Numerical Differential Protection of Power Transformer using GA Trained ANN

Neha Gupta, Harish Balaga, D. N. Vishwakarma

Abstract: This paper presents the use of ANN as a pattern classifier for differential protection of power transformer, which makes the discrimination among normal, magnetizing inrush, over-excitation, external fault and internal fault currents. The Back Propagation Neural Network Algorithm and Genetic Algorithm are used to train the multi-layered feed forward neural network and simulated results are compared. Comparing the simulated results of the above two cases, training the neural network by Genetic algorithm gives more accurate results (in terms of sum square error) and also faster results than Back Propagation Algorithm. The GA trained ANN based differential protection scheme provides faster, accurate, more secured and dependable results for power transformers.

Keywords: Artificial neural network, Differential protection, Genetic algorithm, Power transformer, Pattern classification.

I. INTRODUCTION

In power system, transformer is one of the essential elements and thus transformer protection is of critical importance. The most common method of transformer protection is differential relay which involves converting the primary current and secondary currents in a common base and comparing them. The main challenge in differential protection is to discriminate between an internal fault and other operating conditions such as magnetizing inrush current, over excitation.

Numerical differential protection has been improved significantly since its inception in 1969 [l]. In 1988, the first industrial application of the differential relay was introduced [3]. A contemporary design of hardware for a digital differential protection algorithm is given in [5]. A number of more or less reliable protection criteria- supporting the traditional biased differential characteristic combined with 2nd and 5th harmonic restrain have been developed in [1]. They include direct wave shape identification, protective algorithms based on equivalent circuit composed of inverse inductance [4]. The basic concept of apparatus protection, in particular, protection of power transformer by means of differential relay can be seen in many books [17]-[19]. Several algorithms have been proposed to detect winding faults in single phase and three phase transformers and the results show that the algorithms perform well [7].

A recursive algorithm suitable for microprocessor based power system relaying and measurement has been proposed in [6]. Many authors described application of Artificial Neural Network (ANNs) in power systems [10]-[16]. In [13] and [14], it was suggested that a feed-forward neural network (FFNN) has been trained to discriminate between power transformer magnetizing inrush and fault currents.

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The result show that a FFNN can be consider as an alternative method to make the discrimination between inrush and fault currents in a digital relay implementation.

Transformer inrush is recognized on the basis of the second harmonic components in differential currents (above 16%), which can be obtained by the various digital filters. Other authors, of [4], determine the transformer operating conditions on the basis of calculations of unforeseen operating conditions on mathematical transformer models, while the results of the calculation are continuously compared with actual transformer operating conditions. Such calculations are questionable in real time execution, since the mathematical model must be significantly simplified, resulting in the loss of information on the content of higher-harmonic components in transformer current. Considering these factors, many researchers continued their work to develop new algorithms for transformer protection; however, all of these algorithms are either based on the transformer equivalent circuit model or require some transformer data, and this may become susceptible to parameter variations.

In the recent past, numerical protection was introduced to improve the protection scheme. As with classical protection, new numerical protection can also lead to unnecessary operation due to inability of protection algorithms to distinguish transient states from faults. To overcome this difficulty ANN based techniques are introduced to power system protection because of their advantages like possibility of learning from examples, generalization ability, parallel computation, nonlinear mapping nature etc. There has been extensive research on applications of ANNs over the last few years, particularly in the field of pattern recognition. The ANN-based algorithms have been successfully implemented in many pattern or signature recognition problems. Because this particular protection problem can also be considered as a current waveform recognition problem, the use of ANN seems to be a good choice. The application of ANN to achieve some protective relay functions is a matter of research. The ANN-based approach can detect normal, magnetizing inrush, and over-excitation currents based on recognizing their wave shapes, more precisely, by differentiating their wave shapes from the fault current wave shapes. It gives a trip signal in the case of internal fault only and exercises restraint under healthy, magnetizing inrush and over-excitation conditions.

