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FAULT DETECTION AND CLASSIFICATION FOR ONLINE DETECTION IN DISTRIBUTED ELECTRICAL SYSTEM

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ABSTRACT:-

This paper proposes a novel method for transmission- line fault detection and classification using oscillographic data. The fault detection and its clearing time are determined based on a set of rules obtained from the current waveform analysis in time and wavelet domains. The method is able to single out faults from other power-quality disturbances, such as voltage sags and oscillatory transients, which are common in power systems operation. An artificial neural network is classifies the fault from the voltage and current waveforms pattern recognition in the time domain. The method has been used for fault detection and classification from real oscillographic data of a Brazilian utility company with excel- lent results.

KEYWORDS: *Artificial neural networks (ANNs), fault classification, fault detection, transmission lines, wavelet transforms.*

I. INTRODUCTION

Modern electric power systems have three separate components - generation, transmission and distribution. Electric power is generated at the power generating stations by synchronous alternators that are usually driven either by steam or hydro turbines. Most of the power generation takes place at generating stations that may contain more than one such alternator-turbine combination. Depending upon the type of fuel used, the generating stations are categorized as thermal, hydro, nuclear etc. Many of these generating stations are remotely located. Hence the electric power generated at any such station has to be transmitted over a long distance to load centres that are usually cities or towns. This is called the **power transmission**. In fact power transmission towers and transmission lines are very common sights in rural areas. The basic structure of a power

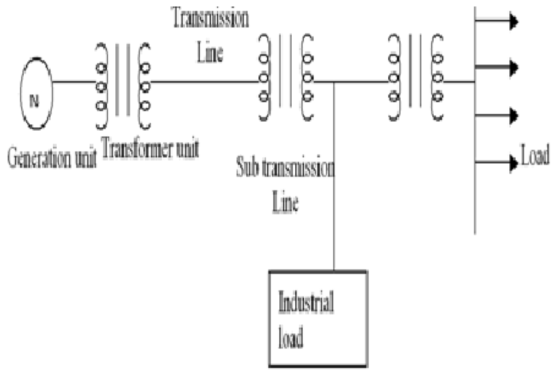


Figure 1: A typical power system.

It contains a generating plant, a transmission system, a sub transmission system and a distribution system. These subsystems are interconnected through transformers T_1, T_2 and T_3. Let us consider some typical voltage levels to understand the functioning of the power system. The electric power is generated at a thermal plant with a typical voltage of 22 kV (voltage levels are usually specified line-to-line). This is boosted up to levels like 400 kV through transformer T_1 for power transmission. Transformer T_2 steps this voltage down to 66 kV to supply power through the sub transmission line to industrial loads that require bulk power at a higher voltage. Most of the major industrial customers have their own transformers to step down the 66 kV supply to their desired levels. The motivation for these voltage changes is to minimize transmission line cost for a given power level. Distribution systems are designed to operate for much lower power levels and are supplied with medium level voltages. Electric power quality is an important issue in power systems nowadays.

