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Intelligent Multifault Classifier for Power Transformer Protection

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Abstract: The main aim of the article is to distinguish between the power transformer internal faults and magnetic inrush currents successfully with superior accuracy and reliable operation speed. To provide best classification, an optimum classification system consisting of three advanced radial basis artificial neural networks for fault classification and discrete wavelet transform for feature extraction has been proposed. Internal faults and inrush currents of transformer have been simulated for a power system network consisting of a power transformer, transmission line and with a series RLC load. The differential currents have been analyzed through Daubechies discrete mother wavelet. The extracted entropies are fed to neural networks. The artificial neural networks have the classification network topology of 12-inputs and 9-outputs. The classification models performance was measured in classification rate, linear regression analysis and mean squared error values. The proposed models have produced the high caliber results.

Keywords: Power transformer protection, artificial neural networks, RBFNN, PNN, GRNN, wavelet transform.

1. INTRODUCTION

The power transformer is the principal component of the power system network. It is responsible for stable and reliable power supply in both transmission and distribution networks. The network performance depends on the power transformer working condition. Hence, there should be an effective protective scheme is required for transformer protection. The transformer was protected by the differential relaying principle against the internal faults. In power transformer protection the relay should be issue trip signal in case of internal faults only not for inrush currents. To clearly distinguish between inrush and internal faults the relay must need a novel classification system. The pattern classification signal analysis is one of the best useful methods. Signal analysis can be done by traditional Fourier and Short Time Fourier transform. Despite they are good at signal analysis, they have the drawbacks of constant time-frequency and fixed window analysis, such drawbacks was overcome by utilizing a variable-frequency resolution analysis called as wavelets transform (WT).

In WT, Discrete wavelet transform (DWT) was utilized to extract the features of differential current waveforms because; it composes the original signal at several resolutions without losing original signal properties. DWT with multi resolution waveform analysis was proposed in paper [1] to extract the waveform features at different levels of resolution. Authors [2]–[4], proposed for non-linear transient signal analysis Daubechies family wavelet is best suitable. The maximum energy of the signal is generally localized from level 1 to level 4 hence in articles [3]–[5], db4 mother wavelet with level4 decomposition was employed for feature extraction.

The usage of artificial neural networks (ANNs) has grown tremendously to interrogate the complex problems. The main reason is their adaptive capability i.e., ANNs have the ability to learn and establish precise, complex relationship between different numeric variables without any preconceived model being imposed. These ANNs are often applied in systems to produce satisfactory results where no mathematical model or algorithm is available to accurately represent the phenomenon. Hence in article [6], feed forward

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neural network is used by splitting the single feed forward network into two parallel processing networks and it can be applicable in case of two ANNs provision at a time. Without splitting the network the problem of processing time was reduced in article [7] by genetic algorithm trained ANN. To produce the satisfactory results and to reduce the processing time in article [8] radial basis neural network (RBFNN) was proposed.

Although the RBFNN bestow the better pattern recognition and classification capability, its performance was depending upon the two or more parameters. Hence, a modified model of RBFNN called as probabilistic neural network (PNN) can only effected by one parameter (smoothing factor) was proposed in article [9] and the modified model results are compared with RBFNN results. In article[10] the optimal smoothing factor was chosen by particle swarm optimization technique. To classify effectively even in noisy conditions, the combined S-transform and PNN was proposed in article [11]. Power system fault transients are recognized and analysed by using a PNN in paper [12]. Even though, the RBFNN and PNN provide the good pattern classification, they required a complex iterative training of weight vectors. This problem was successfully overcome by generalized regression neural network (GRNN), simply assign the input vectors to centroid vectors and keep the weight vectors between the rad-bas units and outputs identical to the correspondent target vectors. In article [5], a well suited GRNN based transformer differential relay protection was proposed and the performance of the network was compared with the conventional pattern recognition neural network. The power system transient stability analysis was conducted with GRNN and the stability condition of power system was predicted with high accuracy in article [13].

2. SIMULATION OF POWER SYSTEM NETWORK

The pattern samples data of magnetizing inrush and internal faults were generated through the simulation of a power system network as given [5] consisting of a100 MVA, 220/110 kV, $Y_g - Y_g$ three phase power transformer in conjunction with a 100miles transmission line and a series RLC load of 50 MVA. All the possible types of faults i.e., single line to ground faults (LG-A, LG-B, LG-C), two lines to ground faults (LLG-AB, LLG-AC, LLG- BC), three lines to ground fault (LLLG-ABC) and Inrush currents have been simulated.

3. WAVELET TRANSFORM

Wavelet transform (WT) is very useful in many engineering fields for providing the superior solutions. When a signal is analysed through Fourier transform, it provides only the frequency content of the signal i.e., it lacks the time domain localization information. This problem was overcome by short time Fourier transform (STFT), it can represent a sort of compromise between the time and frequency localization information, but STFT had a drawback of fixed window frequency analysis. To conquer all these drawbacks there is a need of an effective time-frequency representation technique. WT is a superior technique which can provide best time-frequency representation of a signal with flexibility. WT has the characteristic nature of analysing the signal with variable size windows known as multi resolution analysis (MRA).

