Towards a New Paradigm for Ultrafast Transmission Line Relaying

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***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 validated using field data. 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 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.**

***Index Terms*—Transmission Line Relaying, Wavelets Transform, Modal Analysis, Artificial Neural Networks, Power System Faults, Line Switching, Lightning Strike, Current Transformers**

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. Modern numerical distance relays make use of low pass and antialiasing filters - to reject high frequency content and apply Nyquist sampling theorem- and special DSP hardware to perform sophisticated math functions [1]. 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 [2]. This puts more stringent requirement on the filters used in the relay. Additionally, distance relay can only protect up to 85% of the line instantaneously [3]. 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 relays connected to substation LANs, a communication link between relays is a cyber-threat. With all limitations mentioned above, a new relaying principle is needed. This principle has to be using currents only, fast, and finally does not need any communication link for its operation. Such a principle is provided and theoretically tested in this paper.

Except for traveling wave fault location techniques that are still not very popular with relay manufacturers [4], little is done with the high frequency components of the transients even though it has been known that high frequency components of faults and transient events contain rich information [5]. This is mainly because the traditional mathematical method at hand was Fast Fourier Transform [6]. FFT transform requires the signal be stationary in the wide sense for the calculation of coefficients to be accurate, i.e. the signal can't have any temporal variations for the calculation of coefficients to be correct and accurate. Short Window Fourier Transform [7] can solve some of the problems with FFT but it introduces other issues. However most signals encountered in power systems are not stationary but have their characteristics change with time.

Multiresolution analysis (MRA) is a signal processing tool that has been introduced in the nineties [8] to solve some of the problems inherent in Fourier transform analysis methods. Wavelets[9] are usually used along with MRA to solve this very exact problem. Wavelets have a strong localization property that enables studying changes not only in time but also in frequency feasible. It is known from the uncertainty principle [10] that if the signal spans a small portion of the time domain then its Fourier Transform will span a large portion of frequency domain. DWT on the other hand does not suffer from such a limitation. On the contrary, the signal is approximated at various levels –frequency bands- and changes in time manifest themselves at the coefficients of the wavelets only around the time which the event occurred. Such property makes it ideal to detect disturbances and study power system transients [11].

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 localization property of wavelets makes it very convenient in locating faults [12].

The use of ANN for fault classification and detection has been given in [13, 14, 15] where voltage and current samples are fed directly to the ANN for fault detection and

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classification on the protected line. In [14] and [13] samples of voltages and currents are used as a feature vector to train ANN. With the advent of wavelets, special wavelets transforms are applied to voltage and current waveforms before they are fed to the ANN for training. In [16] and [17], DWT is applied to voltages and currents but instead of feeding the details coefficients to the ANN, entropy (energy) of the signal is captured and fed instead to the ANN to make fault type classification between faults on the same transmission line. In [18] and [19], DWT is applied to voltage and current signals at a relay location resulting in series of details coefficients that are fed to the ANN for fault detection and type classification. In [20] the energy of certain current levels and approximations is used to train a probabilistic classifier, and using this energy feature a decision is made whether a transient signal if due to a fault or non-fault condition on a line. A detailed look at literature reveals that very few attempts have been done to harness the power of the wavelets details coefficients alone and understand their underlying structure. Moreover, existing classification techniques as the ones in [19] and [20] do not take transients on adjacent lines into account which could mislead these schemes. Additionally, symmetrical line configuration has been universally assumed which is a configuration nearly nonexistent in real power systems.

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. It is shown that using the details coefficients of a subset local currents only, distinction can be made between fault and non-fault conditions on a protected transmission line without using any voltage signals at all. The algorithm proposed 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. It is also shown that the same apply for lightning strikes and line switching cases, i.e., the algorithm can tell which line is causing which transient event. Just as FFT produces coefficients that correspond to certain frequencies, wavelets details also give information regarding the oscillatory components of the signal localizing them in time. In this regard, DWT is used to extract useful oscillatory information about the signal. Oscillatory information is manifested in the wavelets details coefficients at various levels. It is shown 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.

The paper is organized as follows: The solution methodology is given in part II. Simulation platform which consists of a description of EMTP model and the creation of transients' cases for ANN training is described in part III. The structure of the feature vector is given in section IV. Simulation results are presented in part V. Conclusions and future research are provided at the end of the paper.

