Power system fault detection and classification using Wavelet Transform and Back Propagation Neural Network

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Abstract—Transmission lines constitute the major part of power system. Transmission and distribution lines are vital links between the generating unit and consumers to achieve the continuity of electric supply. To economically transfer large blocks of power between power systems and from remote generating sites, High voltage (HV) and Extra high voltage (EHV) overhead transmission systems are being used. Transmission lines are exposed to atmosphere, hence chances of occurrence of fault in transmission line is very high. The major faults in transmission lines are line to ground fault, line to line fault and three phase faults. During the occurrence of faults, the line current and voltages undergoes transients. These transients are computed using discrete wavelet transform. Wavelet theory is the mathematics, which deals with building a model for non-stationary signals, using a set of components that look like small waves, called wavelets. The main advantage of wavelet transform over any transform is that the size of analysis window varies in proportion to the frequency analysis. Wavelet transform offer a better compromise in terms of localization. The maximum detail coefficient, energy of the signal and the ratio of energy change of each phase currents and voltages are computed from the transients produced by each phases due to faults using discrete wavelet transform (DWT) and the computed data is forwarded a neural network. As literature suggests, various Neural Networks have been used in the recent times, to improve the protection scheme in the transmission lines. They have been used in fault classification, fault section estimation, adaptive relaying and fault diagnosis. Many of these methods are based on back propagation, Radial basis function and Finite Impulse response neural networks. A typical Back Propagation Neural Network (BPNN) is a non-linear regression technique which attempts to minimize the global error. The BPNN consists of three layers: an input layer with three neurons, a hidden layer with two neurons and an output layer with two neurons. The features extracted by the fault signal using wavelet transform is fed as input to the BPNN which is trained properly so as to classify the fault into either line to ground fault, line to line fault or three phase faults.

Keywords— Faults, Transmission Lines, Wavelet, ANN, BPNN.

I. INTRODUCTION

Electric power is generated, transmitted and distributed via large interconnected power systems. The generation of electric power takes place in a power plant. Then the voltage level of the power will be raised by the transformer before the power is transmitted to overcome transmission line losses. Electric power is proportional to the product of voltage and current this is the reason why power transmission voltage levels are used in order to minimize power transmission losses. The primary objective of all power systems is to maintain the continuous power supply. During normal operating conditions, current will flow through all elements of the electrical power system within pre-designed values which are appropriate to these elements’ ratings. However, natural events such as lightning, weather, ice, wind, heat, failure in related equipment and many other unpredictable factors may lead to undesirable situations and connection between the phases conductors of a transmission lines or the
phase conductors to ground, these types of events are known as faults. A falling tree on a transmission lines could cause a three-phase fault where all phases share a point of contact called fault location. In different occasions, fault could be a result of insulation deterioration, wind damage or human vandalism.

![Power System Structure](image)

**Figure 1. Power system structure**

**A) Faults in power system**

In an electric power system, a fault is any abnormal flow of electric current. For example a short circuit is a fault in which current flow bypasses the normal load. An open circuit fault occurs if a circuit is interrupted by some failure. In three phase systems, a fault may involve one or more phases and ground, or may occur only between phases. In a "ground fault" or "earth fault", current flows into the earth. The prospective short circuit current of a fault can be calculated for power systems. In power systems, protective devices detect fault conditions and operate circuit breakers and other devices to limit the loss of service due to a failure.

In a polyphase system, a fault may affect all phases equally which is a "symmetrical fault". If only some phases are affected, the resulting "asymmetrical fault" becomes more complicated to analyze due to the simplifying assumption of equal current magnitude in all phases being no longer applicable. The analysis of this type of fault is often simplified by using methods such as symmetrical components.

