IMPLEMENTATION OF ANN BASED TECHNIQUE FOR TRANSFORMER PROTECTION

A DISSERTATION

Submitted in partial fulfillment of the requirements for the award of the degree

of

MASTER OF TECHNOLOGY

in

ELECTRICAL ENGINEERING

(With Specialization in Instrumentation and Signal Processing)

By

VIPIN PRATAP

DEPARTMENT OF ELECTRICAL ENGINEERING
INDIAN INSTITUTE OF TECHNOLOGY ROORKEE
ROORKEE - 247 667 (INDIA)

JUNE, 2013

No.- MT/251/RPM/MT/2013.

INDIAN INSTITUTE OF TECHNOLOGY ROORKEE
ROORKEE

CANDIDATE'S DECLARATION

I hereby declare that the work presented in this dissertation entitled **"IMPLEMENTATION OF ANN BASED TECHNIQUE FOR TRANSFORMER PROTECTION"** submitted in partial fulfilment of the requirement for the award of the degree of **Master of Technology** with specialization in **Instrumentation and Signal Processing,** in the **Department of Electrical Engineering, Indian Institute of Technology Roorkee, Roorkee** is an authentic record of my own work carried out from July 2012 to June 2013 under the guidance and supervision of **Dr. R. P. Maheshwari** and **Dr. Manoj Tripathy**, Department of Electrical Engineering, Indian Institute of Technology Roorkee, Roorkee.

I have not submitted the matter embodied in this report for the award of any other degree of this or any other institute.

Date: 17/6/2013

Place: Roorkee

VIPIN PRATAP

CERTIFICATE

This is to certify that the above statement made by the candidate is true to the best of my knowledge and belief.

Dr. R. P. Maheshwari

Professor

Department of Electrical Engineering

Indian Institute of Technology Roorkee

Roorkee-247667, Uttrakhand

India

Dr. Manoj Tripathy

Assistant Professor

Department of Electrical Engineering

Indian Institute of Technology Roorkee

Roorkee-247667, Uttrakhand,

India

ACKNOWLEDGEMENT

I wish to express my deep sense of gratitude and sincere thanks to my beloved guides **Prof. R. P. Maheshwari** and **Dr. Manoj Tripathy**, Department of Electrical Engineering, IIT Roorkee, for being helpful and a great source of inspiration. Their keen interest and constant encouragement gave me the confidence to complete my work. I wish to extend my sincere thanks for his excellent guidance and suggestion for the successful completion of my work.

My sincere thanks to the Head, Electrical Engineering department, I.I.T. Roorkee for providing necessary research facilities to carry out this work and valuable suggestions and motivations provided by other faculty members of the department are duly acknowledged. I also wish to thank supporting staff of Instrumentation & Signal Processing lab for all necessary help provided by them.

It is difficult for me to express my gratitude to my parents for their affection and encouragement. Last but not the least; I am indebted to all my classmates from Instrumentation and Signal Processing group for taking interest in discussing my problems and encouraging me.

VIPIN PRATAP
(11528025)
M.TECH (I &SP)

ABSTRACT

Transformer are cardinal part of power system and costly device it is responsible for the persistence of the supply any discrepancy on transformer can led to the power failure thus it need to be well protected from all types of faults.

Mostly differential protection is employed for the protection of the transformer because it provides the overall protection of transformer from all types of internal fault .Discrimination between inrush and internal fault is always a tedious task for the protection of transformer as modern transformer protection failed by conventional harmonic based thresholding techniques therefore new intelligent methods are proposed now a days for the protection of Transformer.

Earlier techniques where based on the threshold and these techniques where harmonic restraint methods comparing different harmonic ratios, now these techniques not applicable because due to the modern core transformer with high permeability and low coercion core material.

For the detection of internal fault this dissertation proposed the algorithm consist of the two techniques of the artificial neural network i.e., radial basis function and back propagation compare with the support vector machine .We have classified internal fault from the other four conditions of the transformer .The dataset required for simulation is formed by the simulation done on the PSCAD with the real time simulation data available from the Jabalpur electricity board in which we perform the simulation for active and reactive power in all the above conditions of the transformer.