Multi Resolution Analysis (MRA): MRA is a vital characteristic in WT, it can decompose the actual signal at different levels of resolution and the actual time domain signal can reproduce from the decomposed signal without losing any information. The DWT using MRA is shown in Figure 1.

MRA can be represented in mathematical form as:

$$A_i = d_{i+1} + A_{i+1} = d_{i+1} + d_{i+2}, \ldots, + d_{i+n} + A_n \tag{1}$$

Where

A_{i+1} is the approximated version of the given signal at level $i + 1$. n is the decomposition level,

d_{i+1} is the detailed version of the signal that displays all transient phenomena at level $i + 1$.

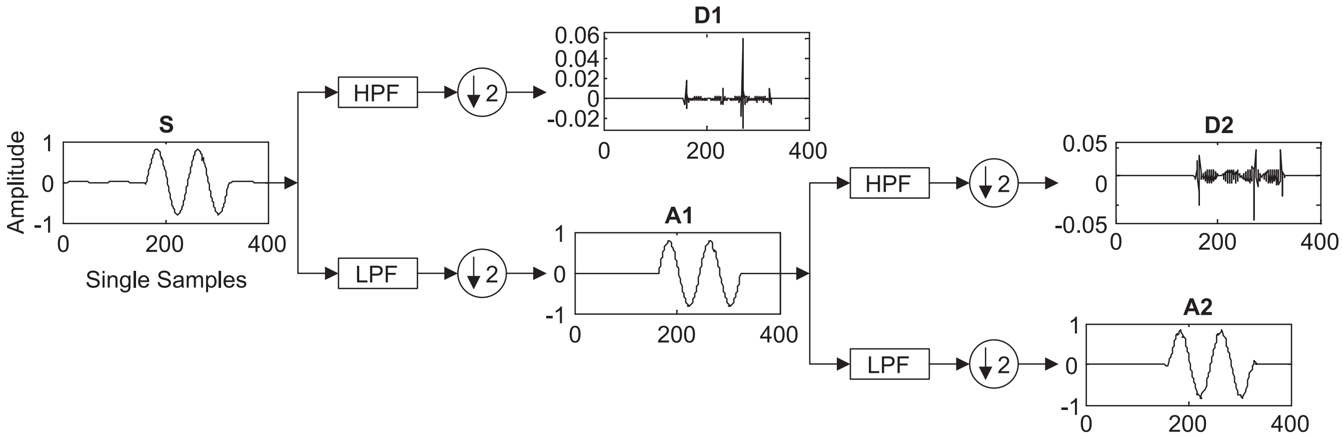


Figure 1: DWT decomposition

In MRA, long time windows are used for extract the low frequency information whereas short time windows are used to get the high frequency information. This property makes the WT an ideal tool for analysing the transient and nonlinear signals. WT has two types of decompositions, (1) Continuous wavelet transform (CWT) (2) Discrete wavelet transform (DWT).

In practical implementation, CWT decomposition produces redundant data of a signal and at every possible scales wavelet coefficients calculation is an expensive task. Instead, if the scales and shifts are selected in powers of two, called as dyadic scales, then the analysis become redundant free and much more efficient. Such an analysis can be obtained from DWT; hence in this work DWT is employed. In case of DWT, the scaling and translation parameters are n, m and $n = n_0^m$ and $m = am_0 n_0^m$ where n_0, m_0 are fixed constants with $n_0 > 1$ and $m_0 > 1$, $(a, b) \in z$ where z is the set of positive integers. DWT referred as:

$$\text{DWT}\,(a, b) = \frac{1}{\sqrt{m_0^a}} \sum_{p=-\alpha}^{p=\alpha} s[k]\,\psi\left(k - \frac{m_0^a b n_0}{m_0^a}\right) \tag{1}$$

Where ψ is the wavelet function and $s[k]$ is the discretized signal function. In DWT, the first and foremost step is, signal is passed through low pass and high pass filters simultaneously. The outputs of high pass and low pass filters are referred as detail (D_n) and approximation (A_n) coefficients. The approximated and detailed frequency bandwidths are given in equations (2) and (3) respectively. At each level of decomposition, the frequency resolution is doubled by filtering and the time resolution is halved by down sampling. According to Nyquist's theorem criteria, if a signal has a sampling frequency f_s then it can have the highest frequency component is half of the sampling frequency. The first level of decomposition can cover up to the frequency band from $f_s/2$ to $f_s/4$, the second detail level covers from $f_s/4$ to $f_s/8$ and this process continues up to a predefined level of decomposition. In this work, the sampling frequency has been taken as 4 kHz i.e., 80 samples per cycle. For analysis of fast decaying, low amplitude and short duration type of transient signals, Daubechies family prefers to be optimum [2]–[4] when compared with the Haar, Coiflet and Meyer family wavelets, because of its inherent orthogonally property and effective low-pass and high-pass filter banks. In this article DB4 is chosen as the optimum mother wavelet over level-3 of decomposition. Detailed explanation of Wavelet decomposition process along with the schematic diagram, cut off frequencies etc., is given in [5]. The corresponding decomposition of fault and inrush currents are shown in Figure 2. The DWT decomposition bandwidths are tabulated in Table 1.