II. POWER SYSTEM QUALITY

The demand for clean power has been increasing in the past several years. The reason is mainly due to the increased use of microelectronic processors in various types of equipments such as computer terminals, programmable logic controllers and diagnostic systems. Most of these systems are quite susceptible to disturbances in the supply voltage. For example a momentary power interruption or thirty percent voltage sag lasting for hundredth of a second can reset the PLCs in an assembly line. The amount of waveform distortion has been found to be more significant nowadays due to the wide applications of nonlinear electronic devices in power apparatus and systems. Without determining the existing levels of power quality, electric utilities cannot adopt suitable strategies to provide a better service. Therefore an efficient approach of justifying these electric power quality disturbances is motivated. Several research studies regarding the power quality have been conducted. Their aims were often concentrated on the collection of raw data for a further analysis, so that the impacts of various disturbances can be investigated. Sources of such disturbances can be located or further mitigated. However, the amount of acquisition data was often massive in their test cases. Such an abundance of data may be time consuming for the inspection of possible culprits. A more efficient approach is thus required in the power quality assessment. The implementation of the discrete Fourier transform by various algorithms has been constructed as the basis of modern spectral analysis. Such transforms were successfully applied to stationary signals where the properties of signals did not evolve in time. However, for those non-stationary signals any abrupt change may spread over the whole frequency axis. In this situation, the Fourier transform is less efficient in tracking the signal dynamics. A point-to-point comparison scheme has been proposed to discover the dissimilarities between consecutive cycles. This approach was feasible in detecting certain kinds of disturbances but fail to detect those disturbances that appear periodically. With the introduction of new network topologies and improved training algorithms, neural network technologies have demonstrated their effectiveness in several power system applications. Once the networks have been well trained, the disturbances that correspond to the new scenario can be identified in a very short time. This technique has also been applied in the power system applications. However, it can only be applied to detect a particular type of disturbance. When encountering different disturbances, the network structure has to be reorganized, plus the training process must be restarted. A method of detecting power quality disturbances based on neural networks and wavelets has been proposed. In this method, the fundamental component is removed using wavelets and the remaining signal corresponding to disturbances is processed and given as input to ANN. However, this method fails to detect voltage sag/swell and also new ANN's have to be developed for different rated load voltages and sampling frequencies. Recently with the emergence of wavelets it has paved a unified framework for signal processing and its applications. Fourier transforms rely on a uniform window for spreader frequencies. Wavelet transforms can apply various lengths of windows according to the amount of signal frequencies. Characteristics of non- stationary disturbances were found to be more closely monitored by wavelets. The transient behavior, cavities and discontinuities of signals can be all investigated by wavelet transforms. For example, if there is an instantaneous impulse disturbance, which happens at a certain time interval it may contribute to the Fourier transform, but its location on the time axis is lost. However, by wavelets both time and frequency information can be obtained. In other words, the wavelet transform are more local. Instead of transforming a pure 'time domain' in to a pure' frequency domain ', the wavelet transforms find a good compromise in time - frequency domain. In This work an algorithm, this overcomes all these difficulties and can accurately detect and classify the disturbances present in the signal. This method is independent of the load voltage and can be easily customized for different sampling frequencies. In this approach, for detecting each disturbance a particular wavelet is used. The method uses wavelet filter banks in an effective way and does multiple filtering to detect the disturbances. The performance evaluation of different wavelets in the proposed method shows the capability of a particular wavelet in detecting a particular disturbance.

III. QUALITY IMPROVEMENT

Current harmonics are a problem because they cause increased losses in the customer and utility power system components. Transformers are especially sensitive to this problem and may need to be derated to as much as 50% capacity when feeding loads with extremely distorted current waveforms (current total harmonic distortion above 100%). Loads with highly distorted current waveforms also have a very poor power factor; because of this, they use excessive power system capacity and could be a cause of overloading. Voltage source electronic adjustable speed drives (ASD) often have a total power factor of approximately 65% because of the highly distorted current. This total power factor could be corrected to approximately 85% using line-side chokes (reactors) on the drive. The chokes limit the rate of rise and the peak value of the line current, dramatically reducing the current THD. In addition, current harmonics can distort the voltage waveform and cause voltage harmonics. Voltage distortion affects not only sensitive electronic loads but also electric motors and capacitor banks. In electric motors, negative sequence harmonics (i.e. 5^{th}, 11^{th}, 17^{th}), so called because their sequence (ABC or ACB) is opposite of the fundamental sequence (see Figure 2.9), produce rotating magnetic fields. These fields rotate in the opposite direction of the fundamental magnetic field and could cause not only overheating but also mechanical oscillations in the motor-load system.

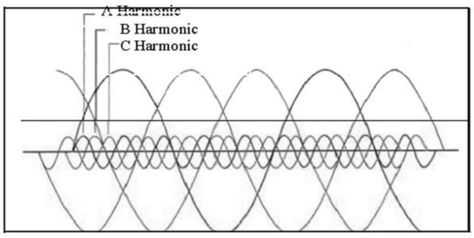


Figure 2: Balanced 3-phasevoltage with 3 Phase harmonic.