But in order to obtain still more effective and fast discrimination, Genetic Algorithm (GA) has been introduced to train the ANN architecture.GA has been used for training of ANN for fault classification in parallel transmission line in [20]. The genetic algorithm is implemented with neural network to determine automatically the suitable network architecture and the set of parameters from a restricted region of space in [21]. A simple real-number string is used to codify both architectures and weights of the networks in [22].

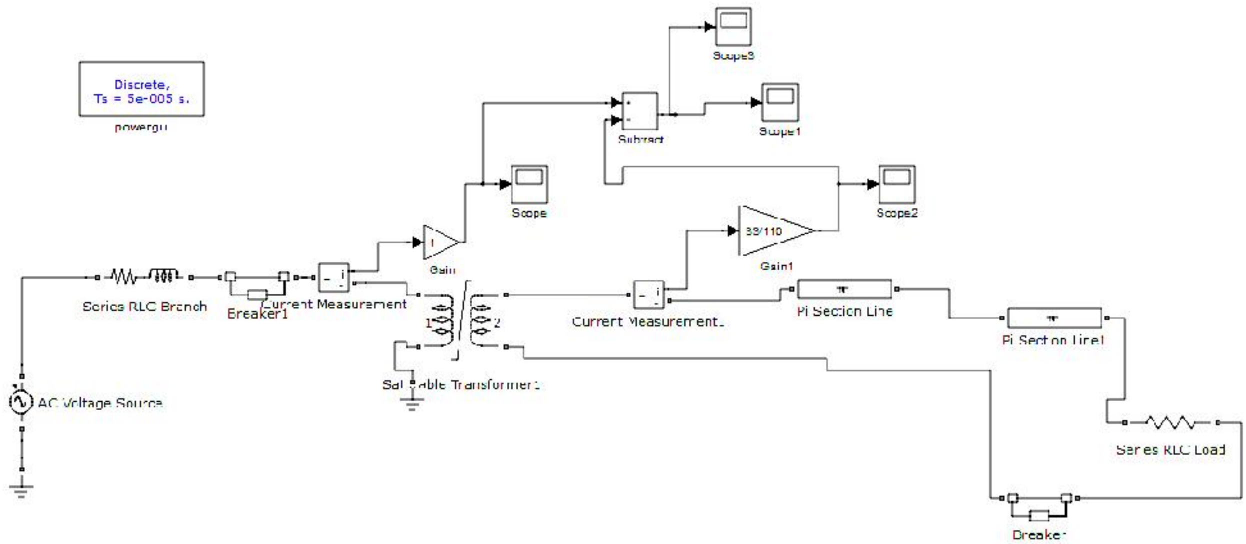

Fig.1. Simulated power system model

Introduction of the mechanics and real world application of GA can be seen in many books [23, 24].

In this work, an attempt has been made to design a novel relay using ANN which can recognize all the possible conditions, such as normal, inrush, over-excitation, external fault, and internal fault, and give the trip signal in case of internal fault only. The developed ANN was trained by using feed forward back propagation algorithm and Genetic algorithm. Network is two layered with four neurons in the output layer and 10 neurons in hidden layer and is fed with full cycle data. The training data are obtained using SimPowerSystems, MATLAB software package for all of the possible conditions, as described above. The ANN-based algorithm has been tested to evaluate the performance of the proposed method in terms of accuracy and speed, and the encouraging results have been obtained.

II. SIMULATION OF THE POWER SYSTEM TO PREPARE THE PATTERNS

A single-phase 110/33 kV power system included a 200 km transmission line, as shown in Fig. 1**,** has been used to produce the required test and training patterns. The simulation was done by means of SimPowerSystems (MATLAB) software. Table 1 represents the associated data with this power system. The combination of condition of system is shown in Table. 2, have been produced using this system to train the ANN. Faults are located at different points of transmission line. *Also***,** they involve inrush current and over excitation condition with different voltage angles and with different loads. As the inputs to the network are samples taken from the waveforms generated by creating different operating conditions, they themselves define the range to decide the operating condition. Here secondary current is converted to primary side to make a common base. Breakers are connected at different positions for obtaining data for above different conditions of power transformer.