$$A_n = \left[0, \frac{f_s}{2^{n+1}}\right] \tag{2}$$

$$D_n = \left[\frac{f_s}{2^{n+1}}, \frac{f_s}{2^n} \right] \tag{3}$$

Table 1
Decomposition of Frequency Bandwidth up to Level-3

Decomposition Level	*Approximation bandwidth (kHz)*	*Detail bandwidth (kHz)*
1	A_1 – (0-1000)	D_1 – (1000-2000)
2	A_2 – (0-500)	D_2 – (500-1000)
3	A_3 – (0-250)	D_3 – (250-500)

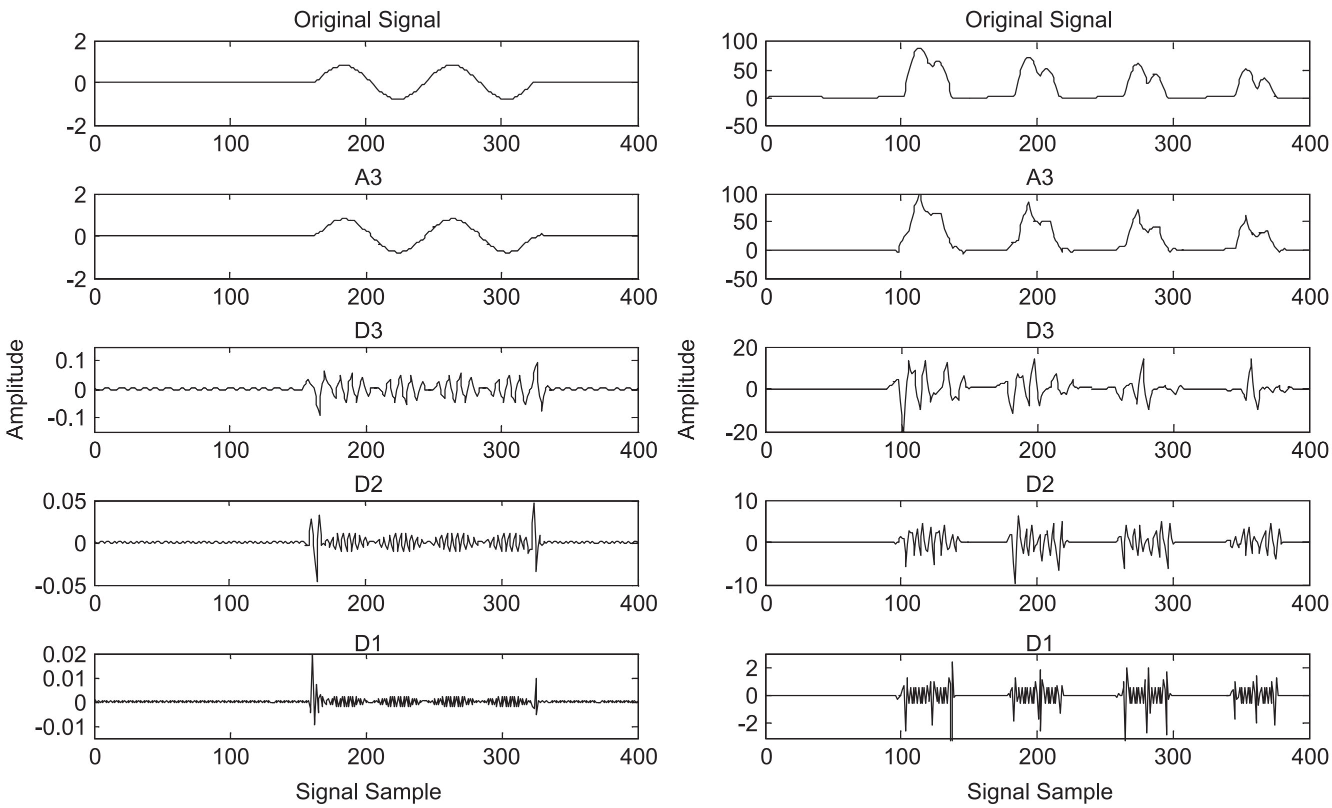


Figure 2: Wavelet decomposition of (a) fault (b) inrush currents

4. PROPOSED ANN ARCHITECTURES

The usage of artificial neural networks (ANNs) has grown tremendously to interrogate the complex problems. The main reason is their adaptive capability i.e., ANNs have the ability to learn and establish precise, complex relationship between different numeric variables without any preconceived model being imposed. ANNs can be used for pattern recognition and classification. The pattern classification quality is not depending on the power system network model, but it depends on the neural network topology and choice of learning laws. Considering on these properties three radial basis networks; RBFNN, PNN and GRNN are used for pattern recognition and classification of differential currents. The extracted data from DWT is used for the training and testing of neural networks. The total data is arranged in moving window format, these models have the topology of 12 inputs and 9 outputs and the output codification of neural networks is mentioned in Table 2.

