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Research Paper on Transformer Protection through Artificial Neural Network

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ABSTRACT

The demand for a reliable supply of electrical energy for the need of modern world in each and every field has increased considerably requiring nearly a no-fault operation of power systems. The crucial objective is to mitigate the frequency and duration of unwanted outages related to power transformer puts a high pointed demand that includes the requirements of dependability associated with no false tripping, and operating speed with short fault detection and clearing time. The statistical features of the wavelet components are calculated and are used to train a multilayer feed forward neural network designed using back propagation algorithm to discriminate various conditions. The ANN is tested by varying the hidden layers, number of nodes in the hidden layer, learning rate and momentum factor, and the best suitable architecture of ANN is selected having least mean square error during training. The results obtained are accurate and encouraging.

Keywords: Inrush current, Artificial Neural Network, Artificial Intelligence, Learning Error Rate, Hidden Layer, Momentum.

1. INTRODUCTION

Power transformers are a class of very expensive and vital components of electric power systems. Protection of large power transformers is a very challenging problem in power system relaying. The high pointed demand includes the requirements of dependability associated with no false tripping, and operating speed with short fault detection and clearing time.

TRANSFORMER INRUSH PHENOMENA

To properly set a protection function, it is necessary to have a basic understanding of the power system events the function is intended to detect. To set the inrush restraint function for transformer differential protection requires some understanding of transformer inrush events, including the causes and characteristics of these events. This section of the paper defines a transformer inrush event. The section continues on to discuss how power system conditions influence the severity and characteristic of the inrush event, and finishes by describing the common power system events that cause transformer inrush.

A transformer inrush event is actually magnetizing inrush current. The windings in a transformer are linked magnetically by the flux in the transformer core. The exciting voltage drives the flux in the core. An increase in the exciting voltage therefore increases the flux. To maintain this additional flux, which may be in the saturation range of the core steel of the transformer, the transformer draws more current which can be in excess of the full load rating the transformer windings. This additional current is the inrush current necessary to supply the magnetizing branch of the transformer. To show magnetizing inrush current graphically, consider the equivalent circuit of transformer shown in Figure 1.

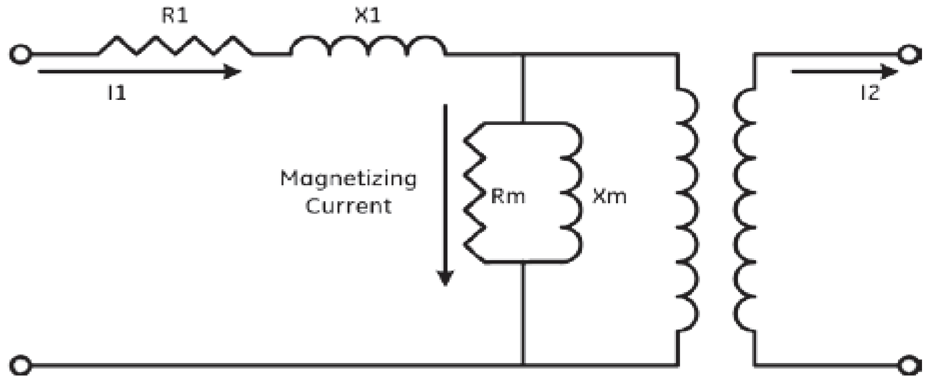

Fig 1. Transformer Equivalent Circuit

In an ideal transformer (with a 1:1 turns ratio), the currents I1 and I2 are equal except for the small current flowing through the shunt element of the magnetizing branch. The increase in flux caused by an increase in the exciting voltage draws more current through the magnetizing branch. When the transformer is being energized, this current flows through only one winding. In this example, the current I1 is the inrush current. During inrush events other than energization, the magnetizing inrush current may appear in both windings, with the inrush current more prevalent in one winding. Remembering the differential current is, then in any inrush event, the magnetizing inrush current results in a differential current. This differential current can lead to operation of the differential protection. Figure 2 is an example of magnetizing inrush current and the resulting differential current.