TABLE I
SIMULATED POWER SYSTEM PARAMETERS

Transformer nominal power & frequency	16 MVA, 50 Hz
Transformer winding parameters	R=.002 pu, L=.08 pu
Transformer core loss resistance	500 pu
Line parameters (200 km)	R=.2568 ohm/km, L=2e-3 H/km, c=8.6e-9 F/km

TABLE II
TRAINING PATTERN DATA GENERATION

Condition system	*Normal: when there is no fault.* *Internal fault*: Transformer secondary is shorted. *External fault*: faults at different locations of transmission line. *Inrush*: At different voltage angles by closing the breaker connected *Over-excitation:* At different over voltages
Voltage angle	0, 10, 20…..to 180 degree
Load(MW)	200, 400, 600, 800 and 1000

III. DEVELOPMENT OF THE PROPOSED NEURAL NETWORK

The developed ANN is one of the ANNs that are biologically inspired, and uses an approach similar to human brain to make decision and to arrive at conclusion. Each neuron in each layer generates one normalize output, as a function of its normalized inputs. The used network architecture is multi-layered with one input layer, one hidden layer, and one output layer. All layers are fully connected and of the feed forward type. The outputs are nonlinear functions of the input, and are controlled by weights that are computed during learning process. The Multi-Layered Feed Forward Neural Network is most commonly used in power system protection applications.

A. Back Propagation Algorithm

The Multi-Layered Feed Forward Neural Network Algorithm is usually trained by an algorithm known as error back propagation algorithm. In this method the actual response of the network is subtracted from the desired response to produce error signal. This error signal is then propagated backward through the network. The synaptic weights are adjusted so as to make the actual response of the network much closer to the desired response. This algorithm is developed on the basis of the least square method.

B. Overview of Genetic Algorithm

GA is an optimization technique based on the principle of genetics and natural selection. A GA allows a population composed of many individuals to evolve under specified selection rules to a state that maximizes the "fitness".

The classical optimization methods have limitations in searching for global optimal point.Due to the fact that GA is a multipoint search method rather than the conventional single point search methods.GA promises the global optimum point to be reached.Moreover GA uses only the value of objective function. The derivatives are not used in the search procedure.

In GA,the design vector is represented as string of real numbers,each number represents a 'variable'.This string is called a 'chromosome'.GA starts with a group of chromosomes known as 'population'.

The basic operations of natural genetics-reproduction, crossover and mutation are implemented during numerical optimization. "Reproduction" is a process in which the individuals are selected based on their fitness value relative to that of the population. Thus individuals with higher fitness values have a greater chance of being selected for mating and subsequent genetic action.

After reproduction, the 'crossover' is implemented. Crossover is an operator that forms a new chromosome called 'offspring' from two parent chromosomes by combining part of the information from each. So, first two individuals are selected from the mating pool generated by the reproductin operator. Next, a crossover is performed by taking random weighted average of two parents.

The offsprings obtained from crossover are placed in the new population The 'mutation' is performed after crossover.

Mutation functions make small random changes in the individuals in the population, which provide genetic diversity and enable the genetic algorithm to search a broader space.

C. Network Architecture and Training

The first step to formulate the problem is identification of proper input and output set. Various architectures and combination of input sets were attempted to arrive at the final configuration with a goal of maximum accuracy. The simulated model parameters are given in table.1. Differential currents are typically represented in discrete form. These signals are sampled at a sampling rate of 16 samples per cycle (over a data window of one cycle). These samples are used for training and testing the developed NNs. Inputs to ANN is selected as 16 samples of differential currents (i.e., $I_d = I_1 - I_2$). One hidden layer is taken and number of neurons is varied from 7 to 56 in order to arrive at final architecture. After enough experimentation, one hidden layer of 10 neurons apart from 16 inputs and 4 outputs has been selected. Transfer function for hidden layer is chosen as 'tansig' and for output layer it is chosen 'logsig' for both architectures.