Table 2
ANN's 9 output codification

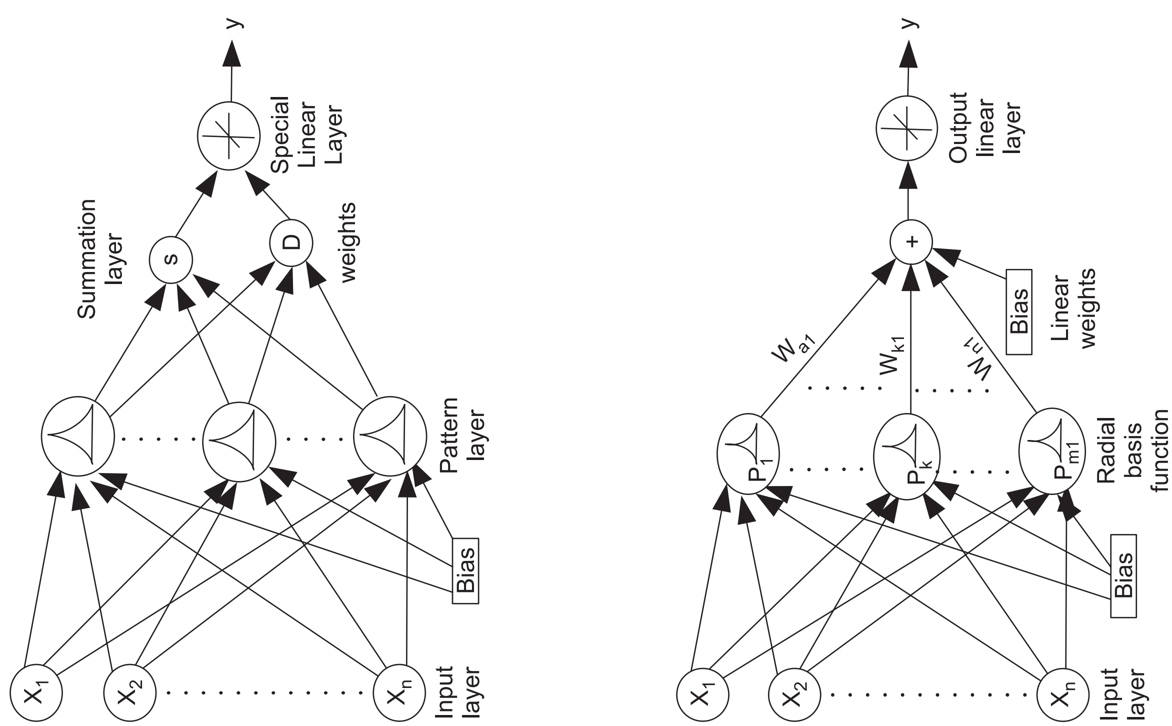
Operating case	*Output pattern*
Normal	1 0 0 0 0
A-G	0 1 0 0 0
B-G	0 0 1 0 0
C-G	0 0 0 1 0
AB-G	0 1 1 0 0
AC-G	0 1 0 1 0
BC-G	0 0 1 1 0
ABC-G	0 1 1 1 0
Inrush	0 0 0 0 1

4.1.1. Hidden Layer

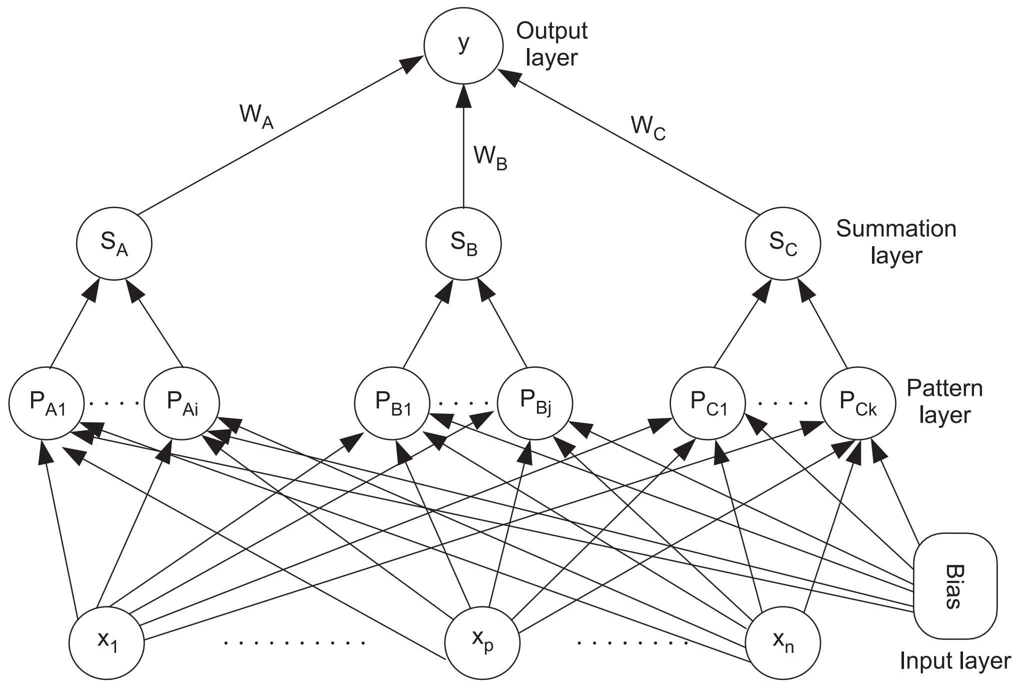
The GRNN and PNN are a kind of radial basis networks which are generally used for approximation of function. The three networks have the similar structure of input and hidden radial basis layers but rather different in output layers. When the inputs applied to these networks the hidden layer calculates the distance between the input and training vectors and generates a vector, which indicates how much close of the input to a training set of vectors. Every neuron net input is the product of its weighted inputs and its bias. If a neurons weight and input vectors are equal, then its weighted input and net input will be 0 and its corresponding output will be 1.

