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DWT-ANN Based Analysis of Inrush and Fault Currents in Power Transformers

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Abstract - *This paper introduces discrete wavelet analysis of inrush and fault current in power transformer and elimination using artificial neural network algorithm. The proposed analysis helps ANN to easily discriminate among the inrush current and fault current. In typical relay system, the relay tends to trip even at the start because of inrush current. In this paper, the offline model of relay model is built in MATLAB environment and the data is collected for inrush and fault current conditions. Since, the wavelet transform has the characteristic of multi-scale analysis and good time and frequency domain localization, fits to extract sudden-change signals in transient processes, and detects irregularity of signals very well. Further analysis using DWT is done and energy as a feature is extracted at only 7th decomposition level to decide whether the relay should trip or not using ANN algorithm. The 7 level decomposition is carried out using DWT and ANN yields 100% accuracy in results.*

Key Words: *Transformer, DWT, ANN, Magnetizing inrush Current, Protection schemes.*

1.INTRODUCTION

Power transformers are important elements of power system. So it is very important to avoid any maloperation of required protective system. For many years, differential protection has been used as the primary protection of power systems. It contains the differential relay, which operates for all internal fault types of power transformer and block due to inrush current. The major drawback of the differential protection relays stem from its potential for mal-operation caused by the transient inrush current, which flow when the transformer is energized. The inrush current contains a large second harmonic component. Most of the methods for digital differential protection of transformers are based on harmonic content of differential current. These methods are based on this fact that the ratio of the second harmonics to the fundamental component of differential current in inrush current condition is greater than the ratio in the fault condition.

However, the second harmonic may also be generated during faults on the transformers. It might be due to saturation of CTs, parallel capacitances or disconnected transformers. The second harmonic in these situations might be greater than the second harmonic in inrush currents.

Thus, the commonly employed conventional differential protection based on second harmonic restraint will face difficulty in distinguishing inrush current and internal faults. Thus, an improved technique of protection is required to discriminate between inrush current and internal faults [1].

To overcome this difficulty and prevent the mal-function of differential relay, many methods have been presented to analyze and recognize inrush current and internal fault currents. As both inrush current and internal faults are non-stationary signals, wavelet based signal processing technique is an effective tool for power system analyze and feature extraction [2-6]. However the wavelet-based methods have better ability of time-frequency analysis but they usually require long data windows and are also sensitive to noise. The method presented in [6] uses WT and ANFIS to discriminate internal faults from inrush current. Since the values of wavelet coefficients at detail 5 (D5) are used for pattern recognition process, the algorithm is very sensitive to noise.

In [5], a new algorithm was presented which discriminate between the inter-turn fault and magnetizing inrush current. The algorithm used wavelet coefficients as a discriminating function. Two peak values corresponding the |d5| level following the fault instant are used to discriminate the cases studied. As criterion compare the two peak values, hence no threshold settings are necessary in this algorithm, but it is observed that in noisy environment it is difficult to identify correct switching instant and there the strategy fails.

Moreover, feed forward neural network (FFNN) [7-10] has found wide application for detection of inrush current from internal faults but they have two major drawbacks: First, the learning process is usually time consuming. Second, there is no exact rule for setting the number of neurons to avoid over-fitting or under-fitting. To avoid these problems, a Radial Basis Function Network (RBFN) has been developed [11]. RBFs are well suited for these problems due to their simple topological structure and their ability to reveal how learning proceeds in an explicit manner. In some methods differential current harmonics are used as inputs to fuzzy logic [6], [12]. The problem associated with these methods is the need to design neural networks and fuzzy laws, which require a huge number of training patterns produced by simulation of various cases. In [14] an energy index is defined by calculation of 9-level frequency contours using S-transform to distinguish inrush current from internal fault currents. But the disadvantage of this method is determining the threshold value