Genetic Algorithm is used for finding weights and biases of Artificial Neural Network. In this architecture 214 variables (16*10+10*4=200 weights and 14 biases) are to be optimized using GA. The algorithm for finding weights and biases of ANN is divided in two sections. First part is to compute fitness function and second part is to generate weights and biases of ANN using genetic operators.

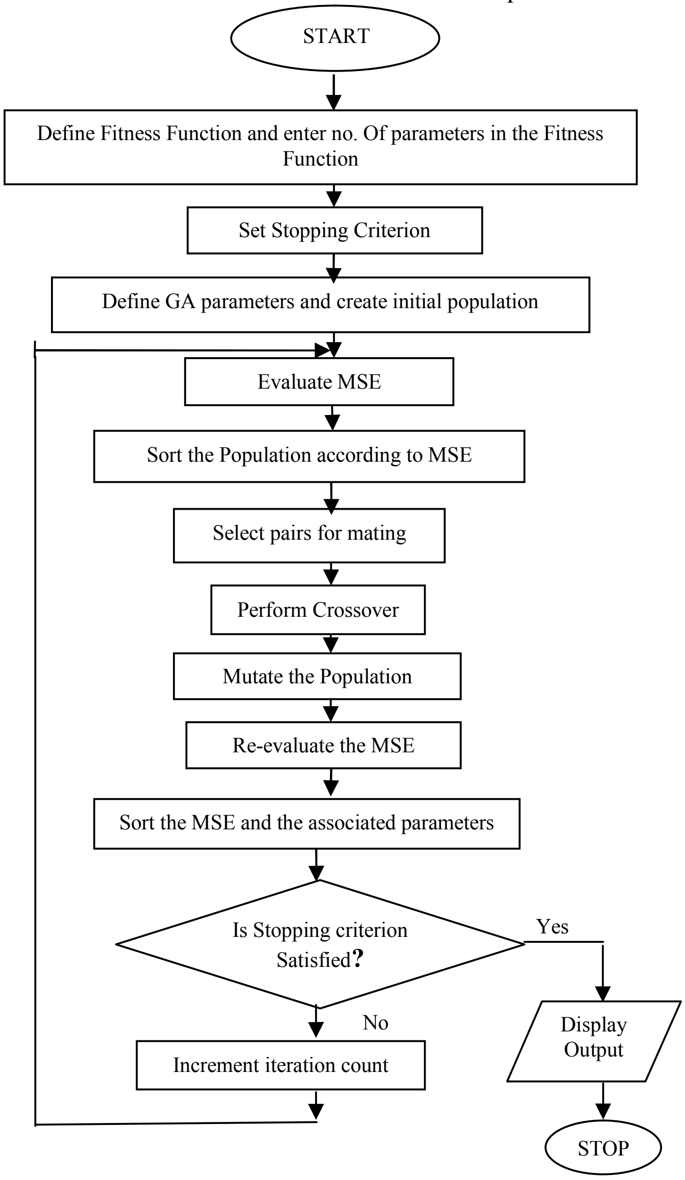

Fig.2. Block diagram for Genetic Algorithm

Algorithm for GA

{

i=0;

Generate the initial population Pi of real coded chromosomes Cji each representing a weight and bias set;

While the current population Pi has not converged

{

Generate fitness value Fji for each Cji € Pi using the Fitness ();

Get the mating pool ready by terminating worst fit individuals and duplicate high;

Using the crossover mechanism, reproduce offspring from parents chromosomes;

Mutate the population;
i=i+1;
Call the current population Pi
Calculate fitness value Fji for each Cji;
}
}