4.1.2. Output Layer

The RBFNN has the linear layer as second layer and computes its weighted input with dot product. In RBFNN both the input and output layers have the biases and the architecture is shown in Figure 3(b). The output layer of PNN is the sum of the contributions of first layer for each class of inputs. The maximum of these probabilities picked out by the *compete* transfer function on the output of the second layer and produces 1 for maximum class and 0 for other classes. The architecture of the PNN is shown in Figure 3(c).



(a) (b)



(c)

Figure 3: Architecture of (a) GRNN (b) RBFNN (c) PNN

The GRNN is similar as RBFNN but differ in second layer with special linear layer. The second layer of GRNN calculates the weighted input with normalized dot product and the architecture of GRNN is shown in Figure 3(a).

4.2. Results of 9-Output Topology

4.2.1. 9 Output Testing Case

Neural network prediction accuracy can be decide based on the classification rate of training and testing pattern samples. Out of 3522 pattern samples, 3022 pattern samples are used for training and 500 samples are randomly selected by networks for testing. The training and testing samples consisting of normal, inrush and internal faults data represented in 9 output codification topology. The 9 windows of Figure 4 and Figure 5 represents the testing classification of data consisting of normal (Normal), single line to ground faults (A, B, C), double line to ground faults (AB, BC, AC), three lines to ground fault (ABC) and inrush (Inrush). have the In those figures the red dotted line represents the outputs and the blue line represents the network targets. The training classification rate of three networks is 100%. Figure 4, shows the testing classification of PNN and GRNN respectively. The classification rate of PNN and GRNN is 99.55% whereas, classification rate of RBFNN is 97.99% because, at certain pattern samples RBFNN is committing mal-classification shown in Figure 5. In results RBFNN clearly reveals the misclassification when compared with the remaining networks.

4.2.2. Testing Error Histograms

The error histograms are drawn in between the network target and output values. The total number of instances in case of 9 output training case is 27,198 (9×3022) and total number of instances in case of 9 output training case is 4500 (9 outputs $\times$ 500 samples). The training error values of the RBFNN, PNN and GRNN are distributed around of 4.8 e^{-8}, 1.33 e^{-16} and 0 respectively. Figure 6 represents the testing error histograms of the RBFNN, PNN and GRNN. The thin orange line in the figure represents the zero error line and the surrounding blue bars are the error values of respective instances. The error values of RBFNN is