Single-phase non-linear loads, like personal computers, electronic ballasts and other electronic equipment, generate odd harmonics (i.e. 3^{rd}, 5^{th}, 7^{th}, 9^{th}, etc.). The troublesome harmonics for single-phase loads are the 3^{rd} and odd multiples of the 3(9^{th}, 15^{th}, etc.). These harmonics are called "triplens" and because the A-phase triplen harmonics, B-phase triplen harmonics and C-phase triplen harmonics are all in the phase with each other. They will add rather than cancel on the neutral conductor of a 3-phase 4-wire system. This can overload the neutral if it is not sized to handle this type of load.

When non-linear loads are a considerable part of the total load in the facility (more than 20%), there is a chance of a harmonics problem. Another consideration is the amount of current distortion produced by the non-linear loads. Electronic ballasts, for example, come with current THD ranging from 6% to 100%. It is important to avoid electronic ballasts with more than 20% current THD. PWM ASDs typically produce close to 100% current THD, which can be reduced to less than half by installing inexpensive 3% impedance line-side reactors (chokes).

Another important way to check for harmonic currents is to measure the current in the neutral of a 3-phase 4-wire system. If the neutral current is considerably higher than the value predicted from the imbalance in the phase currents, there is a good possibility of heavy presence of triplen harmonics.

Harmonics only mean trouble if the power system is not designed to handle them. High harmonic neutral currents are a problem only if the neutral is not properly sized. Current harmonics are not a problem to a transformer if it is derated appropriately. Even some voltage distortion below 8% THD at the point of utilization is acceptable as long as sensitive equipment is not affected. However, it is always important to be aware of the presence of harmonics and to try to minimize them by purchasing low distortion electronic ballasts and reactors for PWM ASDs. This will not only keep the harmonics in check and improve the power factor in the facility, but will also save energy by reducing losses on power system components. In addition, any time there is a considerable increase of non-linear loads, it is important to check power system components to prevent problems.

The fundamental idea behind wavelets is to analyze the signal at different scales or resolutions, which is called multi resolution. Wavelets are a class of functions used to localize a given signal in both space and scaling domains. A family of wavelets can be constructed from a mother wavelet. Compared to Windowed Fourier analysis, a mother wavelet is stretched or compressed to change the size of the window. In this way, big wavelets give an approximate image of the signal, while smaller and smaller wavelets zoom in on details. Therefore, wavelets automatically adapt to both the high frequency and the low-frequency components of a signal by different sizes of windows. Any small change in the wavelet representation produces a correspondingly small change in the original signal, which means local mistakes are not influence the entire transform. The wavelet transform is suited for non- stationary signals, such as very brief signals and signals with interesting components at different scales.

Wavelets are functions generated from one single function ψ, which is called mother wavelet, by dilations and translations

$$\psi_{a,b}(x) = |a|^{-1/2}\,\psi\left(\frac{x-b}{a}\right)$$

-----1

Where ψ must satisfy ∫ ψ (x) dx = 0.

The basic idea of wavelet transform is to represent any arbitrary function f as a decomposition of the wavelet basis or write f as an integral over a and b of $\psi_{a,b}$.

Let $a = a_0^m, b = nb_0 a_0^m$ with m, n € integers, and $a_0>1, b_0>0$ fixed. Then the wavelet decomposition is

$$f = \sum c_{m,n}(f)\psi_{m,n} \quad \text{--------(2)}$$

In image compression, the sampled data are discrete in time. It is required to have discrete representation of time and frequency, which is called the discrete wavelet transform (DWT).

Wavelet Transform (WT) was used to analyze non-stationary signals, i.e., whose frequency response varies in time. Although the time and frequency resolution problems are results of a physical phenomenon and exist regardless of the transform used, it is possible to analyze any signal by using an alternative approach called the multi resolution analysis (MRA). MRA analyzes the signal at different frequencies with different resolutions. MRA are basically designed to give good time resolution and poor frequency resolution at high frequencies and good frequency resolution and poor time resolution at low frequencies. This approach is useful especially when the signal considered has high frequency components for short durations and low frequency components for long durations. Which are basically used in practical applications?