Algorithm for Fitness function

{
Let (Ii,Ti), i=1,2,..N where Ii=(I1i,I2i…Ili) and Ti=(T1i,T2i,…Tni) represents the input-output pairs of the problem to be solved by ANN with configuration l-m-n.
For each chromosome Ci=1,2,…p belonging to the current population Pi whose size is p
{
Extract weights and biases from Ci
Keeping theses weights and biases setting train the ANN for N input instances;
Calculate error Ei for each of the input instance using the formula
Ei=Tji-Oji;
Where Oi is the output vector calculated by ANN;
Find root mean square E of the errors Ei, i=1,2,…N

Calculate the fitness value Fi for each of the individual string of the population as Fi=1/E;
}
Output Fi for each Ci=1,2….pi
}

ANN was trained for 1000 epochs. The training functions and parameters are given in table- 3. The authors have made use of the multicore processor functionality by using parallel processing toolbox available in MATLAB. All 4 cores of the Intel core I5 processor are made to run in parallel during the training process. This significantly improved the speed of training.

Since the networks have to distinguish among five kinds of signals, 5 sets of example signals (cases) have been obtained for this purpose. These cases are normal, magnetizing inrush, over- excitation, internal fault currents and external faults currents. Following figure -3 show the differential line currents of three phase transformer at different conditions.

Signal is sampled at 800 Hz (16 samples per cycle).The input data set for the neural network is organized in the form of a moving data window with a fixed window length of a full cycles each input set has 16 samples.

165 training samples generated by SimPowerSystems in MATLAB, have been used to train and test the neural network. These training sets of samples contain 5 different conditions of power transformer (normal, magnetizing inrush, over-excitation, internal fault conditions and external fault conditions). For each case, signals are sampled at the sampling rate of 16 samples per cycle (over a data window of one cycle).These samples are arranged in form of full cycle data to feed as input to the ANN. The outputs of the networks have a unique set (*e.g.*, 0000 = normal, 1000= inrush, 0100=over excitation, 0010=internal fault and 0001 =external fault). This network *i.e.* with 4 outputs monitors all the conditions occurring in the power transformer and it issues the trip signal only in case of fault condition.For training the network, Back Propagation and Genetic Algorithms were used and results were compared. After training ANN model was tested with all possible sets of data under different operating conditions of power transformer by using both Back Propagation and Genetic Algorithm.

TABLE III
GA PARAMETERS

No. of Variables	214
Population Size	1000
Scaling Function	Rank
Selection Function	Roulette Wheel
Mutation Function	Uniform
Mutation Rate	0.01
Crossover Function	Heuristic
Generations	1000
Function Tolerance	1e-16