Contents

List of Figures

List of Tables

Abbreviations

SVM	Support Vector Machine
BPNN	Back Propagation Neural Network
RBFNN	Radial Basis Function Neural Network
TDP	Transformer Differential Protection
LM	Levenberg Marquardt
GD	Gradient Decent
NN	Neural Network
ANN	Artificial Neural Network
HR	Harmonic Restraint
WI	Waveform Identification Technique
AI	Artificial Intelligence
PSCAD	Power System Computer Aided Design
EMTDC	Electromagnetic Transients in DC
CT	Current transformer
CB	Circuit Breaker

Chapter 1

Introduction

1.1 Introduction

Transformer is the static device used to transfer energy from primary side to secondary side .It mainly used to increased or decreased the voltage levels .Transformer is important device because it need at all the ends of power system i.e. transmission distribution and generation ends, it step up the voltage to overcome the losses at generating station and step down to meet the industrial demands at the transmission to feed the high end consumers and again step down to safety limits for the household used at distribution end.

Therefore it needs to protect the transformer from faults that occur inside or outside the transformer protection zone.

Now a day with use of electronic devices the mechanical actuators and relays are replaced by the electronic circuits .Numeric and digital relays are example these are popular because they have faster response time, cheaper and light weight.

1.2 Objective of present work

Differential protection is uses for the transformer more than 10MVA .It has been widely used and most effective technique for protection of power transformer.

The present work objective is to protect transformer from all types of the internal fault and external disturbances and to improve the transformer protection over the conventional techniques.

In inrush 2nd harmonic is more prominent in nature but for modern core material are designed such that to reduce the 2nd harmonic currents thus the methods which were based in the ratio of the 2nd to fundamental or 3rd harmonic to fundamental those methods had failed to protect transformer.

The conventional harmonic restraint method failed because the high 2nd harmonic may be generated during internal fault and low 2nd harmonic during the inrush.

The objective is to make algorithm which can overcome the conventional problems of harmonics and sustain the healthy and normal conditions of transformereffectively the method should work as to detect any changes in the conditions of the transformer.The main aim is to protect transformer from internal fault in fast time and effectively, whiles maintaining relay stability at inrush and other conditions.

1.3 Differential protection of the Transformer

It has been most popular and widely used technique for the protection of transformer from internal fault. In this method difference of current from both primary and secondary are fed to the relay if there is no fault the magnitude of the current from CT secondary side will be same and zero current will pass through the relay hence no fault has occurred if there is fault magnitude differed and relay will operate.

$$I_d = I_1 - I_2 \qquad \text{....... (1.1)}$$

Where i_d is the differential current, and i_1 and i_2 are the current on primary and secondary side of the transformer

$$I_r = \frac{I_1 + I_2}{2} \qquad \text{....... (1.2)}$$

i_r is the restraining current

$$I_d \geq I_r + I_p.\%slope \qquad \text{....... (1.3)}$$

i_p is the no load current

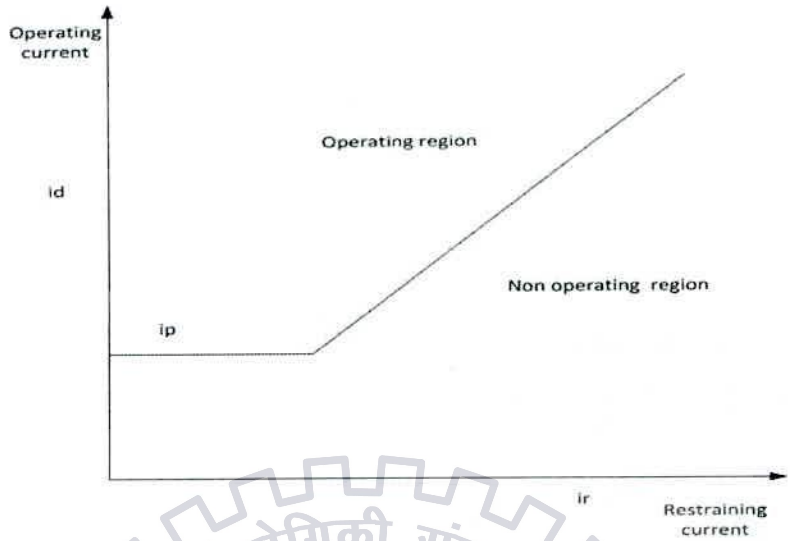


Fig 1.1: Depicting the differential protection of the transformer

1.4 Literature survey

H. K. Verma G. C. Kakoti *et al* .shows a paper which represent the fault discrimination on the basis of thresholding values above the threshold indicate a inrush/overexcitation condition calling for a restraint and a value below the threshold shall confirm an internal fault requiring an immediate circuit-breaker tripping [1].