which can be different in transformers with different capacity and may change in noisy environment. Support Vector Machine (SVM) [14], Hidden Markov Model. (HMM) [15] and Gaussian Mixture
Models (GMM) [16] are used as new classifiers for detection of internal fault and inrush currents. In [14] the extracted features are chosen from differential currents which due to large data window could not be effective than those methods use less features based on preprocessing step like WT, but the performance and detection capability of SVM is better than HMM and GMM.
In this paper, Artificial Neural Network (ANN), however, have been proposed and have demonstrated to be an effective alternative for performing transformer fault detection even location of fault, while avoiding the need for a mathematical model. In addition, the ANN can perform this function on-line through the use of inexpensive monitoring devices. These devices obtain the necessary measurements in a non invasive manner. Different advantages of using ANN's instead of other fault detection techniques are discussed in more detail in [7].
The main problems facing the use of ANN are the selection of the best inputs and how to choose the ANN parameters making the structure compact, and creating highly accurate networks. For the proposed system, the feature selection is also an important process since there are many features after feature extraction. To get perfect results Energy feature is chosen for ANN implementation. In case of many input features require a significant computational effort to calculate, and may result in a low success rate.

2. Wavelet Transform

Wavelet analysis is about analyzing the signal with short duration finite energy functions. They transform the considered signal into another useful form. This transformation is called Wavelet Transform (WT).
Let us consider a signal f(t), which can be expressed as-

$$f(t) = \sum_{l} a_l \varphi_l(t) \qquad (1)$$

Where, l is an integer index for the finite or infinite sum. Symbol al are the real valued expansion coefficients, while $\varphi_l(t)$ are the expansion set.
If the expansion (1) is unique, the set is called a basis for the class of functions that can be so expressed. The bases are orthogonal if-

$$\langle \psi_l(t)\psi_k(t) \rangle = \int \psi_l(t)\psi_k(t)dt = 0 \quad k \neq l \qquad (2)$$

Then coefficients can be calculated by the inner product as-

$$\langle f(t), \varphi_k(t) \rangle = \int f(t)\, \varphi_k(t)\, dt \qquad (3)$$

If the basis set is not orthogonal, then a dual basis set $\varphi_k(t)$ exists such that using (3) with the dual basis gives the desired coefficients.
For wavelet expansion, equation (1) becomes-

$$f(t) = \sum_{k}\sum_{j} a_{j,k}\, \varphi_{j,k}(t) \qquad (4)$$

In (4), j and k are both integer indices and $\varphi_{jk}(t)$ are the wavelet expansion function that usually form an orthogonal basis. The set of expansion coefficients a_jk are called Discrete Wavelet Transform (DWT).
There are varieties of wavelet expansion functions (or also called as a Mother Wavelet) available for useful analysis of signals. Choice of particular wavelet depends upon the type of applications. If the wavelet matches the shape of signal well at specific scale and location, then large transform value is obtained, vice versa happens if they do not correlate. This ability to modify the frequency resolution can make it possible to detect signal features which may be useful in characterizing the source of transient or state of post disturbance system. In particular, capability of wavelets to spotlight on short time intervals for high frequency components improves the analysis of signals with localized impulses and oscillations particularly in the presence of fundamental and low order harmonics of transient signals. Hence, Wavelet is a powerful time frequency method to analyze a signal within different frequency ranges by means of dilating and translating of a single function called Mother wavelet.
Formulation of DWT is related to filter bank theory in many of the good references. It divides the frequency band of input signal into high and low frequency components by using high pass h(k) and low pass g(k) filters. This operation may be repeated recursively, feeding the down sampled low pass filter output into another identical filter pair, decomposing the signal into approximation c(k) and detail coefficients d(k) for various resolution scales. In this way, DWT may be computed through a filter bank framework, in each scale, h(k) and g(k) filter the input signal of this scale, giving new approximation and detailed coefficients respectively. The filter bank framework is shown in Fig 1. The down pointing arrow denotes decimation by two and boxes denote convolution by h(k) or g(k).