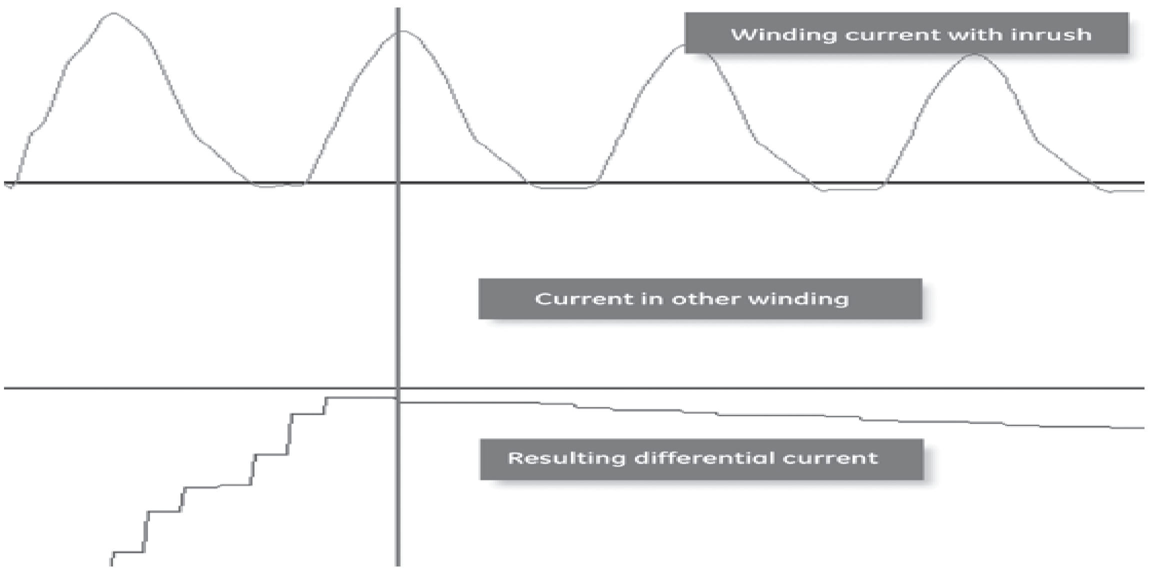

Figure 2. Inrush Current and Resulting Differential Current

2. TRANSFORMER PROTECTION

Inrush Current

Inrush current is defined as the maximum, instantaneous input current drawn by an electrical device during starting or turn on. Alternating current transformers may draw several times their normal full-load current when first energized, for a few cycles of the input waveform. During energization of power transformer a transient current up to 2 to 5 times flow for several cycles and is known as magnetic inrush. In simple words, When a transformer is initially connected to a source of AC voltage, it is often noticed when switching in a transformer on no-load that the ammeter registers an initial current rush (which, however, rapidly dies down) greatly in excess of the normal no-load current and sometimes even greater than the normal full-load current of the transformer. This is inrush of magentising current or simply inrush current. This is due to saturation of magnetic core which in turn due to an sudden change in the system voltage which may be caused by switching transients and out-of-phase synchronization of a generator or restoration after the clearance of fault. It decreases slowly due to the damping effect of winding resistance and takes several cycles to settle to normal current value. The value of inrush current depends on the core material, residual flux and instant of energization. Other than energization inrush current in power transformer also occurs during voltage recovery after the clearance of an external fault or after the energization of a transformer in parallel with a transformer that is already connected to power system. It contains dc offset, odd harmonics and even harmonics. Second harmonic content initially i.e. during starting is less and increases as the magnitude of inrush current decreases. Rate of decrease of unipolar inrush current is less in comparison to bipolar inrush current.

The main problem associated with magnetizing inrush current is false operation of differential relay based on second harmonic restrain method in addition to damage of power transformer windings by increasing the mechanical forces like short circuit current if remain in a high value for longer time.

Inrush current can be divided in three categories:-

1) Energization inrush current :- Energization inrush current result of re- energization of transformer. The residual flux in this case can be zero or depending on energization timing.
2) Recovery inrush current:- Recovery inrush current flow when transformer voltage is restored after having been reduced by system disturbance.
3) Sympathetic inrush current :- Sympathetic inrush current flow when multiple transformer connected in same line and one of them energized.

Mathematical derivation of inrush current

Power transformer is considered whose core is initially unmagnetized. The transformer primary winding is connected to a supply voltage v(t) and the secondary is made open.