H. K. Verma and A. M. Basha *et al.* presented microprocessor-based differential relay restraining on inrush, over-excitation and heavy external faults has been successfully developed for power transformer protection. The paper overcome failure of existing second-harmonic restraint differential relays [2].

R. K. Bansal, B. K. Joshi, S. P. Singh and R. N. *et al.* Bandopadhaya. Successfully implemented a microprocessor based differential protection with inrush restraint and fault. They succeed in getting a trip signal as the fault occurs. However, under switching inrush current condition an indicating signal, rather than a tripping output is sent. The whole execution of the protection algorithm takes place in less than1666 us [3]

H. K. Verma A. M. Basha e*t al.* suggested a method in which inrush is detected by checking for a prolonged zero current, an unusual apparent half time period and a difference in the amplitude of successive peaks. The same checks are utilized in the relay to yield a blocking signal on severe through faults since the current waveforms for this condition are similar to those for inrush. [4].

J.C. Yeh, a C.E. Lin, a C.L. Huang, a C.L. e*t al.* Cheng b in these paper harmonic analysis of inrush current from an energy viewpoint has been carried out[5].

A. M. Shah, B. R. Bhalja e*t al.* developed new SVM-based differential protection Scheme which effectively differentiates internal faults with other type of disturbances in a power transformer in which wavelet transform is used to extract the features [6].

Tsair-Fwu Lee, Ming-Yuan Cho, and Fu-Min Fang e*t al.* Uses particle swarm optimization (PSO) algorithm to improve the performances of Artificial Neural Network (ANN) and Support Vector Machine (SVM) to get better classification accuracy and faster operation [7].

M. Tripathy, R. P. Maheshwari, and H. K. Verma, e*t al.* It makes use of ratio of voltage to frequency and amplitude of differential current for the determination of operating conditions of the transformer [8].

S. Ala, M. Tripathy, and a K. Singh e*t al.* In the proposed method, space vector analysis of the differential signal and their time characteristic shapes in park's plane is used as a core classifier to discriminate between magnetizing inrush and internal fault of a power transformer [9].

M. Tripathy, R.P. Maheshwari and H.K. Verma et *al.* proposed a novel technique to distinguish between magnetising inrush and internal fault condition of a power transformer based on the difference in the current wave shape is developed. A comparison of performance between RBPNN and heteroscedastic-type probabilistic neural network (PNN) has been showed [10].

Manoj Tripathy, Rudra Prakash Maheshwari, and H. K. Verma *et al.* proposed a core classifier to discriminate between the magnetizing inrush and the internal fault of a power transformer. The particle swarm optimization is used to obtain an optimal smoothing factor of PNN which is a crucial parameter for PNN [11].

Manoj Tripathy *et al.* proposed analgorithm, which utilized the Neural Network Principal Component Analysis (NNPCA) and Radial Basis Function Neural Network (RBFNN) as a classifier [12].

Z. Moravej , D.N. Vishwakarma, S.P. Singh *et al.* shows a classifier by use of (feed forward back propagation) FFBP and RBFN (radial basis function network) and discuss the drawbacks of FFBP and shown the advantages of RBFN over FFBP.They discussed drawback of FFBP technique that they are time consuming and problems of over fitting, no exact rule for selecting neurons [13].

1.5 Organization of Dissertation

Chapter 1 is the overview for the transformer differential protection; it shows the issues regarding the transformer protection and the methods to find the solution. Literature survey has been presents with some new latest papers literature review discussed the demerits of the harmonic based techniques and shows the advantages of the new waveform identification techniques such as ANN based methods BPNN, RBFNN, RBPNN, and SVM for efficient transformer protection.

Chapter 2 is the modeling and simulation of different operating conditions of the transformer in which differential model for active and reactive power has been drawn and simulation on performed on them to get the waveform for active and reactive power and thus the differential current.

Chapter 3 is the ANN based technique for transformer protection in this chapter BPNN and RBFNN has been used to classify between inrush and the fault samples and also multiples operating conditions of transformer using multiple class classification. BPNN and RBFNN architecture, implementation, results have been discussed and shown.