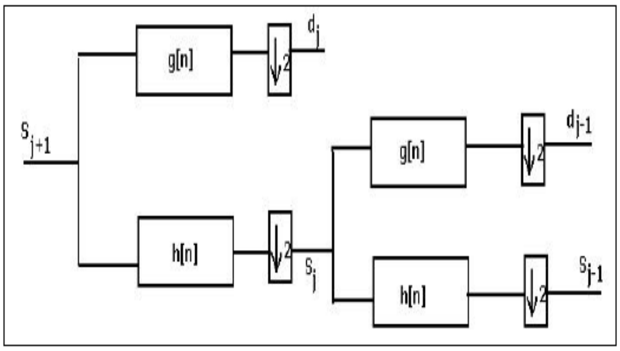

Fig. 1: Two band Multi-resolution analysis of Signal

The coefficients of filter pair are associated with the selected mother wavelet. The sampling frequency in this paper is taken to be 20 kHz and Table I shows the frequency levels of the wavelet function coefficients.

Table-I: Frequency Components of Wavelet Function Co-efficients

Decomposition Level	Frequency Components (Hz)
d1	10000-5000
d2	5000-2500
d3	2500-1250
d4	1250-625
d5	625-312.5
d6	312.5-156.25
d7	156.25- 78.125
a7	0-78.125

3. Simulation and data collection

The Simulation has been performed in MATLAB using 11kV/440V, 25kVA, 50Hz three phase transformer with external circuit breakers to tap both primary to secondary fault.