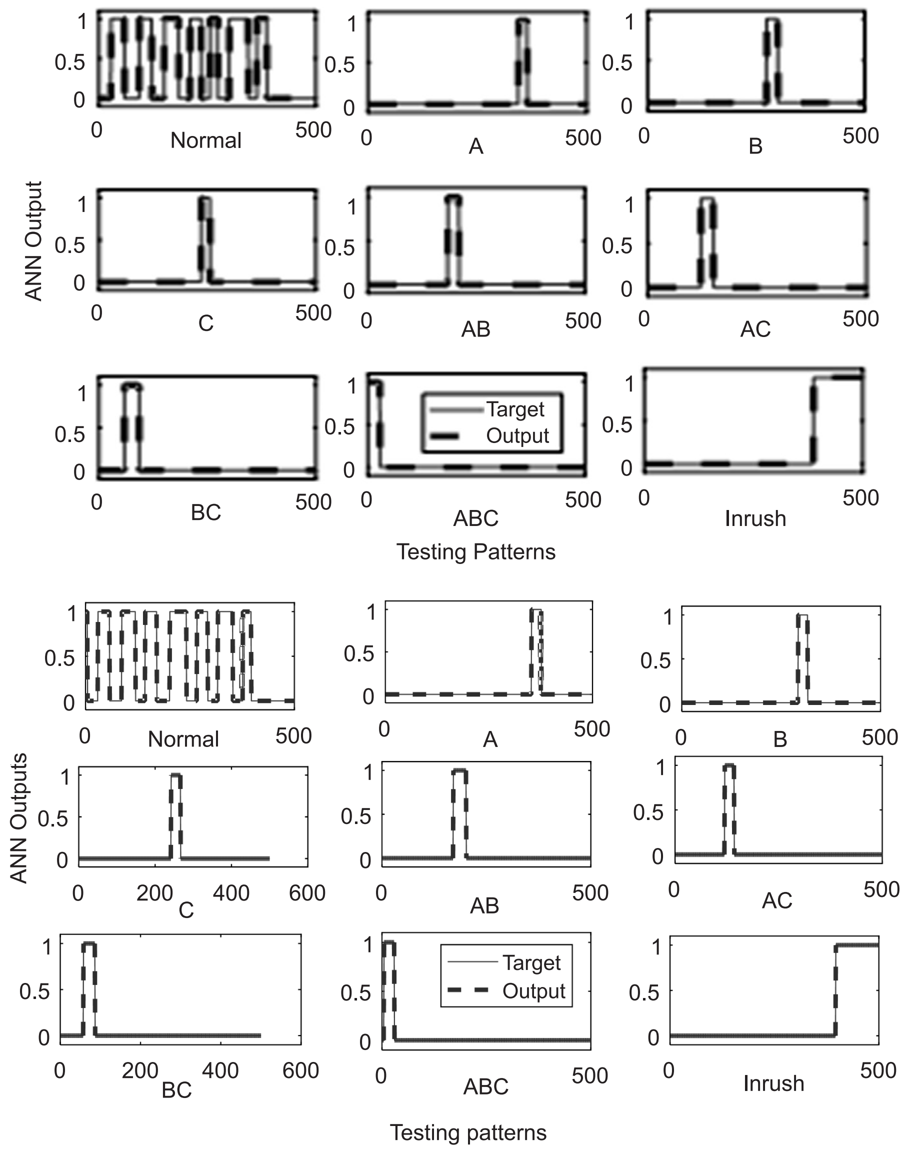


Figure 4: Nine output models' Testing classification of (a) PNN (b) GRNN

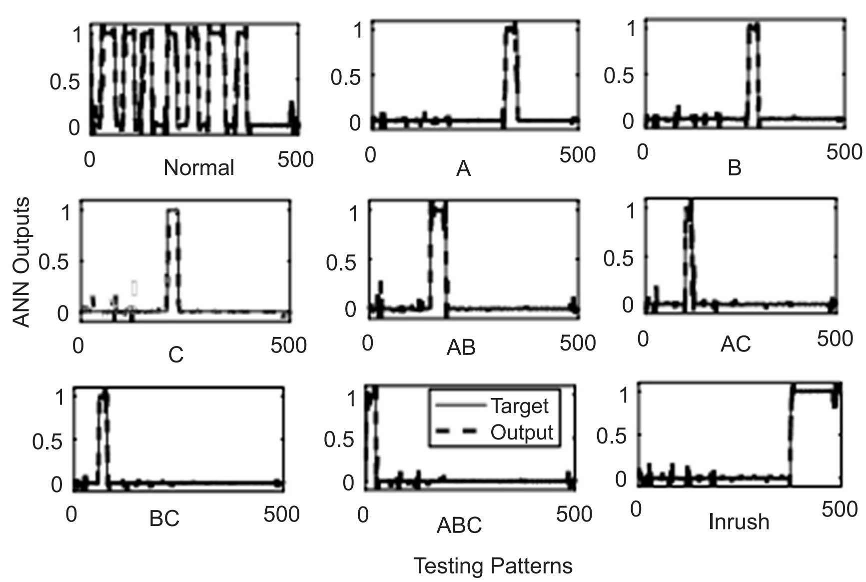
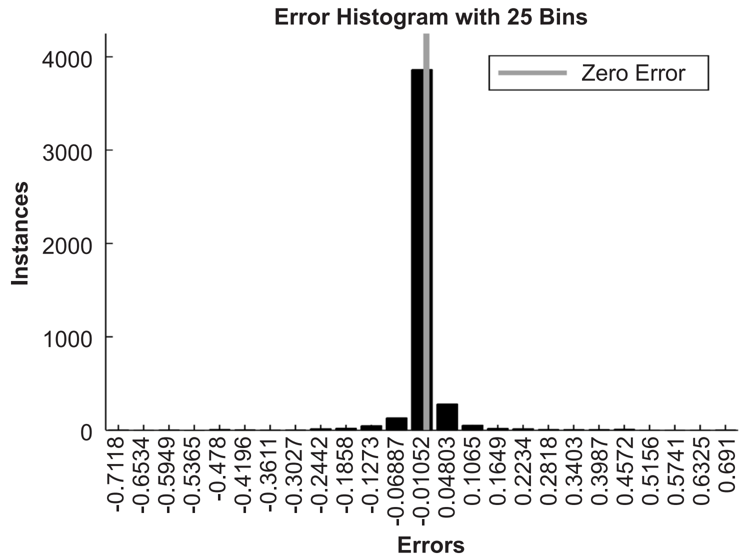
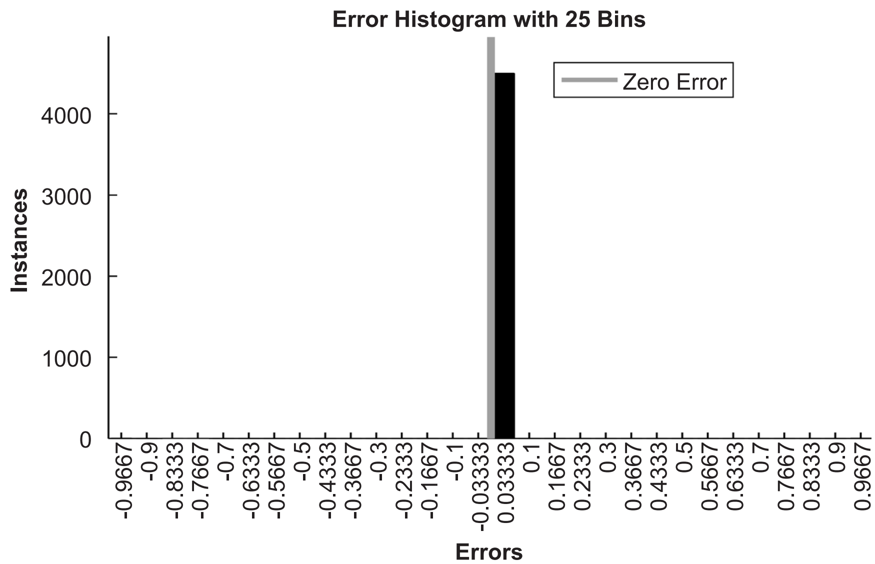