IV. ARTIFICIAL NEURAL NETWORKS

One type of network where the nodes are 'artificial neurons' are called artificial neural networks (ANN's). An artificial neuron is a computational model inspired in the natural neurons. Natural neurons receive signals through synapses located on the dendrites or membrane of the neuron. When the signals received are strong enough (surpass a certain threshold), the neuron is activated and emits a signal though the axon. This signal might be sent to another synapse, and might activate other neurons.

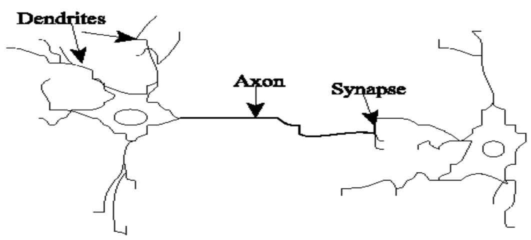


Figure 3: Natural neurons (artist's conception).

The complexity of real neurons is highly abstracted when modeling artificial neurons. These basically consist of inputs (like synapses), which are multiplied by weights (strength of the respective signals), and then computed by a mathematical function which determines the activation of the neuron. Another function (which may be the identity) computes the output of the artificial neuron (sometimes in dependence of a certain threshold). ANNs combine artificial neurons in order to process information.

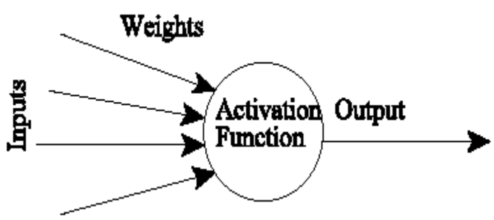


Figure 4: An artificial neuron

The higher a weight of an artificial neuron is, the stronger the input which is multiplied by it will be. Weights can also be negative, so we can say that the signal is inhibited by the negative weight. Depending on the weights, the computation of the neuron will be different. By adjusting the weights of an artificial neuron we can obtain the output C:\WINNT\hinhem.scrwe want for specific inputs. But when we have an ANN of hundreds or thousands of neurons, it would be quite complicated to find by hand all the necessary weights. But we can find algorithms which can adjust the weights of the ANN in order to obtain the desired output from the network.

This process of adjusting the weights is called learning or training. The number of types of ANN's and their uses is very high. Since the first neural model by McCulloch and Pitts (1943) there have been developed hundreds of different models considered as ANN's. The differences in them might be the functions, the accepted values, the topology, the learning algorithms, etc.

Also there are many hybrid models where each neuron has more properties than the ones we are reviewing here. Because of matters of space, we will present only an ANN which learns using the back propagation algorithm (Rumelhart and McClelland, 1986) for learning the appropriate weights, since it is one of the most common models used in ANN's, and many others are based on it.

Since the function of ANN's is to process information, they are used mainly in fields related with it. There are a wide variety of ANN's that are used to model real neural networks, and study behavior and control in animals and machines, but also there are ANN's which are used for engineering purposes, such as pattern recognition, forecasting, and data compression.

V. SYSTEM DESIGN

For the implementation of the proposed system the designing is developed as presented below, the proposed algorithm involves two modules: detection and classification.

VI. FAULT DETECTION

The first step of the detection module is to obtain the transmitting voltage and current samples. The current samples are normalized and passed to discrete wavelet transform (DWT) for obtaining frequency resolved coefficients. The fault detection is carried out through the analysis of the current wavelet coefficient energy. In the case of no fault, no data are transferred.

VII. WAVELET ANALYSIS FOR LINE CURRENT

It is well known that the main power quality deviations are caused by short-circuits, harmonic distortions, voltage sags and swells etc. In order to correct such problems, it is required, in general that, firstly, they should be detected and identified. Whenever the disturbance lasts for only a few cycles, a simple observation of the waveform in a busbar may not be enough to allow one to recognize that there is a problem or not and more difficult is to identify the sort of the problem. The discrete wavelet transform (DWT) has been applied to analyze the currents during short duration disturbances in the transmission line.

The discrete wavelet transform (DWT) is one of the three forms of wavelet transform. It moves a time domain discritized signal into its corresponding wavelet domain. This is done through a process called "sub-band coding", which is done through digital filter techniques.