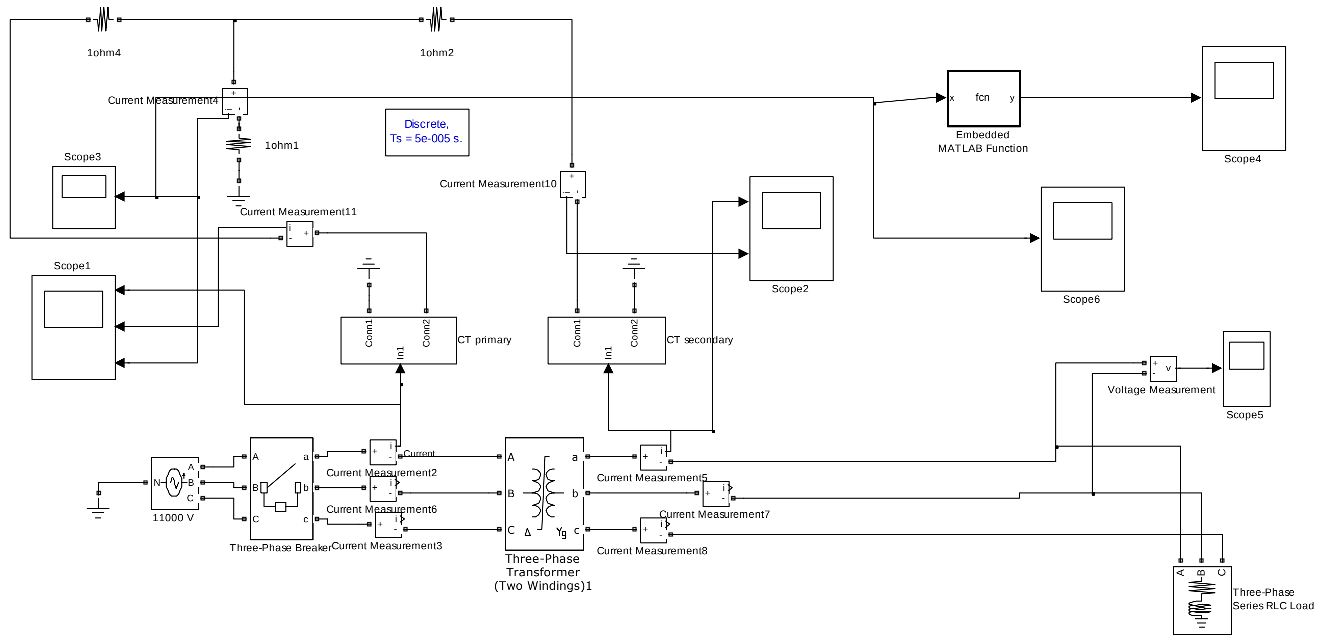

Fig.2 Simulation of Three phase transformer on MATLAB

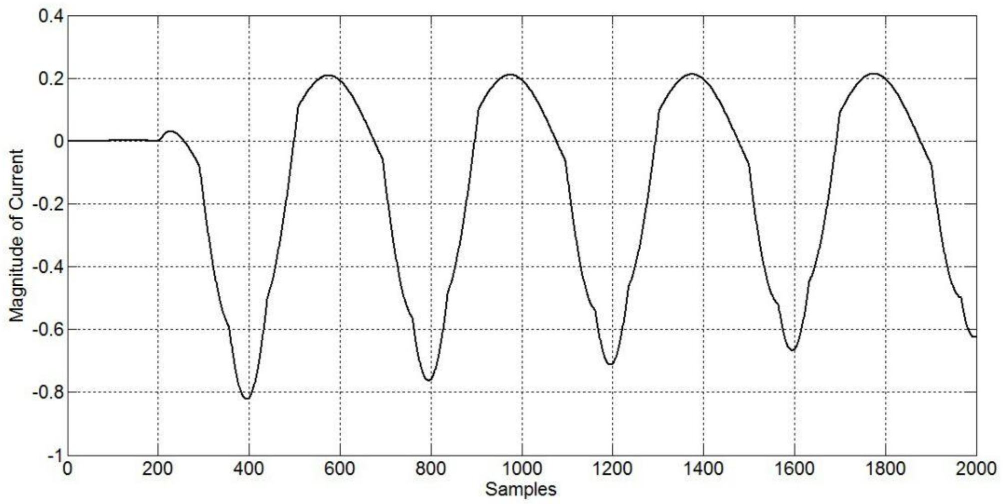

Fig.3 Simulation: Waveform of Inrush Current

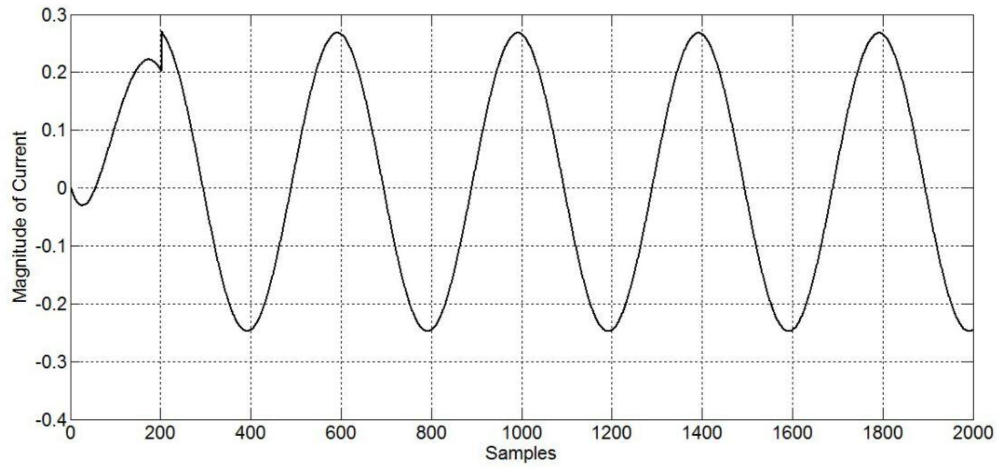

Fig 4: Simulation: Waveform of fault Current

Fig 2 shows offline simulation of three phase transformer and data is collected in scope. Fig. 3 shows the waveform of magnetizing inrush current. Similarly, fig. 4 shows the waveform of fault current.

Since, inrush current has second order harmonics as compared to fault current, the scope data was further investigated and DWT is carried out on these sample data. At each 5^0 instance, the data were collected and 71 samples were recorded in each complete cycle. Using db6 mother wavelet, the 7 level decomposition of the signals are carried out. Since the interest is in second order harmonics, the search is for 100 Hz component is there and it is found in d7 level of decomposition. The data obtained in d7 level is used for mapping energy of the signal. This process is repeated for fault current as well and energy is found out for same as well. There are many features one can extract from the collected data but, after rigorous studies, it is confined that energy will yield improvement in results as compared to others.

