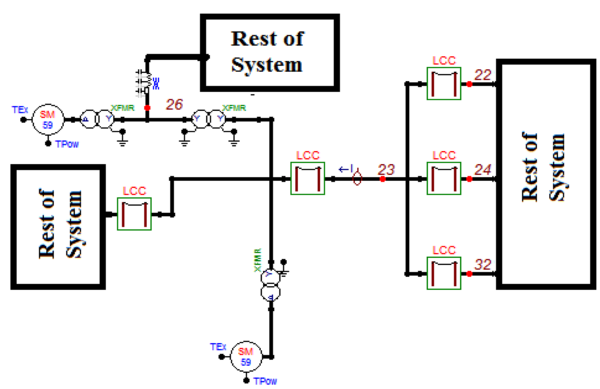

Fig. 1. Portion of the system under study

In our simulations we used very general tower configurations for the lines around the bus being protected. The line connecting buses 23 and 25 is taken from [22] while the lines surrounding it are taken from [23]. All tower configurations have been scanned and inserted in the paper for the convenience of the readers. All of those towers are modeled as lines with frequency depended parameters and a ground return while all others lines in the system are modeled as frequency dependent models with no ground wires. We apply transient cases only to lines 23-25, 23-22, 23-24, 23-32 and 25-27. We don't aim to study transients beyond those lines.

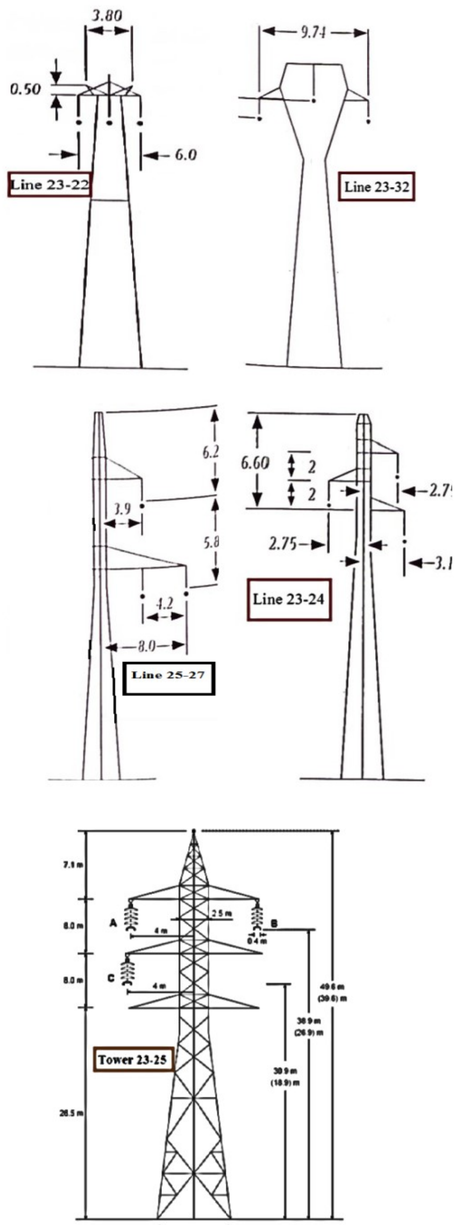

Fig. 2. Tower configurations of lines in the area under study. All graphics has been scanned from the references given in the paper.

All generators in the system are assumed unregulated machines with no exciters or governors. This done mainly because we only interested in one eighth of a cycle of post transient data during which exciters' and governors' time constants are large compared to the period under study.

All power transformers have been modeled by ATP Hybrid Transformer Model according to [24] with typical parameters provided by ATPDraw [25].

Bus capacitance and transformer stray capacitance is accounted for in our simulation platform with the values given in [26] due to their high importance for transient studies. Surge arresters have been added at all buses surrounds the study area. These arresters charactertics are selected according to the guide given in [27].

B. Creation of Transient Cases and Preparation of Cases for Training of ANN

The argument in the paper is that high frequency components of the currents measured at a local relay not only can detect fault and no faults condition on a protected bus but also can detect fault and no fault condition on adjacent lines. A large number of simulations have to be carried out to show the validity of this argument. We present a very general network topology with different tower configurations. Creation of transient cases has been automated using the toolbox released in [28]. For this paper we need to create cases of faults, line switching and lightning. We first describe the creation of fault cases then line switching cases and after that proceeds to describe the lightning strike cases. At this point we should emphasize that the bus under study is bus 23 which is bordered by 4 adjacent lines namely line 23-22, line 23-32, line 23-24, line 23-25. We also study transients for line 25-27. We only train our ANN for the bus under study and the 5 lines just mentioned above. The next subsections describe creation of transient cases for faults, line switching and lightning and creation of feature vector for training.

1) Creation of Transmission line Fault Cases

We create fault cases in batches; a batch for each line. Each batch has fault parameters, these parameters are the following: incipient angle, fault resistance, fault location and fault type. All types of faults have been created i.e., AG, BG, CG, AB, BC, CA, ABG, CBG, ACG, ABC, ABCG. Incipient angles are from 0 to 350 degrees in 10 degrees increments. Fault resistance assumes the values: 0, 20Ω, 100Ω and 1000Ω. The distance take the following values: 5%, 15%, 35%, 50%, 65%, 80% and 95% which are all percentages of total line length. A total of 8066 cases per batch have been created which gives a total of 40330 cases. Fault arc although simulated but was not taken into account during training. This is because fault arc causes little or almost no distortion to phase currents which is consistent with the results in [29] and [30]. We verified the findings of [29] and [30] using the fault arc model given in [31].

