Busbar Protection Using a Wavelet Based ANN

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 passing through the protected bus bar to the other lines connected 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 bus faults but also to identify the faulted line in case of external faults. 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 the 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 schemes, current transformers are installed on incoming and outgoing transmission lines. Currents from the 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 resolve 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 wide 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. This paper seeks to provide; fault protection for the bus, backup 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 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 disturbances [5]. In these applications and others, energy [6] 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 [7]. The application of ANN to bus protection is given in [8] where currents are fed to ANN for training and validation. In [9] a wavelet based scheme is presented for busbar protection where currents going in and out of bus zone are analyzed using DWT. DWT [10] 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.

This paper uses only one set of the three phase currents from any of the lines terminating into the bus for bus protection and backup protection for lines connected to the bus. Modal transformation [11] is used to transform phase signals to modal signals. DWT is used to extract one eighth of a cycle of post-event data. It will be shown that a subset of the modal currents carries enough information for bus protection and backup protection for lines terminating into that bus. It will be also shown that the same subset can be used to classify transient events on the lines terminating into the bus and to identify the line causing the transient disturbance. The feature vector used to train a feedforward ANN [12] is a vector consisting of level 3 details coefficients of the two aerial modes [7] 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 are provided in section III. Results are shown in section IV while conclusions are summarized in the last section.

II. METHODOLOGY

In this paper, it is shown 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 backup protection for lines terminating into 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 in topology towards the ends of the line. In the simplest case this wave will be just a step but, in reality, will be accompanied by oscillating components. Those high frequency oscillating

transient components 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.

The information from the high frequency components is extracted using DWT at level 3. Level 3 is used for computational efficiency as the feature vector, under the sampling frequency used in this paper, with level 1 or 2 will have more coefficients that will make ANN training impossible with modern day PCs because of the high RAM memory needed. Before DWT application, phase currents are decoupled from each other using modal analysis [11]. The modal matrix is calculated at 10 kHz even though it is frequency dependent. We have tried different frequencies for the modal matrix and has not seen any effect on classification. Since current transformers have a bandwidth of 100 kHz [13], we choose the sampling rate such that the maximum frequency available in the signal is 100 kHz. The time step used in EMTP simulations is 1µs which should theoretically give a maximum frequency of 500 kHz in sampled output per Nyquist theory. However, it is given in [14] 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 chosen transmission line three phase currents 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 eighth 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. The coefficients of the two aerial current modes are stacked on top of each other to build one vector that will be used to train the ANN. ANN of an appropriate size is selected for classification. ANN is then trained using various scenarios for transients on lines. If one performs internal and external fault simulations on the bus and its adjacent lines then using the feature vector built above, one can tell whether the bus is faulted or can identify the faulted line. If one only performs line switching cases on the lines terminating on the bus then using the feature vector above, one can tell which line is being switched. If one performs only lightning cases, then using the same feature vector, one 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 one trains 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.
- 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

The topology of the system under study is presented in Fig. 1. This topology is part of IEEE 118 bus case [15]. Three phase currents are being measured from bus 23 to bus 25. Any other current set can be used but focus is casted towards this set due to paper length requirement. The bus that is being protected is bus 23. Selection of bus 23 for study is because it has almost all power system components around it. Bus 23 has three incoming lines into it, namely line connecting bus 23 to bus 22 (line 23-22), line 23-32 and line 23-24. The outgoing line 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.

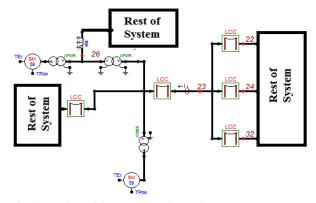


Fig. 1. Portion of the system under study

In the simulations, we used very general tower configurations for the lines around the bus being protected. The tower configurations of the lines in the study area are taken from [16] and will be shown in the full paper. All of those towers are modeled as lines with frequency dependent 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.

All power transformers have been modeled by ATP Hybrid Transformer Model according to [17] with typical parameters provided by ATPDraw [18].

Bus capacitance and transformer stray capacitance are accounted for in the simulation platform due to their high importance for transient studies. Surge arresters have been used to protect all transmission lines in the study area.

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

A large number of simulations have to be carried out to train ANN. We present a very general network topology with different tower configurations. For this paper, one needs to create cases of faults, line switching and lightning. At this point it should be reminded 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 train ANN for the bus under study and the 5 lines just mentioned above only. 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

Fault cases are created 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 increment. 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.

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 same values of fault resistances and incipient angles provided in the same subsection. The bus protection zone includes one meter from each line that terminates on the bus. This is due to EMTP limitation since the time step will need to be very small to account for shorter line lengths when not included within the protection zone, i.e., a fault within the first one meter of any line terminating on the protected bus is considered an internal bus fault.

3) Creation of Line Switching Cases

For line switching cases, a batch is created 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, 360 cases per batch had been created, giving a total of 1800 cases.

4) Creation of Lightning Strike Cases

For lightning strike cases, a batch for each line has been created. We use ATP Heidler type lightning with rising time equal to 4 μ s and a τ equal to 10 μ s. 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 have 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 current modes then extracts the details coefficients corresponding to level 3 aerial modes. After that, the feature vector is built using the coefficients of the two aerial modes of the currents stacked on top of each other. It should be noted that the feature vector can be built by stacking the modes in any order but one has to be consistent in

Table 1

Transient Event Type Correct Classification Accuracy Numbers are Percentages.

Faults	100
Lightning	99
Switching	98.9
Total Correct Accuracy	99.9

building the vector, i.e., one method has to be chosen throughout training or one will get contradicting results. It should be clear at this point that using only two modes instead of three phase quantities makes the proposed approach faster and requires less computational power for training as opposed to other methods that use all voltages and currents for training [19, 20].

Finally, we randomly divide the data set choosing to have 70% of all cases for training, 15% for validation and the last 15% 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, the feature vector is built as described in section III.C with level 3 details of the two aerial mode currents stacked on top each other. After training is accomplished using ANN having 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 could determine the line being hit by a strike with a 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, all transient events are faults; the feature vector built the way described in section III.C; use trial and error to get an appropriate size of ANN that gives good classification results. If one is 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 one needs to see if ANN 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 purpose, 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).

A relay that is programmed such that it processes the local currents using modal analysis and builds 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 as follows:

- The scheme provides ultra-high speed protection with only one eighth of a cycle of post event data.
- The approach does not suffer from CT saturation which
 is considered an improvement over modern differential
 schemes. This is because it has been shown in [21] that
 high frequency transients are measured well before CT
 saturation. Since only one eighth of a cycle of post
 event data is used, the results of [21] apply very well
 for case in hand.
- 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.

Further research is still needed to identify the cases that have been misclassified for another transient event type in table (1). The methodology given in this paper can detect line faults as fast it can detect bus faults. To allow line relays to clear the line fault first, a time delay has to be used to delay the backup protection provided by the proposed methodology. However, a mechanism need to be implemented to detect clearing of the line fault via the line relay using local data only to avoid tripping the bus unnecessarily which is a topic under study.

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