Figure 5: Nine output models' Testing classification of RBFNN

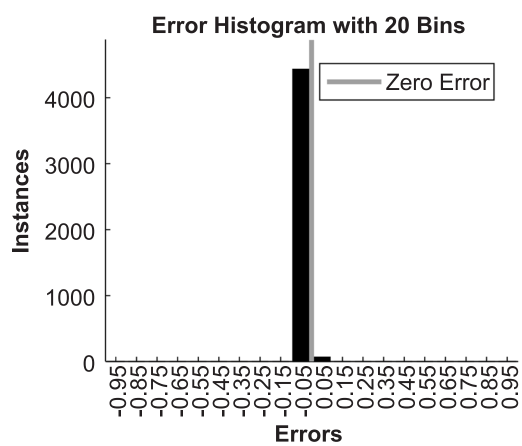
around of 0.0104 with 25 bins shown in Figure 6(a), error values of PNN is around of 0.033 with 30 bins shown in Figure 6 (b), and the error values of GRNN is around of 0.05 with 20 bins shown in Figure 6(c).



(a)



(b)



(c)

Figure 6: Testing error histogram of (a) RBFNN (b) PNN (c) GRNN

4.2.3. Testing Regression Analysis

Linear regression analysis is one of the most standard analyses to represent the relationship between the dependent and independent variables of the network. Based on the data fit, the regression value varies in between zero to one. The training regression values for RBFNN, PNN and GRNN is 1 i.e., for the given data targets and outputs are best fitted. The linear regression analysis for 9 output models' testing case is shown in Figure 7. In regression analysis the black dotted line represents the actual linear relation of target and outputs. The red line indicates the how much the output and targets fit for the given application. The predicted regression values for PNN and GRNN is 0.9955 i.e., the testing output samples and targets are almost fit for the given application. Where as the RBFNN regression value is 0.9799, it means that due to malclassification of samples the outputs are slightly deviated from the actual linear path.