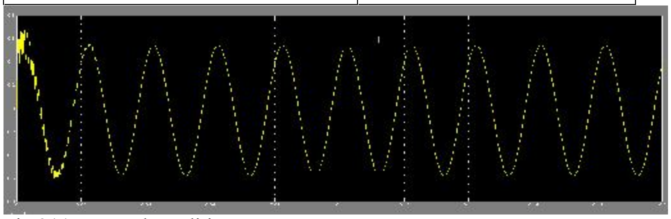
Fig.3(a). Normal condition

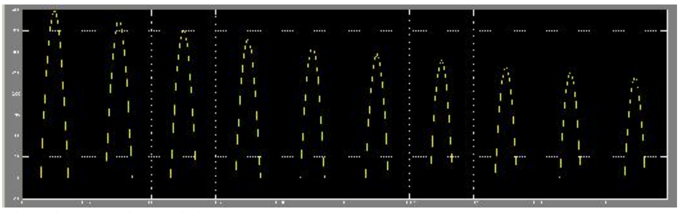
Fig.3(b). Inrush condition

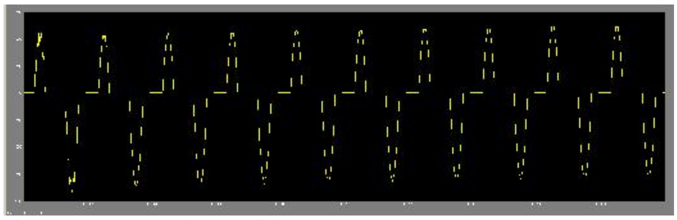
Fig.3(c). Over excitation condition

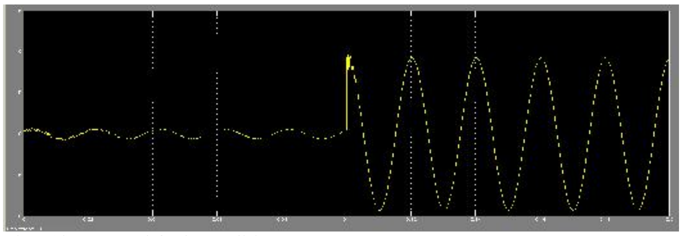
Fig.3(d). Internal fault condition

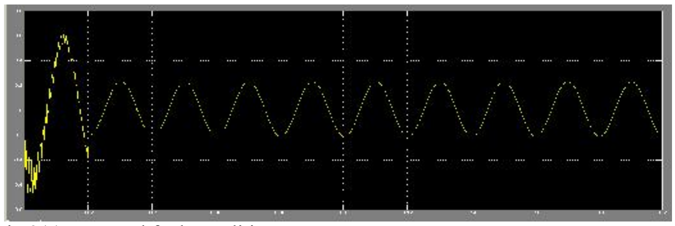
Fig.3(e). External fault condition

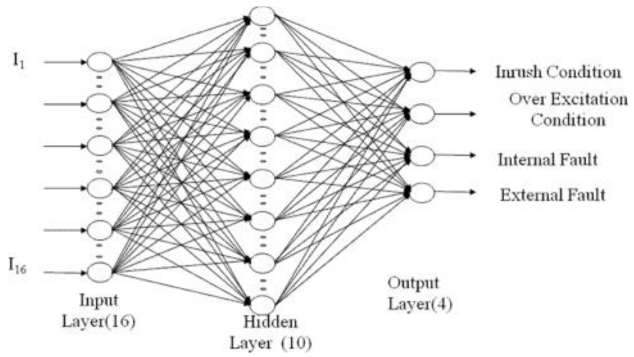

Fig.4. Actual Architecture of ANN

IV. NETWORK PERFORMANCE AND NUMERICAL RESULTS

The Architecture of developed ANN is shown in figure 4. While training with Back Propagation the mean square error obtained is 0.0158 (Training). The following figure 5 shows the mean square error during training. The tested outputs of architecture using Back Propagation are given in Table 4.

But, while the same architecture is trained using Genetic Algorithm, the mean square error is reduced to 3.73e-8. The learning error graph over 1000 generation is shown in the figure 6. The tested outputs of architecture using Genetic Algorithm are given in Table 5 .