Chapter 4 is the SVM based technique for transformer protection in this chapter SVM architecture, designing, parameter selection, choosing best parameters for highest accuracy have been shown. Training and testing with different transformer ratings, multiple class classification and network optimization has been performed and implemented.

Chapter 5 is the comparison of the results of the SVM and ANN based methods merits and demerits and advantages of one over another have been described. Comparison shown among the accuracy, training time and error in the output level.

Chapter 6 we presented our conclusions from the results presented in this dissertation and discussed scope of future research work.

Chapter 2

TRANSFORMER MODELING AND SIMULATION

2.1 Introduction

For the analysis of the transformer Simulation of the different operating conditions of the transformer was done on the software package called PSCAD/EMTDC™ .The Power System Computer Aided Design i.e. PSCAD is simulation software developed by Manitoba HVDC Research Center [14].

PSCAD is the tool which provides us to make transformer design as per the requirements and simulates it on virtual environment and the results obtained from the transducers at the substation which provides us the current and the voltage waveforms but recording signals is not that easy, hence we use PSCAD for getting signals from the transformers and this can be utilized to further analysis and studies. The complier which it uses is the EMTP (electromagnetic transient program) it represents the various power system components [15, 16].

As we knew practical transformer situation are far different from what we realized hence it is not possible to get data from or recording data from transformer in all the cases hence we utilized PSCAD .The best thing using pscad is that we can generate worst conditions that occur on the transformer which may not be possible practically

The main idea behind that is to simulate normal and faulty conditions of the transformer on the PSCAD and then record those signals, interface it with MATLAB to analyses those conditions to build an algorithm for transformer protection

In order to perform simulation we need a transformer data which was obtained from the Madhya Pradesh electricity board Jabalpur and XianElectric Corporation, china [17].

The data specifications are 315MVA 400/220 KV transformer and others were and 150 & 180 MVA transformer

There are five operating conditions of the transformer

2.2 Normal operating condition

In this condition rated or less current flow through the transformer, average value of the differential current is zero, for this conditions the current phasors are equally displaced from each other at an angle of 120^0 i.e. current are in balanced conditions .thus relay should not operate in this condition. Fig 2.1-2.4 showing the model for normal condition and different waveform for powers and current.

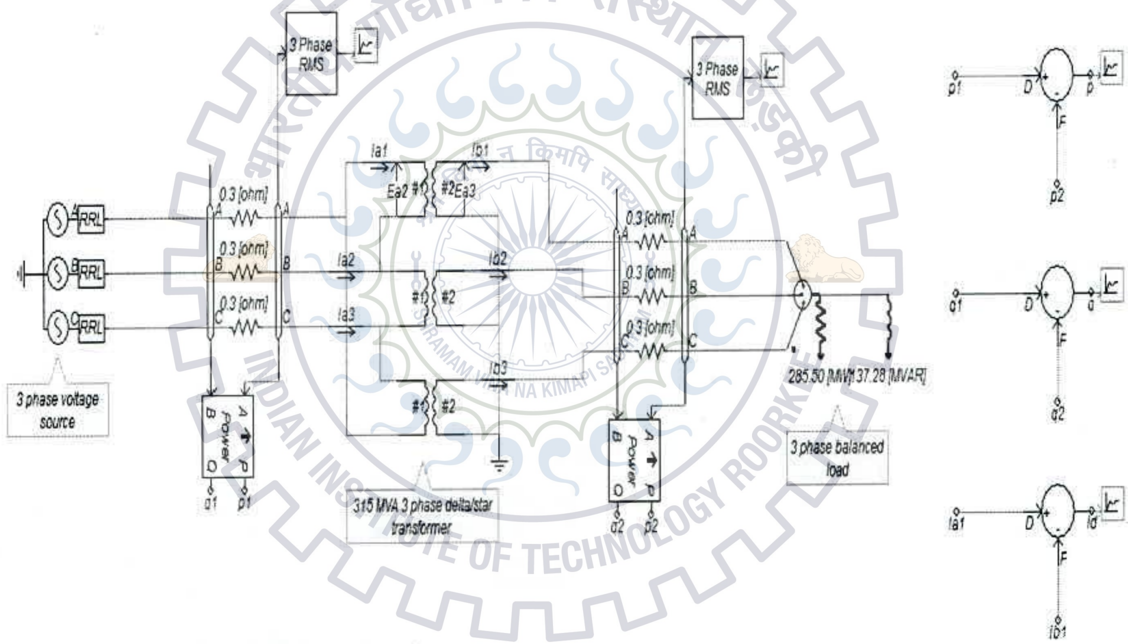


Fig 2.1: Simulation diagram of differential power model for normal condition of transformer