The supply voltage is givenby
$v(t) = V_m \sin(\omega t)$ (2.1)

The applied voltage is expressed as a function of flux in the core and primarycurrent.
The applied voltage is givenby
$v(t) = Ri(t) + N(d\Phi t/dt)$ (2.2)

By neglecting the core loss and resistance equation (2.2) now becomes

$v(t) = N(d\Phi(t)/dt)$ (2.3)
$\Rightarrow \Phi(t) = \left(\frac{1}{N}\right)\int_{-\infty}^{t} v(t)dt$ (2.4)
$\Rightarrow \phi(t) = \phi_{residual} - \phi_m[\cos(\omega t) - \cos(\omega t_0)]$ (2.5)
$\phi_m = Vm/N\omega = \sqrt{2}V/N\omega$ (2.6)
$\Rightarrow \phi(t) = -\phi_m[\cos(\omega t)] + C$ (2.7)

The second term in the equation (2.7) is the integration constant and its value depends on the residual flux in the transformer core and the phase angle of the applied voltage at the instant of switching during energization. The inrush current signal during the energization of a transformer is given in Fig. 2.1.

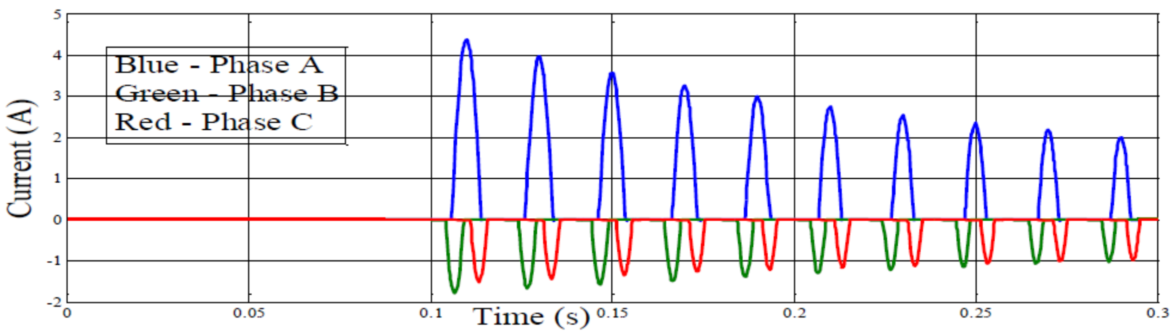

Fig. 2.1 Differential inrush current of all the three phases of a power transformer

If the transformer is energized when the voltage is at its peak then the flux is given by equation(2.8).
$\Rightarrow \phi(t) = -\phi_m[\cos(\omega t)]$ (2.8)
Transformer residual flux is neglected i.e. $\phi_{residual} = 0$
Hence it is clear from the above equation that the constant C is zero. There is no transient in flux and the time variation of fluxis

$\phi(t) = \phi_m \sin(\omega t - \pi/2)$ (For $\omega t > \pi/2$) (2.9)

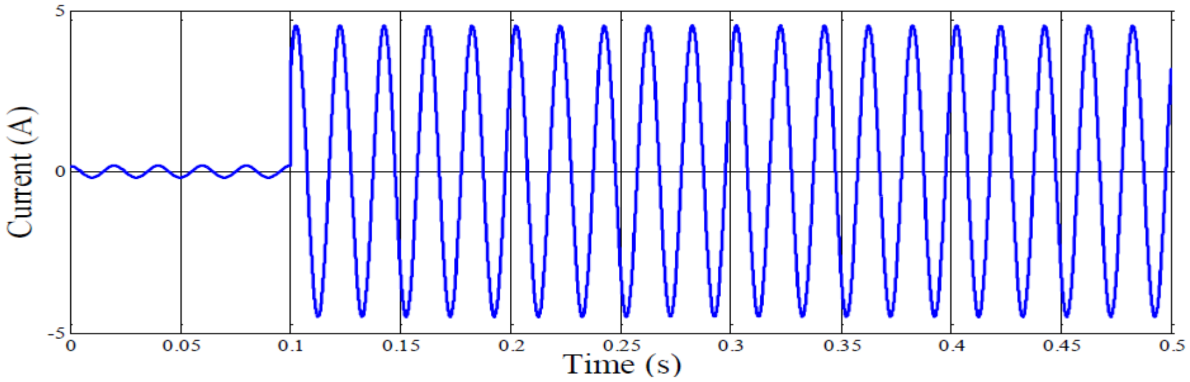

Fig. 2.2 Inrush current when the switching angle is 90degree

If the transformer is energized when the voltage is zero then the flux is given by equation (2.9).