2) Creation of Bus fault Cases

A total number of 1120 bus fault cases have been generated. These faults include all types of faults mentioned in subsection III.B.1, with the values of fault resistances and incipient angles also provided in the same subsection.

3) Creation of Line Switching Cases

For line switching cases, we also create a batch for each line giving a total of 5 batches. Each batch consists of two smaller batches; each of the smaller batches corresponds to switching by one of the circuits breakers in each terminal. For example, line 23-22 would have a smaller batch for switching using the breaker installed on terminal 23 and another smaller batch for switching using the breaker on terminal 22. The variable in switching cases is the moment of switching. Switching times ranges from 0 to 360 degrees in 2 degrees increment. This way we have 360 cases per batch, giving a total of 1800 cases.

4) Creation of Lightning Strike Cases

For lightning strike cases we again create a batch of each line. We use an ATP Heidler type lightning with rising time equal to 4 μs and a τ equal to 10 μs. We kept the rising and tailing times constant during simulations but changing their amplitude which was set to 5 kA, 10 kA, 15KA, 20 kA and 30 kA. Striking distances were the same as the ones used for fault batches: 5%, 15%, 35%, 50%, 65%, 80% and 95% which are all percentages of total line length. The incipient angle was 0, 90,180, 270 and 330 degrees. This amounts to 630 cases per batch giving a total of 3150 cases. No lightning strike cases has been generated for the bus under study because busbars are either indoor or when they are outdoor they are protected either by shield wire or lightning mast (high lattice structure with a spike on top) and sometimes combinations of both depending upon type of layout of substation.

C. ANN Training and Feature Vector Building

Once transient cases are available from simulations, we have a subroutine that transforms pl4 files to mat files using MATLAB. After that MATLAB is invoked to import simulations into workspace, another subroutine is used to transform phase signals to modal signals. At this stage we apply DWT to the two aerial mode currents. We extract the details coefficients corresponding to level 3 aerial modes. Once we extract these coefficients, we build the feature vector consisting of two aerial modes coefficients of the currents stacked on top of each other. One should note that we can build the same feature vector by stacking the modes in any order but we have to consistent in building the vector, i.e., we must choose one method thought our training or we will get contradicting results. It should be clear at this point that using only two modes instead of three phase quantities make our approach faster and requires less computational power for training as opposed to other methods that use all voltages and currents for training [23].

After we build the feature vector we randomly divide the data set. We choose to have 70% of all cases have been used for training while 15% has been used for validation and the last 15% has been used for testing.

IV. Results

This section provides classification results for faults, line switching and lighting.

A. Line Identification in Case of Switching

In case of line switching, we build the feature vector as described in section III.C with level 3 details of the two aerial mode currents stacked on top each other. After we train the ANN with a hidden layer of 40 neurons, we find that a 100% classification was possible. This means that the feature vector can tell which line is being switched if all transient events were just switching.

B. Line Identification in Case of Lightning

If all transient events were just lighting strike cases, then the feature vector built the way described in section III.C section again was able to determine the line being hit by a strike by 100% accuracy. An ANN with only 40 neurons in the hidden layer was enough for 100% accurate classification.

C. External and Internal Bus Faults

In this case, we assume that all transient events are faults; we build the feature vector as described before in section III.C; use trial and error to get an appropriate size of ANN that gives good classification results. If we are only interested in knowing whether a fault is an internal bus or external bus fault, then an ANN with 20 neurons in the hidden layer gives 100% classification accuracy. If we need to see if the neural network can recognize the adjacent line being faulted, then an ANN with 80 neurons is necessary for 100% accurate classification.

D. Transient Event Type Classification

In this section we investigate whether the feature vector proposed can identify the transient event type. For this, we train the ANN with all transient cases given in subsections III.B.1, III.B.2, III.B.3 and III.B.4 such that its output layer has three output classes: one for switching, another one for lightning and a third one for faults. Building the ANN this way and using 50 neurons in the hidden layer gives the classification output in table (1). It has to be kept in mind that the feature vector has to be built consistently the same way for all cases.

Table 1

Transient Event Type Correct Classification Accuracy - Numbers are Percentages.

Faults	100
Lightning	99
Switching	98.9
Total Correct Accuracy	99.9

A relay that is programmed such that it processes the local currents using modal analysis building the feature vector as we proposed can first identify the event type as given in table (1). Once the event is identified, the feature vector is then applied to corresponding ANN of the corresponding type given in IV.A, IV.B or IV.C to determine the line causing such transient event.

V. Conclusions

A new application of wavelet based ANN for bus protection has been presented in this paper. The contributions of the paper are:

- The scheme provides ultra-high speed protection with only one eighth of a cycle of post event data.
- The approach doesn't suffer from CT saturation which is considered an improvement over modern differential schemes. This is because it has been shown in [32] that high frequency transients are measured well before CT saturation. Since we are using only one eighth of a

cycle of post event data, the results of [32] apply very well in our case.

- It has been shown that the backup protection can be provided to adjacent lines as well as identifying internal and external faults.
- The algorithm can not only detect faults, but also can classify transient disturbances on adjacent lines identifying the line causing the transient event.

A disadvantage of this approach is that the ANN architecture used in this paper cannot detect faults that are caused by lightning strikes. Further research is still needed to rectify this issue. The effect mutual coupling of parallel lines has been ignored in this research and is a subject for further investigations. Further research is still needed to identify the cases that have been misclassified for another transient event type in table (1).

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