The Line current signals obtained from the bus bar are applied to the wavelet filters to evaluate the frequency resolution coefficients by passing through high pass and low pass filter.

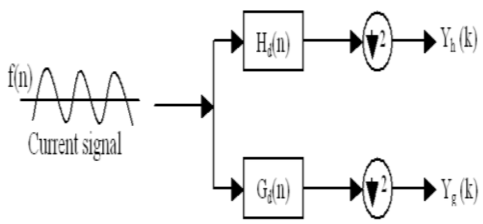


Figure 5: wavelet decomposition of electrical current pulse

To filter the given current signal f(n), a convolution of this signal is done at each filtration using a defined filter coefficient h_d and g_d. A recursive multiplication and accumulation operation is performed on the given current signal to obtain the detail and approximate coefficient as given in eq. 3, 4.

$$cA_1(n) = \sum_k f(n).h_d(-k+2n)$$

$$cD_1(n) = \sum_k f(n).g_d(-k+2n)$$

The f(n) signal is passed through a low-pass digital filter ($h_d(n)$) and a high-pass digital filter ($g_d(n)$). The obtained coefficients are decimated by factor of 2 i.e., half of the signal samples are eliminated.

The DWT operation is performed in two stages. The first consists on the wavelet coefficients determination. These coefficients represent the given signal in the wavelet domain. From these coefficients, the second stage is achieved with the calculation of both the approximated and the detailed version of the original signal, in different levels of resolutions, in the time domain. At the end of the first level of signal decomposition, the resulting vectors $y_h(k)$ and $y_g(k)$ will be, respectively, the level 1 wavelet coefficients of approximation and of detail wavelet coefficients. The fault detection rules are established by means of the analysis of the current waveforms in time domain and in the first decomposition level of the DWT. This level contains the highest frequency components.

For the implementation of DWT based decomposition following steps are used for the calculation of wavelet coefficient:

Step 1: Evaluation of the wavelet coefficients of the signal in study.

Step 2: Evaluation of the square of the wavelet coefficients found at step 1.

Step 3: Calculation of the distorted signal energy, in each wavelet coefficient level.

The "energy" mentioned above is based on the Parseval's theorem which state that: "the energy that a time domain function contains is equal to the sum of all energy concentrated in the different resolution levels of the corresponding wavelet transformed signal". This can be mathematically expressed as:

$$\sum_{n=1}^{N}|f(n)|^2 = \sum_{n=1}^{N}|a_J(n)|^2 + \sum_{j=1}^{J}\sum_{n=1}^{N}|d_j(n)|^2$$

Where,

F(n): Time domain signal in study

N: Total number of samples of the signal

$\sum_{n=1}^{N}|f(n)|^2$: Total energy of the signal f(n)

$\sum_{n=1}^{N}|a_J(n)|^2$: Total energy concentrated in the level 'j' of the approximated version of the signal

$\sum_{j=1}^{J}\sum_{n=1}^{N}|d_j(n)|^2$ Total energy concentrated in the detailed version of the signal, from levels '1 to j'

The obtained energy value for the given current signal is taken as the feature for training the neural network.

VIII. FAULT CLASSIFICATION

In order to classify faults, a feed forward Back propagated neural network architecture is used, which is trained before testing the proposed method. The learning database contains a great variety of faulted scenarios to improve the ANN's generalization capability. By using this strategy, the ANN can classify correctly simulated and real faults in transmission line.

The output of the ANN must indicate which fault type is related to the actual input pattern. Hence, binary coding is used for the ANN's outputs in such a way that a fault is characterized by the presence (1) or absence (0) of one or more phases and of the ground, as shown in Table I, where no fault term indicates that the input pattern is not related to a fault. After the ANN learns, the fault classification is carried out through the analysis of each window obtained from windowing process aforementioned. This means that the most identified fault type prevails. By using this strategy, even if the ANN makes a mistake for some windows, the fault classification will be correct anyway.