Fig 5 and Fig. 6 shows the FFT of the obtained inrush current and fault current which is analyzed and further used for improvisation of differential relay. It is observed that the magnetizing inrush current has significant amount of 100 Hz components which is in support to earlier research done by previous researchers and are helpful to gain right results.

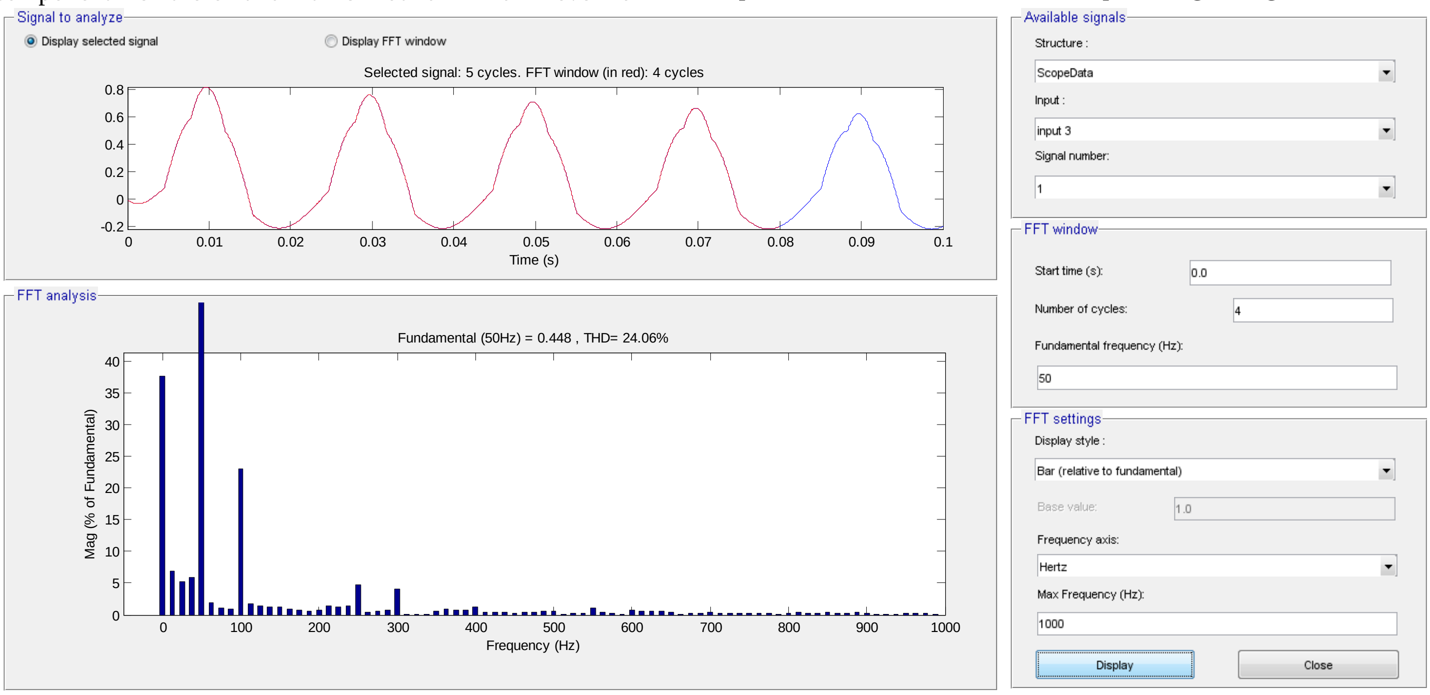

Fig. 5 FFT of INRUSH Current

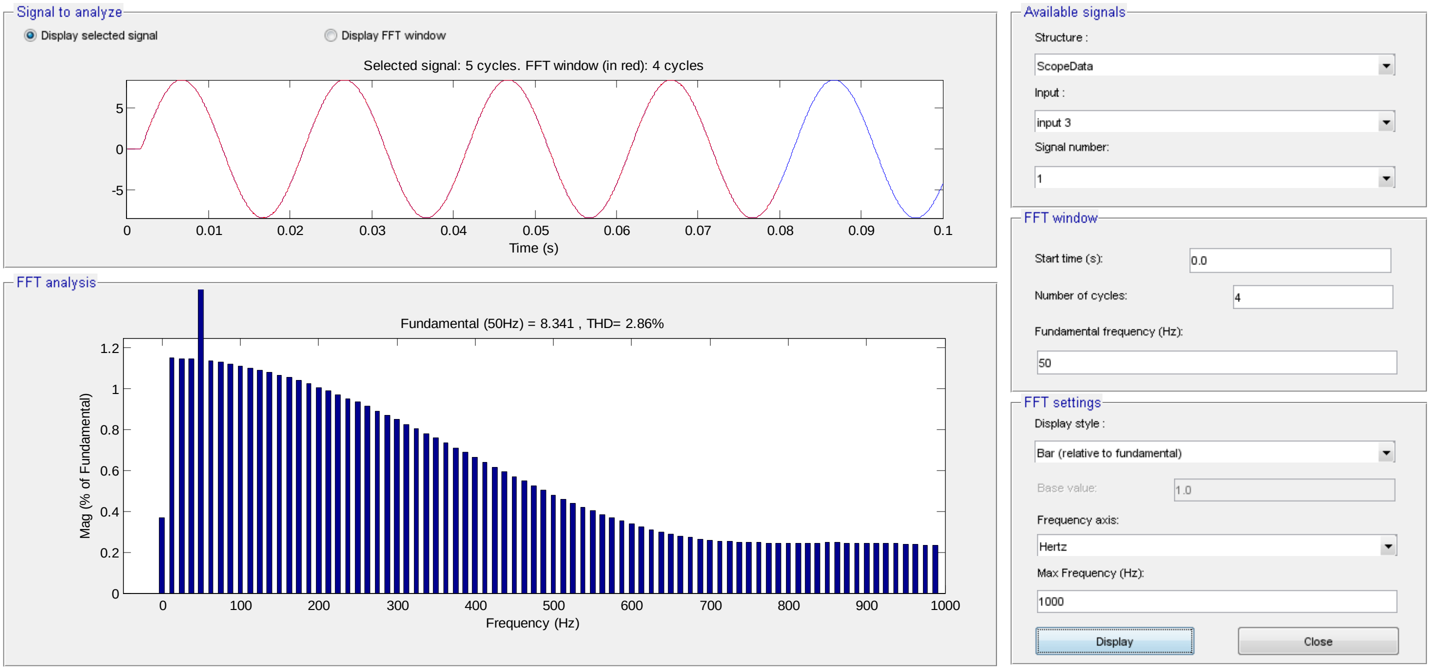

Fig. 6 FFT of Fault condition

4. Artificial Neural Network (ANN)

The application of artificial neural networks to discriminate the fault has given a lot of attention recently. The simplest definition of a neural network, more properly referred to as an 'artificial' neural network (ANN), is provided by the inventor of one of the first neuro computers, Dr. Robert Hecht-Nielsen. He defines