$\Longrightarrow$ $\phi(t) = -\phi_m[\cos(\omega t)] + \phi_m$ (2.9)

Transformer residual flux is neglected i.e. $\phi_{residual} = 0$

It is clear from the equation (2.9) that the constant C is equal toϕ_m.

This equation shows that the flux can reach up to $2\phi_m$ at$\omega t = \pi$which is double the peak value of the steady state flux in the transformer core under normal operating conditions.Theinrush current is given in Fig 3.4 for the transformer that is energized when the voltage is at zero. It is clear that the inrush current in this case is much higher in comparison to the inrush current obtained during energization at voltage angle 90degree given in Fig2.3.

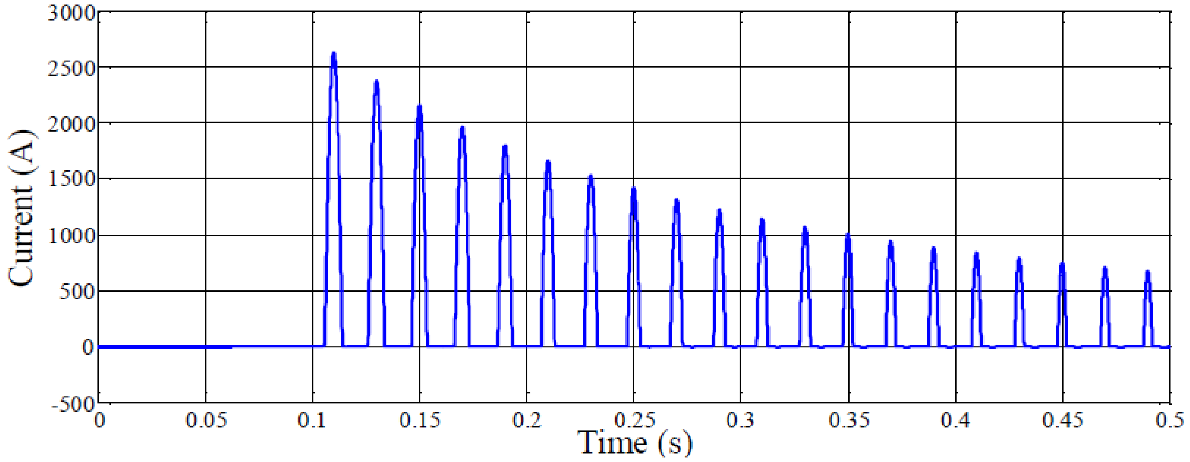

Fig. 2.3 Inrush current when the switching angle is0^0

The analysis of inrush current predicts that excessive flux can build up in the transformer core depending on the instantaneous magnitude of the applied voltage and the residual flux at the instant of applying the voltage to the transformer.

3. METHERDOLOGY

Training of ANN

The process of modifying the weights in the connections with the objective of achieving the expected output is called training a network. The internal process carried out during training is called learning.

Training is grouped into three categories.

a) Supervised Training: Training by a teacher.
b) Unsupervised Training: There is no external teacher or critic to oversee the training process.
c) Reinforced Training or Neuro dynamic Programming: The training of an input-output mapping is performed through continued interaction with the environment in order to minimize a scalar index of performance.