TABLE I: Binary coding of the ANN output

Fault type	Phase A Output 1	Phase B Output 2	Phase C Output 3	Ground Output 4
AG	1	0	0	1
BG	0	1	0	1
CG	0	0	1	1
AB	1	1	0	0
AC	1	0	1	0
BC	0	1	1	0
ABG	1	1	0	1
ACG	1	0	1	1
BCG	0	1	1	1
ABG	1	1	1	0
No fault	0	0	0	0

The neural network is passed with the above stated fault outputs with their possible trained fault current wavelet features. On testing these features are used as knowledge by the neural network for the accurate classification of fault type and their occurrences. For the implementation of the neural network a feed forward BPP architecture is developed with 30 hidden nodes and with tangential sigmoid function for each hidden node. The training of this network is carried out using Least Mean (LM) algorithm. The network is trained with all the possible input patterns obtained for each fault case, with the min. and max. Range of input and output. An epoch limit of 800 iteration, probability of error is given as 0.1 with a learning rate of 0.01. Various fault currents and their corresponding features are explained in the following chapter.

IX. OPERATIONAL FLOW CHART

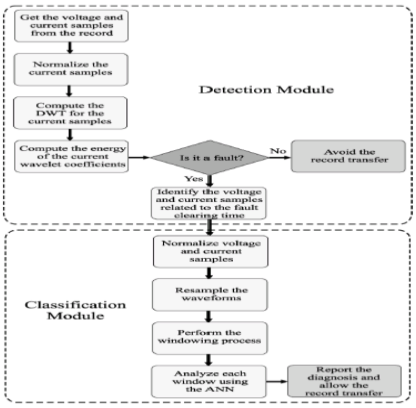


Figure 6: operational flow chart for detection and classification method

X. RESULT OBSERVATIONS

The proposed wavelet and ANN based fault detection and classification architecture is tested on a randomly distributed network as shown below with following specifications,

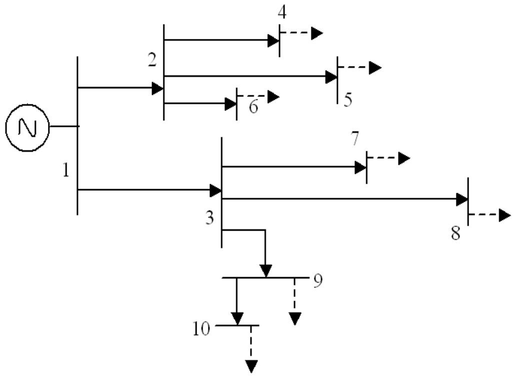


Figure 7: Considered Distributed power system architecture for implementation

The faults were simulated over a 25MV, 13.2KV, 100KM transmission line system.

The obtained simulation results were as illustrated below;

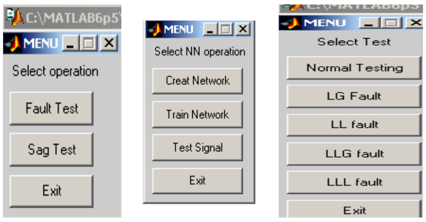


Figure 8: Menu generated for the selection of test operation, NN operation and fault testing conditions

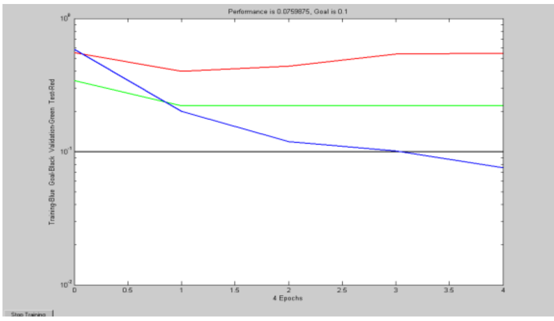


Figure 9: Learning plot for the validation, testing, and training for the generated neural network

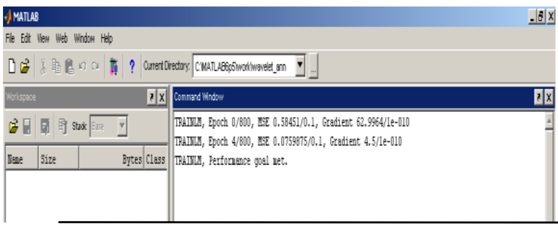


Figure 10: simulation resulting showing the training process of the neural network