a neural network as: "a computing system made up of a number of simple, highly interconnected processing elements, which process information by their dynamic state response to external inputs." An ANN is configured for a specific application, such as pattern recognition or data classification, through a learning process.

4.1 Architecture of neural networks

Neural networks are typically organized in layers. Layers are made up of a number of interconnected 'nodes' which contain an 'activation function'.

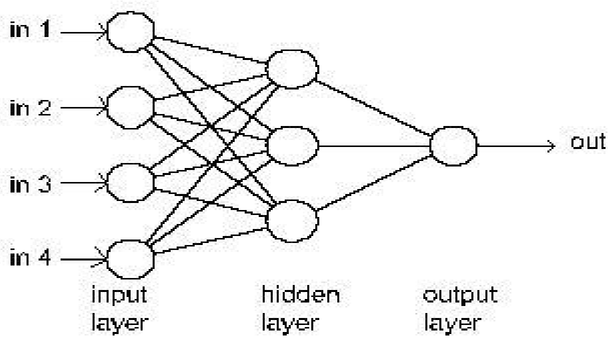

Fig .7 Architecture of ANN

Patterns are presented to the network via the 'input layer', which communicates to one or more 'hidden layers' where the actual processing is done via a system of weighted 'connections'. The hidden layers then link to an output layer' where the answer is output as shown in Fig.7.