II. Solution methodology

In this paper it is argued and shown that the oscillatory information present in the transient signal captured at a single relay location caused by sudden network topology changes contains sufficient information for classification not only between transients on the same line but also between transients on adjacent lines. Any change of configuration on the line causes a traveling wave to be generated traveling from the point of change towards the ends of the line. In the simplest case this wave will be just a pulse- a step- but in reality will be accompanied by high frequency oscillating components. Fourier analysis is not suitable for analyzing such waveforms because those oscillations will be distorted and attenuated as they arrive at the line terminals. However, applying DWT will enable us to see both the spectral and temporal variations of those high frequency oscillations.

Historical treatment of traveling waves - as used in the ladder diagram for example- treat them as if they were pulses traveling down the line with no regard to the oscillatory components they carry. A certain mathematical entity -which is the feature vector to be defined in section IV- is derived from the oscillatory components and called the the transient signature of the event. The transients that are studied in this paper are lightning, line switching and faults. At a certain terminal of the line which is typically a relay location, it is argued and shown that those signatures are unique to the event that originated them and to the line which initiated those events. This means that using this oscillatory information of the event, the line causing it can be determined. Those signatures are a function of the line parameters, the network topology and the instance of the event and of course the type of the event. In essence, the signature of the fault occurring on a certain line will be different form the signature of the fault on adjacent lines. Also, line switching will cause the currents to oscillate in a manner that is different from faults and lightning striking the same line and those oscillatory components are different for different lines as well.

It is argued that the aggregate of all transient signatures caused by a certain transient event –switching or faults for example- originating from a certain line occupies a specific subspace in the n-dimensional space. This subspace is almost linearly separable [21] from all other subspaces generated by other transient events by adjacent lines. The n-dimensional space is the space spanned by all n-dimensional feature vectors used to train the ANN. A relay that is programmed to use these wavelets details not only can detect and classify transients on a protected line but also can detect faults and classify transients on adjacent lines. ANN classification is used to show that this is indeed the case. Static feedforward ANN is a tool used to map a vector from the n-dimensional space to another m-dimensional space. In the case in hand, the feature vector is mapped which is n-dimensional space to another space. These spaces will be described in section V but for now if this mapping is successful then the original n-dimensional subspaces are linearly separable as explained in [21].

Information is extracted from the high frequency components using DWT at various levels. Before DWT is applied, phase currents are decoupled from each other using modal analysis [22, 23]. Modal transformation will decouple current waveforms thus eliminating mutual coupling and untransposed line effects. The modal matrix will be explained in section IV. It is known that CVT introduces transients to the measured voltage signal. It is shown in [24] that a typical CVT with active ferroresonance suppression circuit is a low pass filter with a cut off frequency around 1 kHz which drops to almost 200 Hz when passive ferroresonance suppression circuit is employed. On the other hand classification with currents is preferable because the cut off frequency of current transformers is much larger than the potential transformer or CVT. The useful passband of current transformers is typically 100 kHz [25] and in some cases can go up to 400 kHz [26] or 500 kHz [27]. Since a conservative stance is chosen, the sampling rate is selected such that the maximum frequency available in the signal is 100 kHz to attain the 100 kHz passband of current transformers. The time step used in the EMTP simulations is $1\mu s$ which should theoretically give a maximum frequency of 500 kHz in sampled output according to Nyquist theory. However, it is given in [28] 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 currents modes to convert the signals 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 -or any level depending on which level is used- coefficients is detected. This detection is simply because the pre-event data is assumed steady state so no high frequency components exist in the pre-event data. Once the event is detected, a window of one eighth of a cycle of post event information is used for neural network training. Simulations show that at least one eighth of a cycle has to be used for correct classification. Numerous trials have shown that at least one eighth of a cycle of post-event information has to be present for correct classification or classification fails completely.