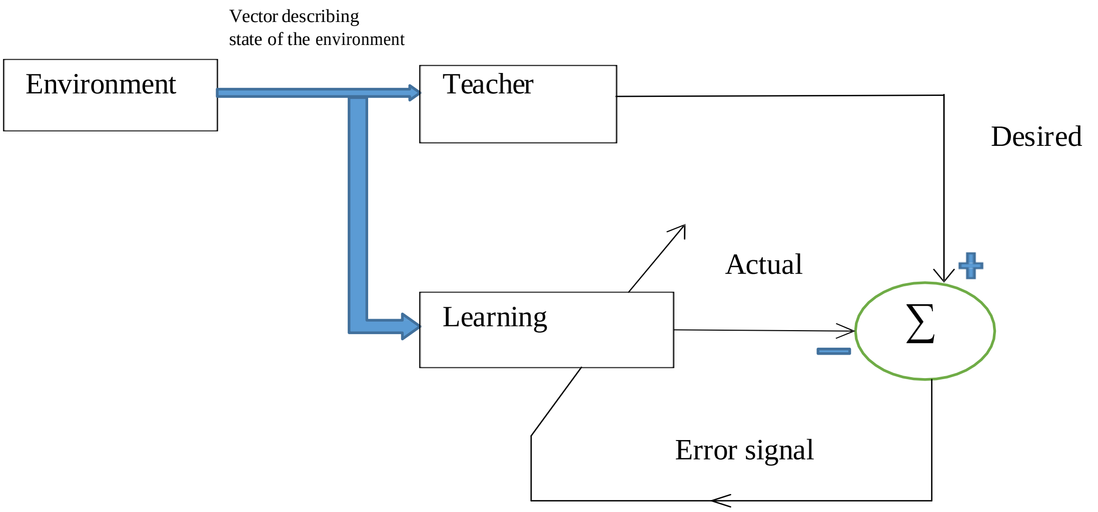

Fig. 3.1 Block diagram of supervised learning

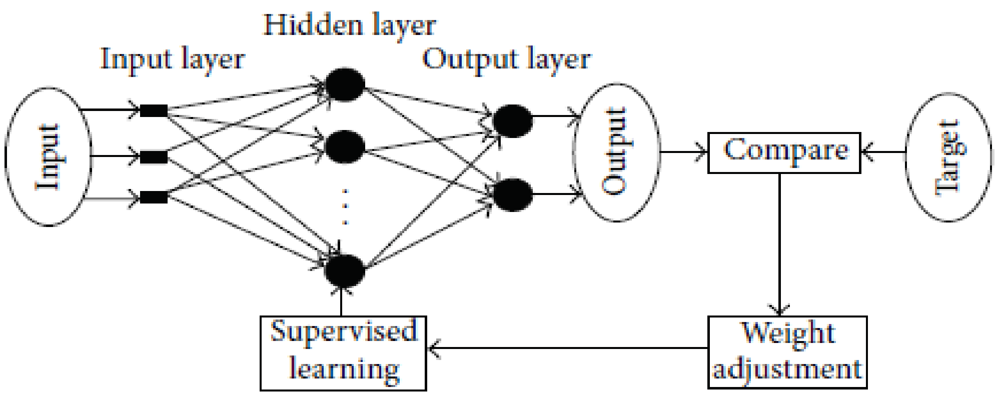

Figure 3.2 Supervised architecture of ANN

Multilayer feed forward ANN

MLF neural networks, trained with a back-propagation learning algorithm, are the most popular neural networks. The basic multilayer feed forward network contains three layers: input, output and hidden. This type of neural network has one input layer, one output layer and any number of hidden layers in between the former two layers. Each network layer contains processing units called nodes or neurons. Each node in a network layer will send its output to all the nodes of the next layer.

Back propagation training algorithm

Back Propagation (BP) learning algorithm is used to train the multi-layer feed- forward neural network. Signals are received at the input layer, pass through the hidden layer, and reach to the output layer, and then fed to the input layer again for learning. The learning process primarily involves determination of connection weights and patterns of connections. The BP neural network approximates the non-linear relationship between the input and the output by adjusting the weight values internally instead of giving the function expression explicitly. Further, the BP neural network can be generalized for the input that is not included in the training patterns. The BP algorithm looks for minimum of error function in weight space using the method of gradient descent. The combination of weights that minimizes the error function is considered to be a solution to the learning problem.

The training algorithm of back propagation involves four stages, i.e.

Initialization of weights

Step 1: Weights are initialized to small random values between 0 to1.

Step 2: While stopping condition is false, steps 3-10 are repeated.

Step 3: For each training pair steps 4-9 are performed.

Feedforward

Step 4: Each input node receives the input signal x_i and transmits that to all nodes in the layer above, i.e. to the hidden units.

Step 5: Each hidden unit (z_j, j=1,…..,p) sums the weighted input signals.

$$z_{in} = V_{oj} + \sum_{i=1}^{n} (x_i \cdot V_{ij}) \quad (3.1)$$

Applying the activation function

$$Z_j = f(z_{in_j}) \quad (3.2)$$

And this signal is sent to all the units in the layer above, i.e. to outputunits.