4.2 Feed-forward networks

Feed-forward ANNs allow signals to travel one way only; from input to output. There is no feedback (loops) i.e. the output of any layer does not affect that same layer. Feed-forward ANNs tend to be straight forward networks that associate inputs with outputs as shown in Fig.8. They are extensively used in pattern recognition. This type of organization is also referred to as bottom-up or top-down.

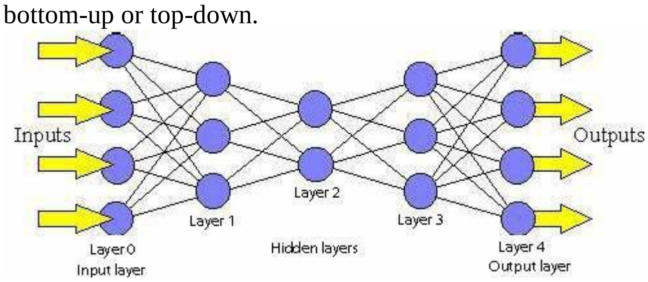

Fig.8. Feed-forward network

In this case, we have used only 1 hidden neurons, as shown in Fig. 9

Fig. 9 Number of Hidden layers used for implementation

The number of hidden neural are dependent of number of training data.

In this paper, the fully-connected multilayer feed-forward neural network (FFNN) was used and trained with a supervised learning algorithm called back-propagation. The FFNN consists of an input layer representing the input data to the network, some hidden layers (in this case 1) and an output layer representing the response of the network. Each layer consists of a certain number of neurons; each neuron is connected to other neurons of the previous layer through adaptable synaptic weights w and biases b as shown in Fig.10.

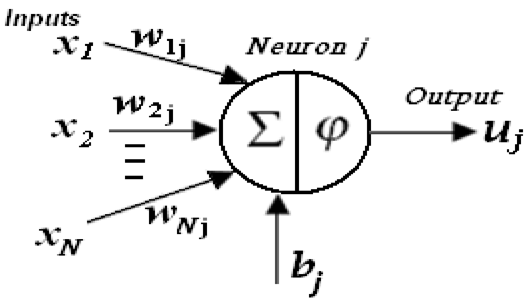

Fig. 10 Information processing in a neural network unit

The ANN is implemented in Simulation environment provided by MATLAB and simulation architecture is shown in Fig. 11

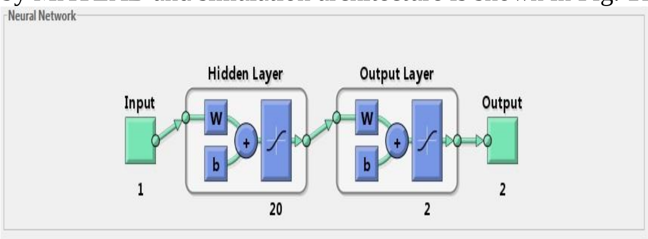

Fig. 11 Simulation of ANN in MATLAB SIMULINK

5. Results and Analysis

The offline simulation has been carried out in MATLAB Simulink and the data collected were used for DWT analysis. The sampling frequency used is 20 kHz and sampling has been as per that. Using db6 mother wavelet and pointing the 100 Hz samples present in d7 level, the energy is calculated and used in ANN to discriminate the inrush from fault current. In general, total of 95 signals were captured, out of which 71 samples were of inrush current and 24 samples were of fault current. As mentioned earlier, the data of inrush current is sampled at the 5^0 instance, which brought us 71 samples of inrush current. For implementation of ANN, 25% data is used and rest for testing purpose. Out of the 25% data which is used for training, 70% of 25% is used for training purpose, 15% of 25% is used for validation purpose and remaining is used testing purpose.