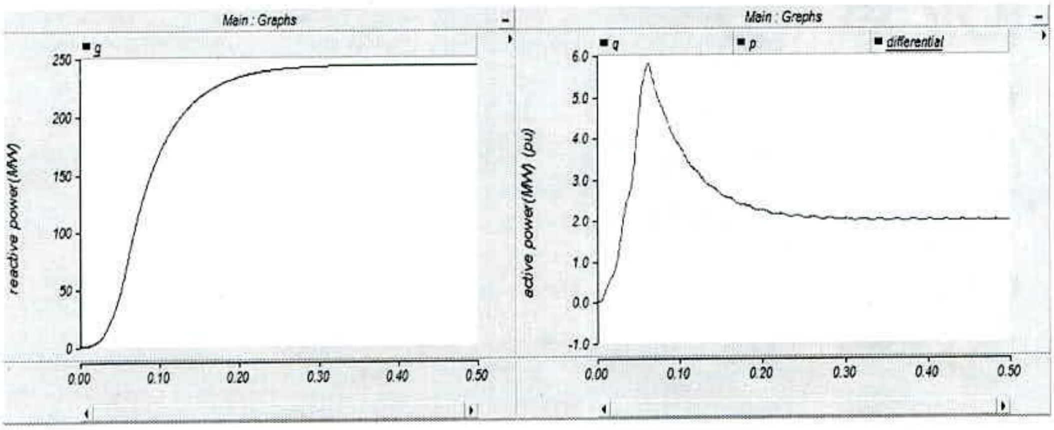


Fig 2.2: Differential reactive/active power waveform of normal condition.

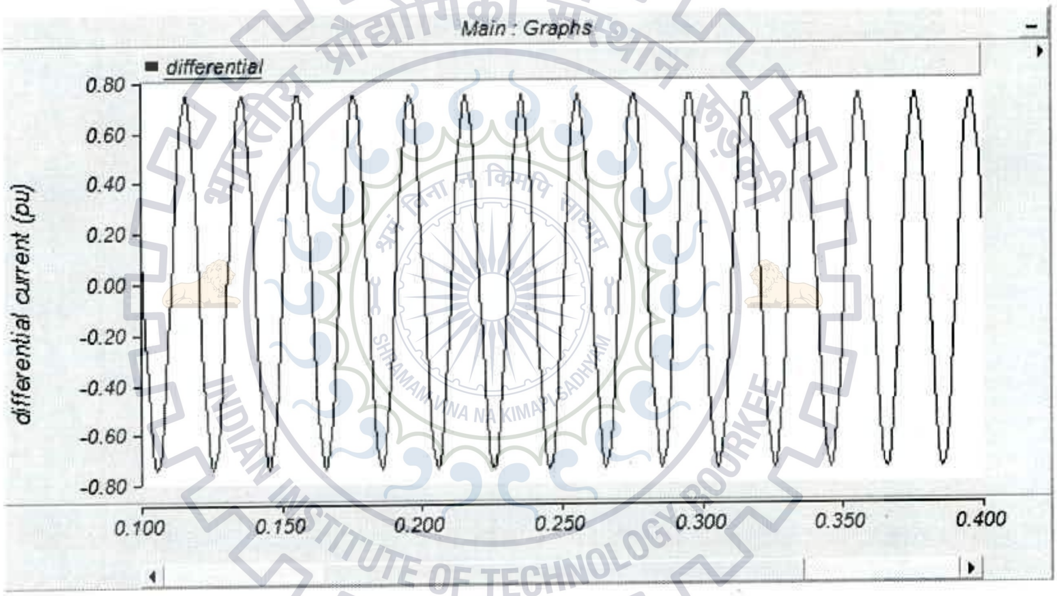


Fig 2.3: Differential current waveform of normal condition of power transformer

2.3 Magnetising inrush current

In this condition whenever transformer is energies from the fault recovery or at the time of commissioning, very high current flows in the primary winding that current is inrush current.