Step 6: Each output unit (y_k, k=1,….., m) sums its weighted inputsignals.

$$y_{in_k} = W_{ok} + \sum_{j=1}^{p} (z_j W_{jk}) \quad (3.3)$$

And activation function is applied to calculate the output signals.

$$Y_k = f(y_{in_k}) \quad (3.4)$$

Back Propagation of errors

Step 7: Each output unit (y_k, k=1,….., m) receives a target pattern corresponding to an input pattern. Error information term is calculated asfollows

$$\Delta_k = (t_k - y_k) f^1(y_{in_k}) \quad (3.5)$$

Where $f^1(y_{in_k}) = f(y_{in_k})(1 - f(y_{in_k}))$ (3.6)

Step 8: Each hidden unit (z_j, j=1,…..,p) sums its delta inputs from units in the layer above.

$$\delta_{in_j} = \sum_{k=1}^{m} (\delta_j W_{jk}) \quad (3.7)$$

The error term is calculated as

$$\delta j = \delta inj f1\,(zin_j) \quad (3.8)$$

Where $f1\,(zin_j) = (zin_j)(1 - f(zin_j))$ (3.9)

Updation of weight and biases

Step 9: Each output unit (y_k, k=1,….., m) updates its bias and weights (j=0,……..,p) The weight correction term is givenby

$\Delta W_{jk} = n\delta_k z_j$ (3.10)And the bias correction term is givenby

$\Delta W_{ok} = n\delta_k$ (3.11)

Therefore

$W_{jk}(new) = W_{jk}(old) + \Delta W_{jk} + m[W_{jk}(old) - W_{jk}(old-1)]$ (3.12) And $W_{ok}(new) = W_{ok}(old) + \Delta W_{ok}$ (3.13)

Each hidden unit (z_j, j=1,…..,p) updates its bias and weight(i=0,….,n) The weight correction terms $\Delta V_{ij} = n\delta_j x_i$ (3.14)

And the bias correction term is

$\Delta V_{oj} = n\delta_j$ (3.15)Therefore

$V_{ij}(new) = V_{ij}(old) + \Delta V_{ij} + m[V_{ij}(old) - V_{ij}(old-1)]$ (3.16) And

$V_{oj}(new) = V_o(old) + \Delta V_{oj}$ (3.17)

Step 10: The stopping condition is checked (minimization of the errors).

4. RESULTS AND PERFORMANCE OF ANN

Simulation Parameter using MATLAB Software:

PARAMETER USED	VALUE
Input Nodes	9
Hidden Layer	16
Output Node	9
Learning Rate	0.2
Momentum Factor	0.9
Training Model	Least mean square error
ANN algorithm used	Back Propagation algorithm

The ANN is trained and tested for each level decompose detail coefficients i.e. for high frequency and low frequency constituents. The performance of ANN by varying the hidden layer nodes, learning rate and momentum factor are given in terms of mean square error in Table 4.1, Table 4.2 and table 4.3 respectively. The weights of the ANN after training using each level detail coefficient data are given for each level. The test results of the ANN using different detail levels are given in Fig. 4.1 and Fig. 4.2 for star-star and delta-star transformer respectively.

Performance of ANN using d1 level data for star-startransformer

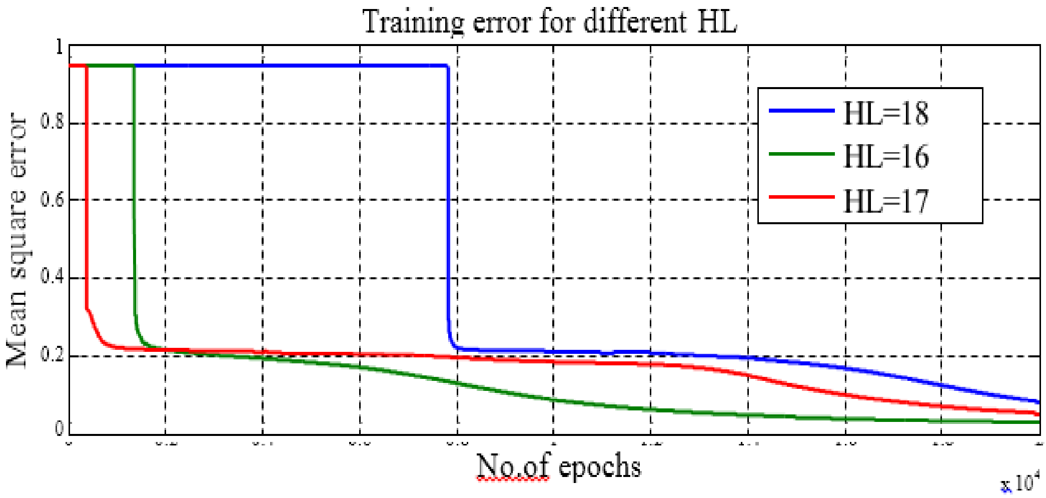

Fig. 5.1 Performance of ANN for different hidden layers.