- Transient fault
- Persistent fault
- Symmetric fault
- Unsymmetrical fault

**i. Transient fault**

Transient fault is a fault that is no longer present if power is disconnected for a short time. Many faults in overhead power lines are transient in nature. At the occurrence of a fault power system protection operates to isolate area of the fault. A transient fault will then clear and the power line can be returned to service. Typical examples of transient faults include:

- momentary tree contact
- bird or other animal contact
- lightning strike
- conductor clash

In electricity transmission and distribution systems an automatic reclose function is commonly used on overhead lines to attempt to restore power in the event of a transient fault. This functionality is not as common on underground systems as faults there are typically of a persistent nature.
ii. Persistent fault
A persistent fault does not disappear when power is disconnected. Faults in underground power cables are often persistent. Underground power lines are not affected by trees or lightning, so faults, when they occur, are probably due to damage. In such cases, if the line is reconnected, it is likely to be only damaged further.

iii. Symmetric fault
A symmetric, symmetrical or balanced fault affects each of the three-phases equally. In transmission line faults, roughly 5% are symmetric. This is in contrast to an asymmetric fault, where the three phases are not affected equally. In practice, most faults in power systems are unbalanced. With this in mind, symmetric faults can be viewed as somewhat of an abstraction; however, as asymmetric faults are difficult to analyze, analysis of asymmetric faults is built up from a thorough understanding of symmetric faults.

iv. Unsymmetrical fault
An asymmetric or unbalanced fault does not affect each of the three phases equally. Common types of asymmetric faults, and their causes:

- line-to-line - a short circuit between lines, caused by ionization of air, or when lines come into physical contact, for example due to a broken insulator.
- line-to-ground - a short circuit between one line and ground, very often caused by physical contact, for example due to lightning or other storm damage.
- double line-to-ground - two lines come into contact with the ground (and each other), also commonly due to storm damage.

B) Type of Faults
There are two types of faults which can occur on any transmission lines; balanced faults and unbalanced faults also known as symmetrical and asymmetrical faults respectively. Most of the faults that occur in power system they are unbalanced three-phase faults. In addition, faults can be categorized as the shunt faults, series faults and simultaneous faults. In the analysis of power system under fault conditions, it is necessary to make a distinction between the types of fault to ensure the best results possible in the analysis.

i. Series Faults
Series faults represent open conductor and take place when unbalanced series impedance conditions of the lines are present. Two examples of series fault are when the system holds one or two broken lines, or impedance inserted in one or two lines. In the real world a series faults takes place, for example, when circuit breakers controls the lines and do not open all three phases, in this case, one or two phases of the line may be open while the others are closed. Series faults are characterized by increase of voltage and frequency and fall in current in the faulted phases.

ii. Shunt Faults
The shunt faults are the most common type of fault taking place in the field. They involve power conductors or conductor-to-ground or short circuits between conductors. One of the most important characteristics of shunt faults is the increment the current suffers and fall in voltage and frequency. Shunt faults can be classified into four categories.
iii. Line-to-ground fault
This type of fault exists when one phase of any transmission lines establishes a connection with the ground either by ice, wind, falling tree or any other incident. 70% of all transmission lines faults are classified under this category.

![Figure 2 Single line to ground fault](image)

iv. Line-to-line fault
As a result of high winds, one phase could touch another phase & line-to-line fault takes place. 15% of all transmission lines faults are considered line-to-line faults.

![Figure 3 Line to line fault](image)

v. Double line-to-ground
Falling tree where two phases become in contact with the ground could lead to this type of fault. In addition, two phases will be involved instead of one at the line-to-ground faults scenarios. 10% of all transmission lines faults are under this type of faults.

![Figure 4 Two line to ground fault](image)

vi. Three phase fault
In this case, falling tower, failure of equipment or even a line breaking and touching the remaining phases can cause three phase faults. In reality, this type of fault rarely exists which can be seen from its share of 5% of all transmission lines faults. The first three of these faults are known as asymmetrical faults.

II. WAVELETS
Wavelets are a powerful tool for the representation and analysis of such physiologic waveforms because a wavelet has finite duration (compact support) as contrasted with Fourier methods based on sinusoids of infinite duration. The Fourier transform is a tool widely used for many scientific
purposes, but it is well suited only to the study of stationary signals where all frequencies have an infinite coherence time. The Fourier analysis brings only global information which is not sufficient to detect compact patterns. Gabor introduced a local Fourier analysis, taking into account a sliding window, leading to a time frequency analysis. This method is only applicable to situations where the coherence time is independent of the frequency. This is the case for instance for singing signals which have their coherence time determined by the geometry of the oral cavity. Morlet introduced the Wavelet Transform in order to have a coherence time proportional to the period. The wavelet transform or wavelet analysis is probably the most recent solution to overcome the shortcomings of the Fourier transform. In wavelet analysis the use of a fully scalable modulated window solves the signal-cutting problem. The window is shifted along the signal and for every position the spectrum is calculated.