The outcome of the DWT is a series of coefficients for each mode and for each level. The coefficients of one level of the two aerial modes of currents are stacked on top of each other to build one feature vector that will be used to train the network. Building the training vector will be explained in section IV. A neural network of an appropriate size is then selected for classification. The choice of the size of network is reached at by trial and error and no universal size has been applied to all classification problems. That is the size of the network is changed till the required classification accuracy is achieved. Once the size of ANN is selected, the ANN is then trained using various scenarios for transients on lines. It is shown that using only two modes of local current information at one end of the line- corresponding to a relay- distinction can be made between various transient events on different lines. It is argued and shown that the feature vector built has sufficient information to distinguish between a fault and non-fault condition on a protected transmission line. It is also shown that the adjacent line causing certain transient events can be determined. This means using local information we can see what is happening on adjacent lines.

In summary, the procedure is as follows:

1) Decouple currents using modal analysis.
2) Apply DWT to the aerial modes using one eighth of a cycle of post event currents.
3) Stack the series of coefficients of the two aerial modes of a certain level on top of each other to create a vector used to train ANN.
4) A neural network of appropriate size is used for training. Training is done using transient scenarios. Those scenarios include: faults, line switching and lightning.

III. Simulation Platform

In this section, the ATP/EMTP model is presented in subsection III-A while in subsection III-B creation of the transient cases for the training, validation and testing of ANN is fully described.

A. EMTP Model

A snapshot of the area under study taken from ATPDraw is shown in figure 1. The IEEE 118 bus is used [29] as a test system. All data is taken from [29] except for machine data and the lines in the area under study. The dyanmic data of IEEE 118 bus system is taken from [30]. The line under study is the line connecting buses 23 and 25 (line 23-25). The selection of this is arbitrary but this specific line was attractive to the simulations for the reasons that follow. Line 23-25 is bordered by three lines connected to bus 23 namely: line 23-22, line 23-32 and line 23-24. Line 23-25 is also connected to line 26-30 via a transformer connecting buses 25 and 26. Line 23-25 is also connected to line 25-27 via bus 27. A synchronous generator is connected to bus 25 via step up transformer.

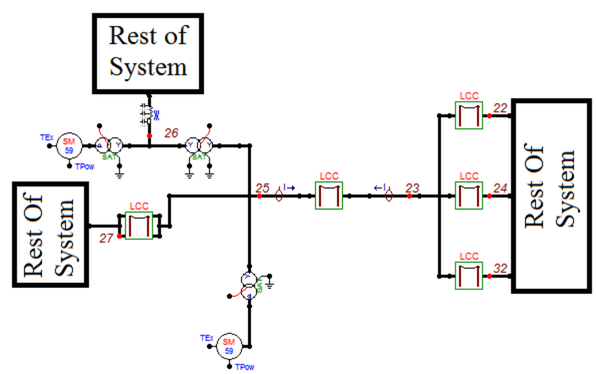

Figure 1. Portion of the system under study

All power transformers have been modeled using ATP Hybrid Transformer Model according to [31] with typical parameters provided by ATPDraw. Initial high frequency components are measured well before CT saturation occurs [32] and since one eighth only of post-fault data is used, the results of [32] apply very well, i.e, no need to model CT saturation effects. Synchronous machines are modeled using ATP SM-59 except for excitation and governor controls. This is because only one eighth of a cycle of post event data is used which is a period much shorter than modern exciter and governor time constants.

In the simulations that follows, very general tower configurations are used for the line under study and its adjacent lines. The line connecting buses 23 and 25 is given in [33]. The tower configurations for the lines bordering lines 23-25 are taken from [34]. All towers are scanned in inserted in the paper for convenience of reader in 2. 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.

Current measurement devices are located at terminals 23 and 25. It should be pointed out as well that no attempt has made to model current transformers because the maximum frequency available in the simulated signals is 100 kHz which is typically less than the useful passband of the CT as given in [25, 26, 27].

It should be pointed out that a surge arrester has been also used in the simulations. The tool in [35] is used to select the characteristic of our surge arrester. Bus capacitance and transformer stray capacitance have also been accounted for with values given in [36] which are extremely important in high frequency transient studies.

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 line but also can detect fault and no fault condition on adjacent lines. A large number of simulations had to be carried out to prove this argument. A very general network topology with different tower configurations is present.

Creation of fault cases, lightning strike cases and line switching cases has been automated. A toolbox that automatically creates transient cases is released in [37]. Creation of fault cases is first described then line switching cases and after that the lightning strike cases. At this point it should be emphasized that the line under study and that is to be protected is line 23-25 which is bordered by 4 adjacent lines namely line 23-22, line 23-32, line 23-24, line 25-27.