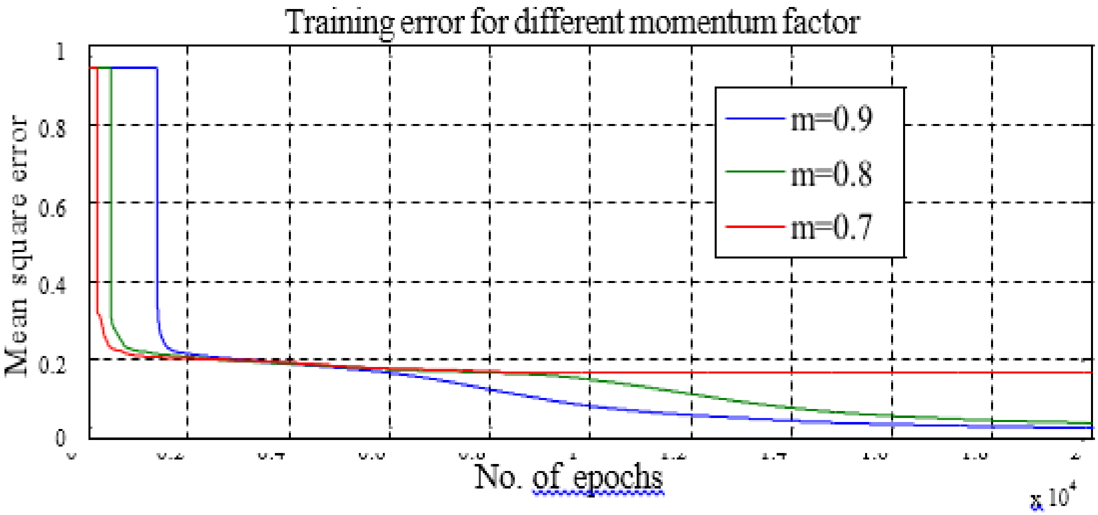

Fig. 5.3 Performance of ANN for different momentum factor

Table: 4.1 Comparison of errors during training of ANN for different hidden layers

No. ofHL	Mean square error during training after 20000iterations
15	0.1677
16	**0.0288**
17	0.0522
18	0.0795

Table: 4.2 Comparison of errors during training of ANN for different learning rates

Learning rate(n)	Mean square error during training after 20000iterations
0.1	0.1304
0.2	**0.0288**
0.4	0.1669
0.6	0.1668
0.8	0.1667

Table: 4.3 Comparison of errors during training of ANN for different momentum factor

Momentum factor(m)	Mean square error during training after 20000iterations
0.7	0.1671
0.8	0.0377
0.9	**0.0288**

The architecture of the ANN having one hidden layer, 16 nodes in hidden layer, 9 nodes in input layer and 9 nodes in output layer is the best out of all the tested architecture as the mean square error in this type is least during training. The learning rate suitable for that network having least error is 0.2 and the momentum factor 0.9 in the same network gives the least error.

CONCLUSION AND FUTURE SCOPE

The current signals for different cases for a power transformerare obtained using MATLAB/SIMULINK. These waveforms are analyzed for extraction of feature vector (containing statistical data) to train the ANN. The performance of trained ANN is tested successfully for the classification of various cases. From the study and analysis carried out in this paper, the performance of neural networks has been found to surpass the performance of conventional methods, which need accurate sensing devices, costly equipment and an expert operator orengineer. The classification ability of the ANN in combination with advanced signal processing technique opens the door for smart relays for power transformer protection with very less operating time and with desirableaccuracy.

FUTURESCOPES

- Prototype modelling based on ANN for protection ofpower transformer.
- Online testing of thealgorithm.
- Comparison of ANN with other classifier like support vectormachine (SVM).
- Application of S transform in combination with ANN for transformer protection

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