Fig. 12 shows the data used for implementation of ANN at different levels of training, validation and testing

Results

	Samples	MSE	%E
Training:	16	3.11223e-7	0
Validation:	4	2.38343e-7	0
Testing:	4	2.26895e-5	0

Fig. 12 Results obtained from ANN

Also for fig. 12, it can be seen that % error obtained is zero, which yields us perfect 100% accuracy in results. In support to above results, the confusion matrix is also obtained for training and testing purpose. Fig. 13 and Fig. 14 shows the confusion matrix obtained from ANN in support to yield results.

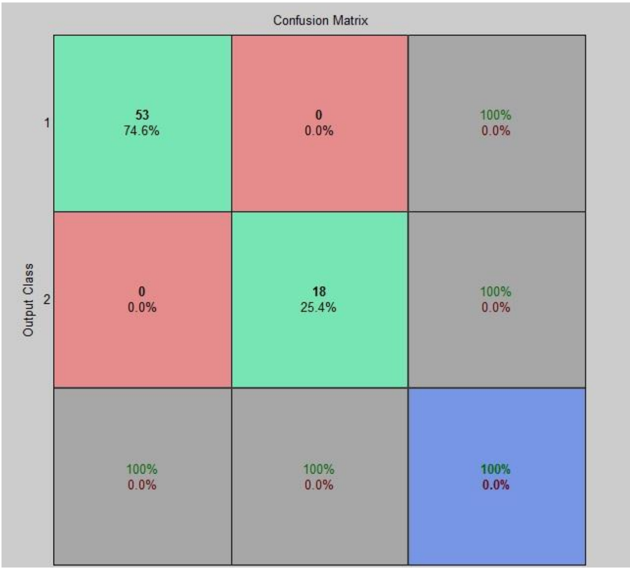

Fig. 13 Confusion Matrix of Sampled Training Data

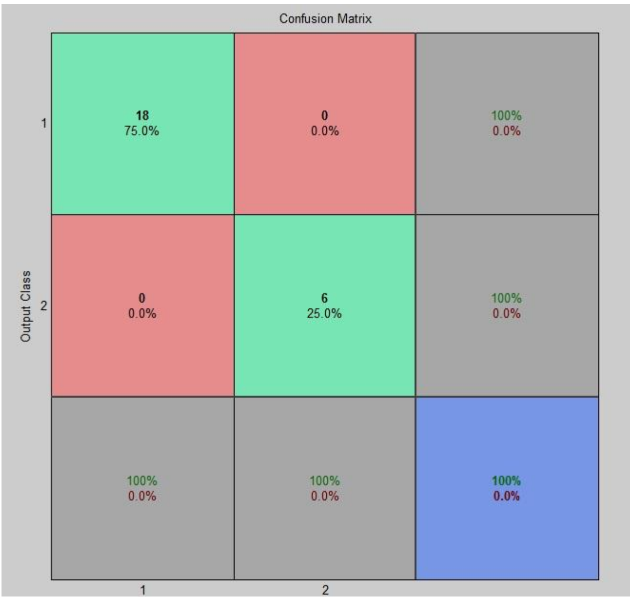

Fig. 14 Confusion Matrix of Sampled Testing Data

From these confusion matrices, it is been seen in (3 X 3)th block, the results are giving 100% results with 0% error.

6. Conclusion

DWT analyzed ANN algorithm method of discriminating magnetizing inrush current from fault current in a transformer is presented in this paper. Discrete Wavelet Transform (DWT) with its inherent time frequency localization property is employed to extract discriminating features from the differential current

The ANN was successes in classifying the type of event from the extracted Energy feature given as input.

The 100% accuracy has been achieved because; the data provided to ANN is of d7 level only where 100 Hz components are present. This helps ANN to train only for these components. The algorithm has been tested successfully in Simulation, by staging these events on the MATLAB. These events are identified in less than one cycle after their inception. This classification may occur for situations in which inception angle, fault resistance and other parameters are very different from those used during the ANN‟s learning. If this is the case, it is necessary to add the misclassified fault record, to the learning database and retrain the ANN.

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