No attempt is made to answer how far the local currents can be used to classify transients on the lines that are beyond the lines directly connected to the line under study. For this reason, ANN is trained for the line under study and the five circuits directly surrounding it only. The next paragraphs describe creation of transient cases for faults, line switching and lightning and creation of feature vector for training.

1) Creation of 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 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. Simulations are created for line 23-25 and it adjacent lines.

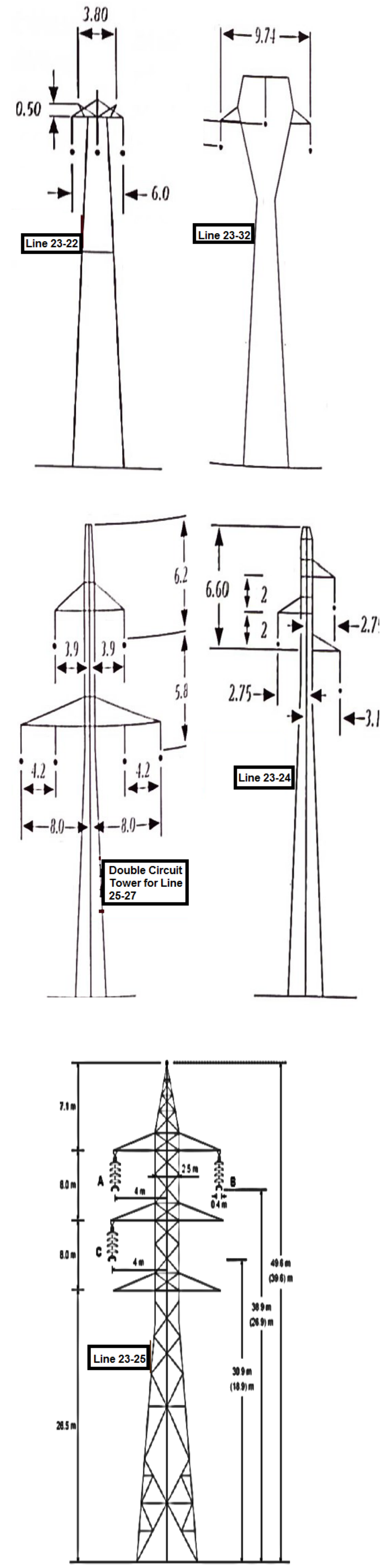

Figure 2. Tower Configurations of lines of the area under study

A total of 8066 cases per batch have been created which gives a total of 48396 cases because line 25-27 is double circuit line, i.e., two batches of faults for line 25-27 have been created: one for each circuit. Fault arc although simulated but was not taken into account during training. This is because fault arc causes, if any, very little distortion to phase currents which is consistent with the results in [20] and [13]. The previous statement has been validated using the fault arc model given in [38].

2) Creation of Line Switching Cases: For line switching cases, a batch for each line has been creating giving a total of 6 batches. Each batch consists of smaller batches; each of the smaller batches corresponds to switching by one of the circuits breakers at 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 have been created, giving a total of 2160 cases.

3) Creation of Lightning Strike Cases: For lightning strike cases a batch of each line has been again created. An ATP Heidler type lightning source with rising time equal to 4 μs and a τ equal to 10 μs. The rising and tailing times are kept constant during simulations but amplitudes have been varied which were 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 3780 cases.

IV. Building of Feature Vector of Transient Signature

After batches have been created, a special subroutine is used to translate the phase quantities to modal quantities. The phase quantities are decoupled using the modal matrix calculated at 10 kHz even though the matrix is frequency dependent. Different modal frequencies for the modal matrix have been tried but this did not affect the classification results at all. The two aerial modes are the only ones used for training. The modal matrix with real entries is given in equation (1). The signs of the entries are only shown to emphasize their physical meaning

$$\begin{pmatrix} Mode1 \\ Mode2 \\ Mode3 \end{pmatrix} = \begin{pmatrix} + & + & + \\ - & + & + \\ + & + & - \end{pmatrix} \times \begin{pmatrix} Ia \\ Ib \\ Ic \end{pmatrix} \tag{1}$$

It should be apparent that Mode1 is the weighted sum of all phase currents which is nothing other than the ground mode current. This ground mode current is known to be very well dependent on the frequency and ground resistance [39]. This is the main reason that this current mode has not been used for building the feature vector for training.