Then this process is repeated many times with a slightly shorter (or longer) window for every new cycle. In the end the result will be a collection of time-frequency representations of the signal, all with different resolutions. Because of this collection of representations we can speak of a multi resolution analysis. In the case of wavelets we normally do not speak about time-frequency representations but about time-scale representations, scale being in a way the opposite of frequency, because the term frequency is reserved for the Fourier transform.

A. Discrete Wavelet Transforms
The wavelet transform describes a multi-resolution decomposition process in terms of expansion of a signal onto a set of wavelet basis functions. Discrete Wavelet Transformation has its own excellent space frequency localization property. Application of DWT in 1D signal corresponds to 1D filter in each dimension. The input Daubechies Wavelet as mother wavelet is divided into 8 non-overlapping multi-resolution sub-bands by the filters, namely db1, db2, db3up to db8, where db is acronym for Daubechies. The sub-band is processed further to obtain the next coarser scale of wavelet coefficients, until some final scale “N” is reached. When a signal is decomposed into 8 levels, the db6 sub-band signal best reflects the original signal, since according to the wavelet theory, the approximation signal at level n is the aggregation of the approximation at level n-1 plus the detail at level n-1.

B. Wavelet Selection
The large number of known wavelet families and functions provides a rich space in which to search for a wavelet which will very efficiently represent a signal of interest in a large variety of applications. Wavelet families include Biorthogonal, Coiflet, Haar, Symmlet, Daubechis wavelets, etc. There is no absolute way to choose a certain wavelet. The choice of the wavelet function depends on the application.

III. BACK PROPAGATION NEURAL NETWORK (BPNN)
In the Back propagation neural network (BPNN) the output is feedback to the input to calculate the change in the values of weights. One of the major reasons for taking the back propagation algorithm
is to eliminate the one of the constraints on two layers ANNs, i.e. similar inputs lead to the similar output. The error for each iteration and for each point is calculated by initiating from the last step and by sending calculated the error backwards. The weights of the back-error-propagation algorithm for the neural network are chosen randomly, feeds back in an input pair and then obtain the result.

After each step, the weights are updated with the new ones and the process is repeated for entire set of inputs-outputs combinations available in the training data set provided by developer. This process is repeated until the network converges for the given values of the targets for a pre defined value of error tolerance. The entire process of back propagation can be understood by Figure 6. The back-error-propagation algorithm is effectively used for several purposes including its application to error functions (other than the sum of squared errors) and for the calculation of Jacobian and Hessian matrices.

This entire process is adopted by each and every layer in the entire the network in the backward direction (Haykin 1994). The proposed algorithm uses the Mean Square Error (MSE) technique for calculating the error in each iteration.

![Figure 6. Structure of back propagation of ANN.](image)

The concept of BPNN can be understand by Figure 6. The algorithm of BPNN is as follows:

1. **Forward propagation**
   
   \[
   a_j = \sum_i w_{ji}^{(1)} x_i \\
   z_j = f(a_j) \\
   y_j = \sum_i w_{kj}^{(2)} z_j
   \]

2. **Output difference**
   
   \[
   \delta_k = y_k - t_k
   \]

3. **Back propagation for hidden layers**
   
   \[
   \delta_j = (1 - z_j^2) \sum_{k=1}^{K} w_{kj} \delta_k
   \]

4. The gradient of error with respect to first layer weights and second layer weights are calculated.

5. In this step the previous weights are updated.
where $aj$: weighted sum of inputs, $wji$: weight associated with the connection, $xi$: inputs,
$zi$: activation unit of (input) that sends a connection to unit $j$, $δk$: derivative of error at $k$th neuron,
$yi$: $i$th output, $yk$: activation output of unit $k$, $tk$: corresponding target of input
and $δj$: derivative of error wrt to $aj$.