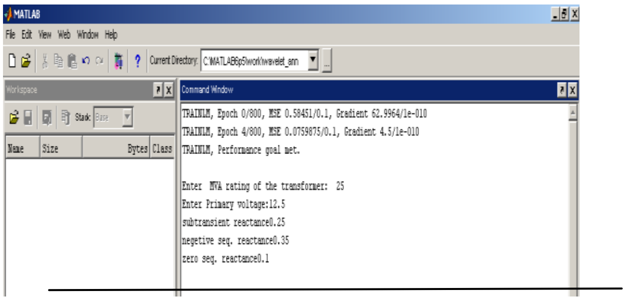


Figure 11: The input test values passed for the simulation of the electrical system

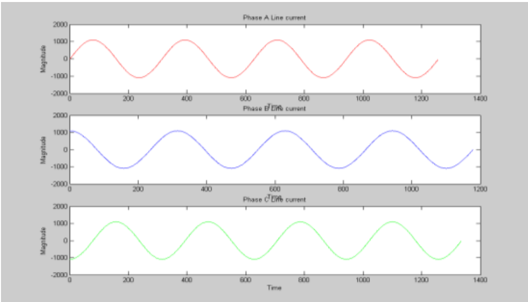
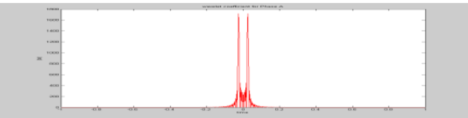
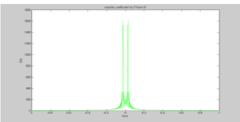
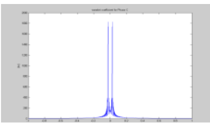


Figure 12: Three line currents generated for transmission



(a)





(b) (c)