Once the modal quantities are available, we run DWT with db4 for 4 levels, starting from level 1 to level 4. Db4 has been used since it has produced good results with previous literature. The outcome of DWT is a series of coefficients for each level and for each mode. Since the first one eighth of a cycle following the transient event is only sought, the details coefficients corresponding to that period are only obtained. Two modes out of the three modes are only used. The details coefficients of one level of Mode2 and Mode3 are stacked on top of each other. It should be emphasized that building the n-dimensional vector this way does not change the temporal content of the feature vector, as long as all other n-dimensional vectors are built consistently this way, i.e., the order of the modes in the feature vector has to be preserved and the vector has to be built using one level only. If the order of modes in the feature vector is changed this amounts to a rotation of n-dimensional space but should not change the results of classification, again as long as all vectors are built consistently.

At this point one should note that the application uses only two thirds of modes of the currents as contrasted to other applications that use all phase voltage and current waveforms for ANN training [18] which amounts to drastic reduction in computational power needed for ANN.

Having created n-dimensional vectors, the input for the ANN is ready. Training of the neural network is then started. The cases are randomly divided into the following categories: 70% of all cases for training, 15% for validation and another 15% for testing. Results are discussed in the following section.

V. Results

This section presents the results of the classification. In section V-A, the results of classification in case all events were faults are shown. In section V-C classification output in case of all events were lighting strikes is shown. In section V-B results in case events were all line switching are presented. Finally, event type classification is provided in section V-D.

In section II, the mapping from n-dimensional space to the m-dimensional space has not been discussed. The dimension of the n-dimensional space is fixed by the length of the feature vector while the dimension of the m-dimensional space is different depending on which space we want to map the n-dimensional space to. In sections V-A, V-B and V-C below, the events are being mapped to the lines causing them which amounts to a mapping from the n-dimensional space to a 6-dimesnioal space (one dimension per line, line 25-27 counted twice for the double circuit). In section V-D, all events are being mapped to an event-type space which is a mapping from n-dimensional space to a 3-dimsnsional space (faults, lightning and switching). It should be apparent that the dimension of the feature space (n-dimensional space) depends on the DWT level used. It should be obvious as well that this dimension is halved as we go one level higher, i.e., the dimension of the n-dimensional space using level 1 is double the dimension of level 2 n-dimensional. For the sampling frequency used in this paper, the dimension of the n-dimensional space is one hundred and sixty eight (168) if level 4 is used to build the feature vector, i.e, each modal current has 84 coefficients.

A. LINE IDENTIFICATION IN CASE OF FAULTS

This section provides the results for classification in case of faults only, i.e. if all transient events are faults only how accurate can the method identify the faulted line.

First, six batches of faults are created as described in III-B1. Creating the feature vector using currents from terminal 23 as described before using any levels from 1 to 4 to train ANN gives the classification accuracy in table I. One immediately sees that classification accuracy for the double circuits of line 25-27 fails. This is to be expected if the reader consults 2 for the tower configuration which shows that from the Thevenin's point of view at the terminal 23 or 25 of the line under study, the same fault case on any circuit will produce the same response due to the symmetry of the tower 25-27. It should be pointed out that the faults on one of the circuits of line 25-27 are confused for faults on the other circuit and vice versa but not with other lines. The percentage accuracy does not change if the currents at terminal 25 are used instead. Training with levels 1, 2, 3 and 4 gives the same classification accuracy but the difference is mainly in the ANN size needed. For reproducibility purposes, an ANN of size 40 in the hidden layer is needed to achieve the results in table I for level 3. Lower levels (levels corresponding to higher frequencies) needed less neurons but the feature vector becomes so long (corresponding to more detailed time resolution). This in turn demands for a high super computer which has been undertaken for level 1 (frequency band from 100 kHz to 50 kHz) and level 2 (50 kHz to 25 kHz). Level 3 (25 kHz to 12.5 kHz) and level 4 (12.5 kHz to 6.25 kHz) can be done on a PC such as the one the author used with Core i7, 3.2 GHz speed, 4 cores and 8 GB of RAM. If the double circuit tower 25-27 is considered to be one line, a 100% correct classification is achieved for faults.