The MSE for each output in each iteration is calculated by

$$MSE = \frac{1}{N} \sum_{i=1}^{N} (E_i - E_o)^2$$

where $N$ is number of iterations, $E_i$ is actual output and $E_o$ is out of the model. This entire architecture of back propagation based ANN is illustrated in Figure 6., which shows the each and every step of algorithm.

The learning rate at which the ANN is learning can be escalated by taking the optimum values of weights in very stage. The total numbers of iterations required for conversing the algorithm for predefined error and time taken in entire training depends upon the following factors:

- The structure of the neural network
- The size of the neural network (number of layers, etc.)
- The complexity of the problem under investigation
- The method of learning adopted (training function)
- The size of the input and output data set (training/learning patterns).

The efficiency and best performance of a developed ANN and the optimum learning method can be estimated by using the final trained network by testing with testing dataset. This testing data set is supposed to be provided by the developer and is a part of network development.

IV. MODELING THE THREE PHASE TRANSMISSION LINE SYSTEM

Figure 7. Snapshot of the studied model.

A. Measurement of voltage, current and preprocessing of data
The three phase Voltage and current waveforms have been generated and sampled at a frequency of 1,000 Hertz. Hence, there are 20 samples per each cycle. A reduction in the overall size of the neural network improves the time performance of the neural network and this can be achieved by
optimizing the feature extraction. By doing this, all of the important and relevant information present in the waveforms of the voltage and current signals can be used effectively.

B. Training and testing

Figure 9. depicts the snapshot of the developed ANN model in Simulink of MATLAB. The Neural Network toolbox in Simulink of MATLAB uses the entire data set in three parts.

The first part is of data set is known as the training data set, which is used for training purpose of the neural network by computing the gradient and updating the network weights until the network converges for given value of errors. The first part is of data set is known as the validating data set and this validation dataset is used by the network during the training process (this is in the form of inputs only without assigning any outputs values) and the error in validation process for entire validating set is monitored throughout the training process.

When the neural network during validation begin the over fitting of the given data, the validation errors increase and when the number of validation process fails and increase beyond a particular value, the training process ends to avoid further over fitting the data and the neural network is returned to the minimum number of validation errors. The third part is testing set, the testing data set is generally not used during the training process. The third part is used to judge the overall performance of the finally developed trained neural network.

If the test data set reaches up to the minimum value of mean square error at any significantly different iteration than the validation set, it means that the neural network will not be able to provide satisfactory performance and needs to be re-architecture.
For the task of training the neural networks for different stages, sequential feeding of input and output pair has been adopted. In order to obtain a large training set for efficient performance, each of the ten kinds of faults has been simulated at different locations along the considered transmission line. In view of all these issues, about 100 different fault cases for each of the 10 kinds of faults have been simulated. Apart from the type of fault, the phases that are faulted and the distance of the fault along the transmission line, the fault resistance also has been varied to include several possible real-time fault scenarios. The fault resistance has been varied as follows: 0.25, 0.5, 0.75, 1, 5, 10, 25, 50 \( \Omega \). Also, the fault distance has been varied at an incremental factor of every 3 km on a 300 km transmission line.

C. Fault detection
The neural network is provided with six inputs during the fault detection process. The inputs are three voltages of respective three phases and three currents of the respective three phases. The value of input voltages and input currents are normalized with respect to the pre-fault values of the voltages and currents respectively. All ten different types of faults and no fault condition have been considered in developing the data set.

The training set consist of total 8,712 input and 8,712 output samples (792 for each of the ten faults and 792 for the no fault case), which basically forms a set of six inputs and one output in each input–output pattern. The output of the neural network is in simple yes or no form, i.e. 1 or 0, which indicates whether the fault has been occurred or not.

The developed architecture of artificial neural network has total five layers. Number of simulations has been carried out and a 6-10-5-3-1 neural network architecture was chosen, i.e. it has three hidden layers with 10, 5 and 3 neurons respectively. The transfer function used for layer 1, layer 2, layer 3 and layer 4 are linear, tansig, tansig and log sig respectively, which gives best results.