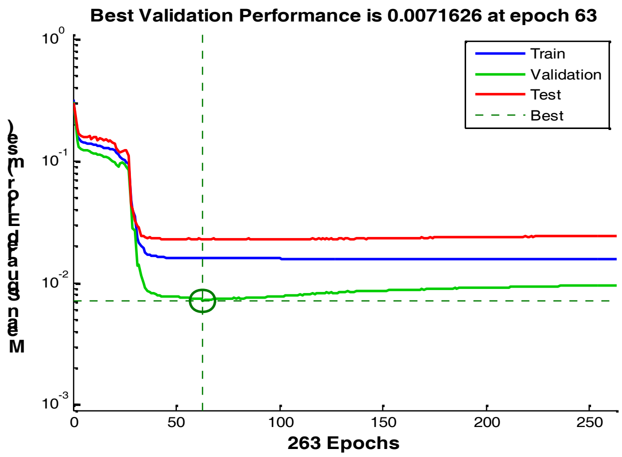

Fig.5 Learning error of ANN for while training with BP

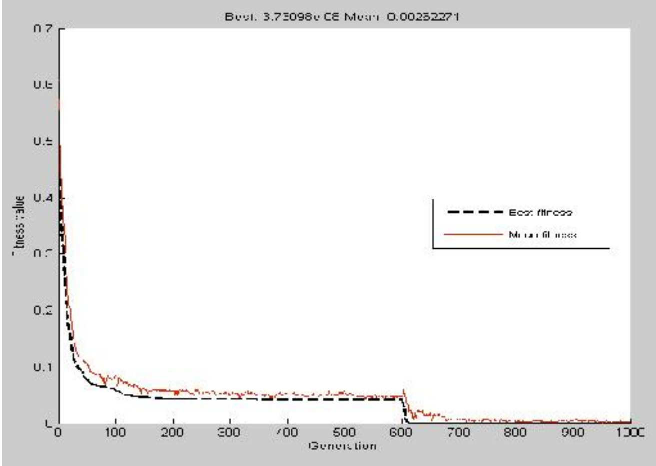

Fig.6. Learning error over 1000 generations.

It can be concluded from results that when ANN was trained using BP, it was not able to distinguish between normal and external fault conditions. It gives 0.3890 instead of ‘0’ under normal condition and 0.4270 instead of ‘1’ under external fault condition at the 4th output neuron. But when same architecture is trained using GA the mean square error is reduced to 10^{-8} and produced more nearer output to 0 or 1 depending on the condition. So it can be seen that when ANN is trained using GA, weight adjustment is enhanced.

TABLE IV
OUTPUT OF ANN USING BACK PROPAGATION

Normal		Inrush		Over excitation		Internal Fault		External Fault	
T	O	T	O	T	O	T	O	T	O
0	0.0018	1	0.9950	0	0.0012	0	1.27e-05	0	0.0017
0	0.0011	0	5.37e-07	1	0.9976	0	3.36e-08	0	0.0011
0	0.0010	0	2.43e-05	0	0.0001	1	0.9921	0	0.0010
0	0.3890	0	0.0005	0	0.0003	0	0.0057	1	0.4270

TABLE V
OUTPUT FOR ANN USING GA

Normal		Inrush		Over excitation		Internal Fault		External Fault	
T	O	T	O	T	O	T	O	T	O
0	8.78e-08	1	0.9999	0	3.56e-08	0	1.28e-11	0	4.06e-12
0	3.06e-12	0	8.20e-09	1	0.9999	0	8.15e-08	0	5.61e-09
0	5.21e-11	0	7.41e-15	0	2.71e-10	1	0.9999	0	6.91e-08
0	1.19e-07	0	1.37e-13	0	4.16e-08	0	9.90e-09	1	0.9999

V. CONCLUSION

In this paper a feed forward NN model for protection of power transformer have been analyzed. The 16_10_4 architecture could correctly discriminate among the different conditions in power transformer such as normal, magnetizing inrush, over-excitation, internal fault and external fault. The ANN has been trained for all the possible sets of simulated data under different operating conditions of transformer. ANN has been trained using Genetic Algorithm and results are compared with back propagation training algorithm. It was inferred that back propagation algorithm minimizes an average sum squared error term by doing a gradient descent in the error space. But there is a possibility of getting struck or oscillating around a local minimum. So the effectiveness of this method is not satisfactory. In addition, the convergence of the back propagation algorithms during training is sensitive to the initial values of weights. If the initial values of the weights are not properly selected, the optimization will be trapped in a local minimum or maximum.

Thus the GA trained ANN is very efficient in solving detection and classification problem. Use of parallel processing toolbox of MATLAB is suggested to improve the training speed of GA. The GA trained ANN based differential relaying for power transformer shows promising security, accuracy and speed.

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