Table I
FAULTS CLASSIFICATION ACCURACY - NUMBERS ARE PERCENTAGES.

Line Under Study	100
Line 23-32	100
Line 23-24	100
Line 23-22	100
Circuit (1) Line 25-27	46
Circuit (2) Line 25-27	54

B. Line Identification in Case of Switching

This section shows the results of classification if all transients are for line switching. Creating the switching events as described in III-B2 and using either end currents, the accuracy in table II is achieved. Training with any level from 1 to 4 gives the same classification result, but the only difference is being the size of the hidden layer. Level 3 required 30 neurons in the hidden layer with lower levels requiring less neurons and higher levels requiring more neurons. Once again switching events on one of the circuits of line 25-27 are confused for the other circuit and vice versa .

C. Line Identification in Case of Lightning Strikes

If all transient events are lightning only as described in III-B3, then using any end data gives the results in table III irrespective of the terminal used or the level used (levels 1 to 4). Level 3 required 30 neurons in the hidden layer with lower levels requiring less neurons and higher levels requiring more neurons. One has to note that in table II and III, the algorithm can't still distinguish between the events on any of the circuits of line 25-27 due to the symmetry with respect to the line being studied.

Table II
SWITCHING CLASSIFICATION ACCURACY - NUMBERS ARE PERCENTAGES

Line Under Study	100
Line 23-32	100
Line 23-24	100
Line 23-22	100
Circuit (1) Line 25-27	48
Circuit (2) Line 25-27	52

Table III
LIGHTNING CLASSIFICATION ACCURACY - NUMBERS ARE PERCENTAGES

Line Under Study	100
Line 23-32	100
Line 23-24	100
Line 23-22	100
Circuit (1) Line 25-27	49
Circuit (2) Line 25-27	51

D. Transient Event Type Classification

Lastly, the algorithm performance is shown when it comes to classification between different transients types. The types of studies in this paper are faults, line switching and lightning. ANN is trained with all transient cases given in subsections III-B1, III-B2 and III-B3 above. The output is shown in table IV. Once again levels 1 through 4 give the same classification accuracy whether bus 23 or 25 is used. The ANN used for table IV has a size of 30 when trained with level 3 currents. It should be pointed out that in table IV most lightning strikes with amplitude 5000 Amp on line 23-22 have been misclassified for faults. A 5000 Amp lighting strike is unlikely in real world lightning strike cases. If we remove all 5000 Amp strikes from training, a one hundred accurate classification accuracy is achieved for event type classification.

It is now a straightforward manner to construct a two layer feedforward network that classify any event to fault, lightning or switching in the first layer then identify the line causing the event in the second layer. Alternatively, a relay can be programmed to classify the events into fault, switching or lightning in table IV. Once this is done, the same event can be applied to the ANN corresponding to that event type.

Table IV
TRANSIENT EVENT TYPE CLASSIFICATION ACCURACY - NUMBERS ARE PERCENTAGES.

Faults	100
Lightning	97.2
Switching	99.8

VI. CONCLUSIONS AND FUTURE RESEARCH

This paper presented an argument that high frequency signals can be used for high speed power system fault detection via transient classification identifying the line causing the transient event.

The contributions of the paper are as follows:

1) It has been shown that currents alone can be used for transient signature of the event.
2) Only two modes are necessary for classification.
3) Only one eighth of a cycle of post event data is necessary for classification.

Although the results in this paper have been shown only to a specific tower, the author has tried different tower configurations and confirmed that the algorithm works for all tower configurations considered. It should be clear that the current method fails if a lightning strike evolves to a fault. This drawback has been addressed separately in a different publication [40]. Additionally, detection of faults on mutually coupled lines has not been addressed in this paper and will be treated in a different publication.

One issue that has not been investigated in this paper is insulation breakdown. The author has not assumed any failure of insulation in the simulations. The cutting of the signal associated with insulation breakdown can potentially mislead the scheme proposed. Further investigations are needed to completely quantify its effect on the proposed relaying scheme. It should be noted, however, that lightning strikes are being chopped by the surge arrester but still being correctly recognized.

Field validation is being performed and results will be shared once all investigations are done.

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