From the training performance plot as shown in Figure 3.6, it is clear that training performance shown by neural network is fine. The overall mean square error of the trained neural network is less than the pre defined value of 0.0001. The value of mean square error is 5.8095e–005 delivered in the end of the training of the network. Hence, this architecture is chosen as final for given input and output.

This data set is used for training purpose of the ANN. After the training of the neural network, its performance is checked by plotting the linear regression plot (available in toolbox) that co-relates the targets to the outputs as shown in Figure 10.

The correlation coefficient (r) is a measure of how well the neural network’s targets can track the variations in the outputs (0 being no correlation at all and 1 being complete correlation). The correlation coefficient in this case has been found to be 0.99982 which indicates excellent correlation.

Another means of testing the performance of the neural network is to plot the confusion matrices for the various types of errors that occurred for the trained neural network. Figure 3.8 plots the confusion matrix for the three phases of training, testing and validation. The diagonal cells in green indicate
number of cases that have been classified correctly by the neural network and the off-diagonal cells which are in red indicate the number of cases that have been wrongly classified by the ANN. The last cell in blue in each of the matrices indicates the total percentage of cases that have been classified correctly in green and the vice versa in red. It can be seen that the chosen neural network has 100 percent accuracy in fault detection.

D. Fault classification
The same process that was employed in Fault Detection is also followed here in terms of the design and development of the classifier neural network. The designed network takes in the sets of six inputs as explained earlier (the three phase voltages and currents values normalized with respect to their corresponding pre-fault values). The neural network has four outputs, each of them...
corresponding to the fault condition of each of the three phases and one output for the ground line. Hence the outputs are either 0 or 1 denoting the absence or presence of a fault on the corresponding line (A, B, C or G where A, B and C denote the respective three phases of the transmission line system and G denotes the ground). Hence the various possible permutations can represent each of the various faults accordingly. The neural network should be capable to accurately distinguish between the ten possible categories of faults. The training set contains total 7,920 inputs and output pattern (792 for each type of fault out of ten faults) with six inputs and one output in each input–output combination. Back-propagation networks with a variety of combinations of hidden layers and the different number of neurons in each hidden layer were analyzed. Of those, the one that achieved satisfactory performance was the neural network 6-38-4, i.e. 6 neurons in the input layer, 1 hidden layer with 38 neurons in it and four neurons in the output layer.

The overall mean square error of the trained neural network is 0.036043 and it can be seen from Figure 13 that the testing and the validation curves have similar characteristics which is an indication of efficient training.

![Figure 13 Mean-square error performance of the network](image)

![Figure 14. Curve of regression Fit for the outputs vs. targets of the proposed ANN.](image)

V. CONCLUSION

The application of artificial neural networks for the detection and classification of faults on a three phase transmission lines system is discussed. The method defined utilizes the three phase voltages and three phase currents as inputs to the neural networks.
The inputs were normalized with respect to their pre-fault values respectively. The results shown in the paper is for line to ground fault only. The other types of faults, e.g. line-to-line, double line-to-ground and symmetrical three phase faults can be studied and ANNs can be developed for each of these faults.

All the artificial neural networks studied here adopted the back-propagation neural network architecture. The simulation results obtained prove that the satisfactory performance has been achieved by all of the proposed neural networks and are practically implementable. The importance of choosing the most appropriate ANN configuration, in order to get the best performance from the network, has been stressed upon in this work. The sampling frequency adopted for sampling the voltage and current waveforms in this research work is 1,000 Hz.

Some important conclusions that can be drawn from the concept are:

- Artificial neural networks are a reliable and effective method for an electrical power system transmission line fault classification and detection especially in view of the increasing dynamic connectivity of the modern electrical power transmission systems.

- The performance of an artificial neural network should be analyzed properly and particular neural network structure and learning algorithm before choosing it for a practical application.

- Back propagation neural networks delivers good performance, when they are trained with large training data set, which is easily available in power systems and hence back propagation networks have been chosen for proposed method.

- The scope of ANN is wide enough and can be explored more. The fault detection and classification can be made intelligent by nature by developing suitable intelligent techniques. This can be achieved if we have the computers which can handle large amount of data and take least amount time for calculations.

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