Figure 13(a),(b),(c) wavelet coefficients for the three line currents passed

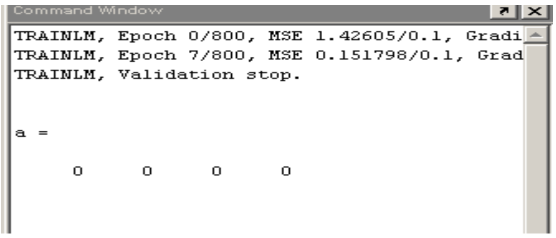


Fig.14: ANN output result for the normal testing

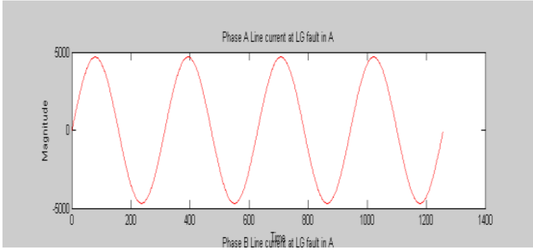


Figure 15: Fault current at phase A for LG fault

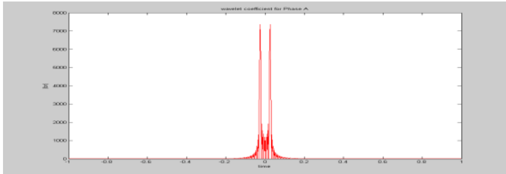


Figure 16: Wavelet coefficient generated for the fault current in line A

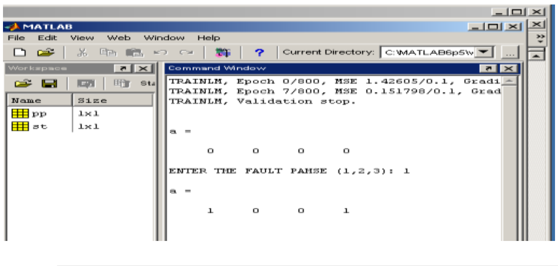


Figure 17: ANN test output for LG fault in Line A

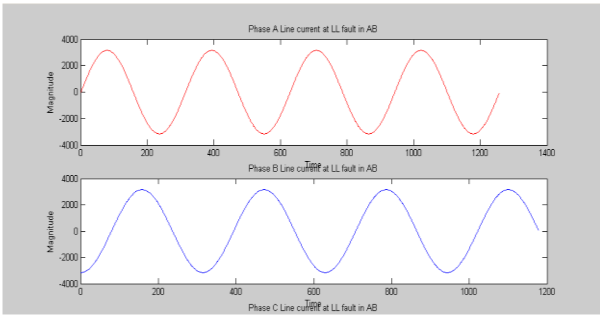


Figure 18: Fault currents generated for LL fault in line AB

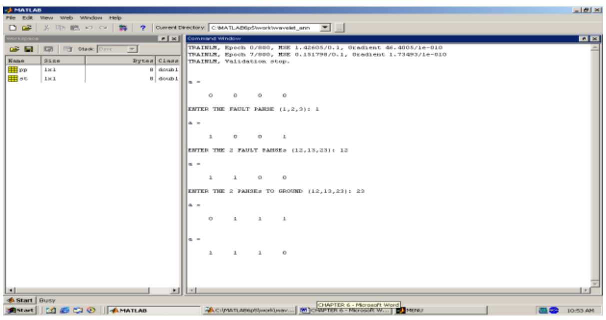


Figure 19: ANN output for LLL fault

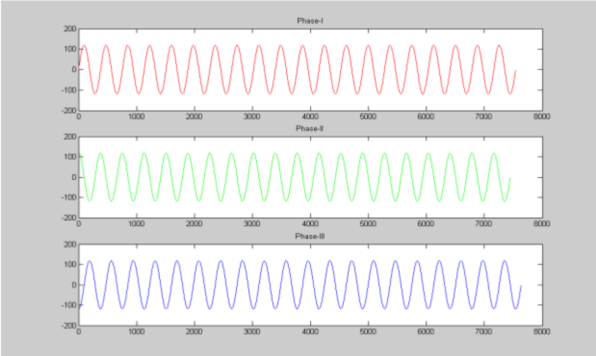


Figure 20: Line current for three phase under sag testing

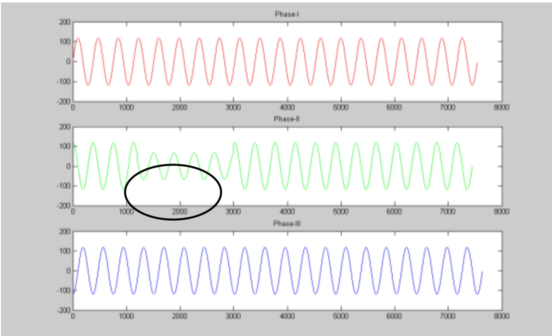


Figure 21: Generated Sage current in phase 2

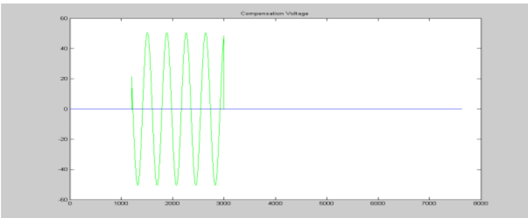


Figure 22: Compensation current generated for sag Compensation

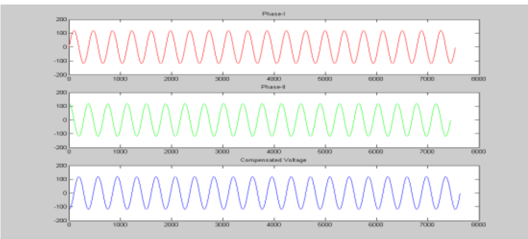


Figure 23: Compensated current after Sag compensation

CONCLUSION

By the integration of these two techniques for fault diagnosis it is observed that the developed neural network detect and classifies the fault current for almost 100% accurately under various conditions. The current disturbances were also detected for almost 100% accurately. The algorithm is tested for distributed network with 10 nodes for different fault conditions and the result obtained from the classification unit is observed to be accurate. The proposed detection architecture for fault diagnosis shows accurate detection and classification under various fault conditions, which provides an efficient architecture for the development of fully automated monitoring systems with classification ability in distributed power system.

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