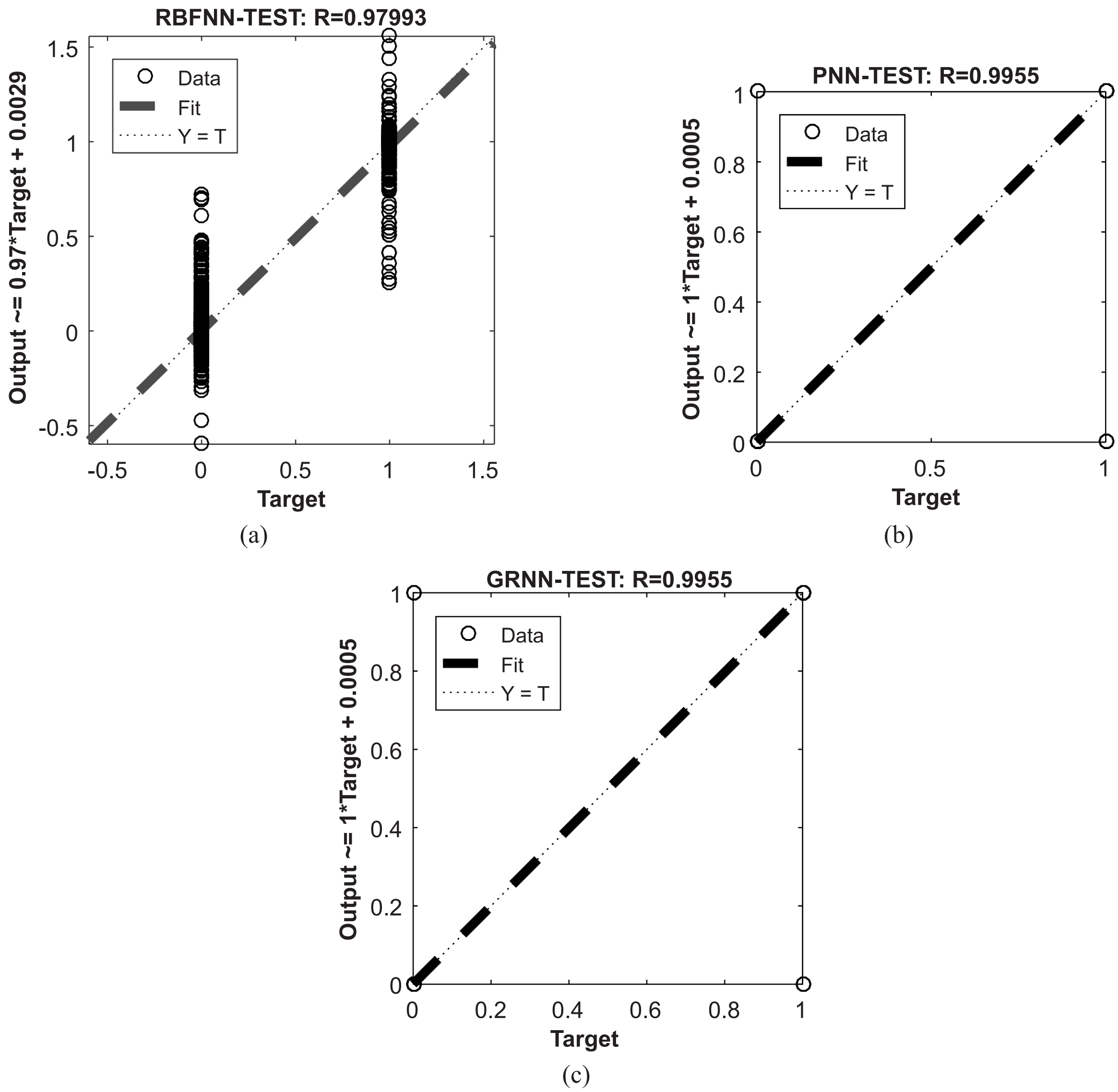


Figure 7: Testing linear regression analysis of RBFNN, PNN, GRNN respectively

4.3. Comparison of Tested Networks

The three RBFNN, GRNN and PNN are compared in terms of architectural parameters. The performance of the networks compared in terms of mse error, maximum (max) error and regression values and mentioned in Table 3. Based on the results PNN and GRNN have the uttermost classification results in all cases.

Table 3
Comparision of proposed networks

Parameter names	*Type of Neural Network*		
	RBFNN	*PNN*	*GRNN*
Neurons of input layer	12	12	12
Neurons of output layer	9	9	9
Hidden layer transfer function	Radial basis	Radial basis	Radial basis
Output layer transfer function	Linear	Compete	Special linear
Training sets of data	3022	3022	3022
Testing sets of data	500	500	500
Training Regression value	1	1	1
Testing regression value	0.9799	0.9955	0.9955
Smoothing factor	0.0103	0.0413	0.0123
Training performance (mse)	$4.8e^{-8}$	$1.33e^{-16}$	0
Testing performance (mse)	0.0103	0.033	0.05
Training maximum error	$3.12e^{-7}$	0	$2.37e^{-15}$
Testing maximum error	0.478	0.0333	0.05

4.4. Pattern Classification Time and Accuracy

Classification time is the key parameter; it plays a vital role in relay operation. The proposed PNN and GRNN have the capability to distinguish between the normal, internal and inrush currents and issues the trip signal with in half cycle i.e. 10 ms, in worst conditions takes 10.25 ms. Meanwhile, RBFNN takes the 12.5 ms for issuing of trip signal. The classification accuracy of three networks for both training and testing cases are represented in Table 4. Based on the results PNN and GRNN have the superior classification accuracy.

Table 4
Pattern classification time and accuracy

Network	*Time (ms)*	*Training accuracy (%)*	*Testing accuracy (%)*
RBFNN	10 – 12.5	100	97.99
GRNN	10 – 10.25	100	99.55
PNN	10 – 10.25	100	99.55

5. CONCLUSION

To conquer the problem of distinguision between the power transformer internal currents and magnetizing inrush currents, an optimum classification system, using of three advanced radial basis neural networks and a superior discrete wavelet transform are tested in this article. Multi resolution analysis (MRA) based DWT is used for feature extraction of fault and inrush currents. All the possible internal faults and inrush currents are classified based on the 12-input and 9-output codification network topology and the results of the models are compared with each other. The RBFNN, PNN and GRNN models produced ultimate accuracy (100%) classification during training and 97.99%, 99.55% and 99.55% accuracy classification respectively during the testing. The results confirmed that the proposed PNN and GRNN models issues trip signal for internal fault events with in half cycle (10 ms) and the RBFNN issues trip signal with in 12.5 ms. The results concluded that the proposed models are best suitable for artificial intelligent based power transformer differential scheme and can be preferred as replacement of the existing schemes.

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