Inrush current flows at the time of switching of the transformer due to the residual magnetism present in the core of the transformer, due to the remanence flux, at no load, transformer core at the time has not been completely magnetized hence it requires a large current to magnetized the core thus it goes to the saturation region .Inrush current can be as large as 5-10 times the normal rated currentand flows for a 8-10 cycle.

Sympathetic inrush current exist when a transformer placed in already energised transformer in parallel then the inrush current flows in the previously energised transformer. When the transformer is energised by closing CB inrush produces which has a dc component the DC component can also saturate already energised transformer resulting in an sympathetic inrushsympathetic inrush flows due to closed path with low impedance between the two transformers.

2.3.1 Factors affecting the Magnetising inrush current

1. Increasing the source resistance can bring the peaks of the inrush current to a lower value.
2. Increasing the Switching angle at which transformer has been switched on, the peaks of the inrush current decreases.
3. Inrush decay time constant or L/R ratio can affects the magnitude of inrush current.
4. Remanence flux present in the core of the transformer can lead to saturated the core can cause high very large current to flows through transformer primary winding.

At first when transformer is not energised it is not completely demagnetized some amount of residual flux present in the core this may range from 50-80% of the max normal flux required by the transformer .The flux required to completely magnetized the core is twice the max flux required by the transformer and hence if there is already some retentivity /residual magnetism present it will add up to as $2\emptyset_m+\emptyset_r$ this lead to transformer in saturation and hence current required will be very large as soon as transformer gets magnetized.Inrush current will slowly die out and,magnetization demagnetized due to decreasing current will not affect the inrush current. fig 2.4-2.6 depicting the model and the inrush current of the power transformer

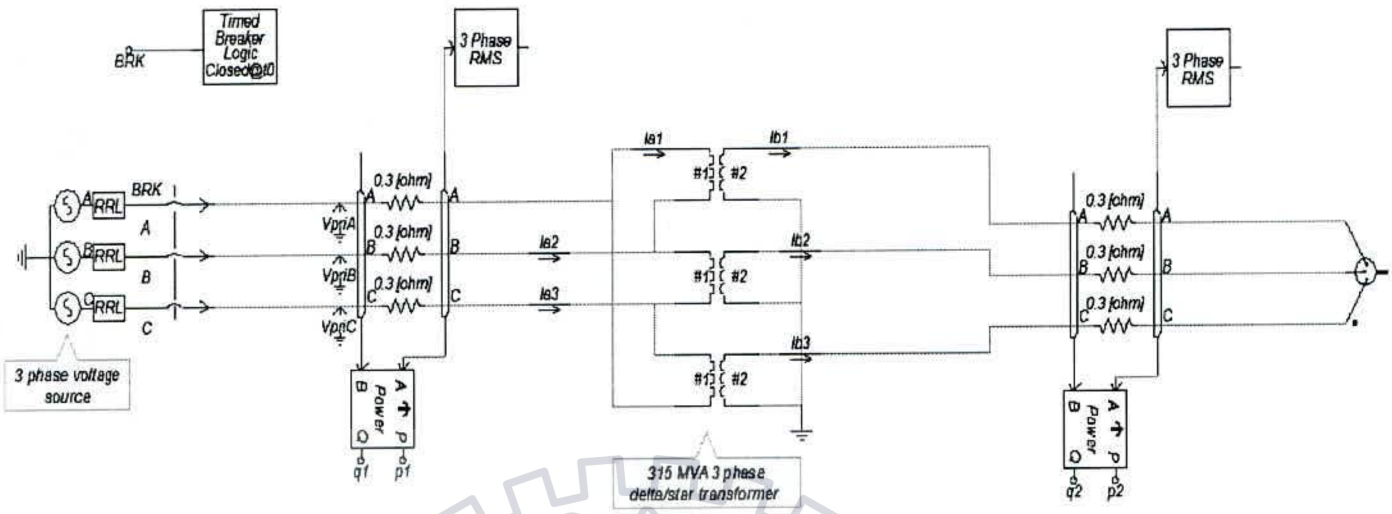


Fig 2.4: Simulation diagram of differential power model for inrush current of transformer

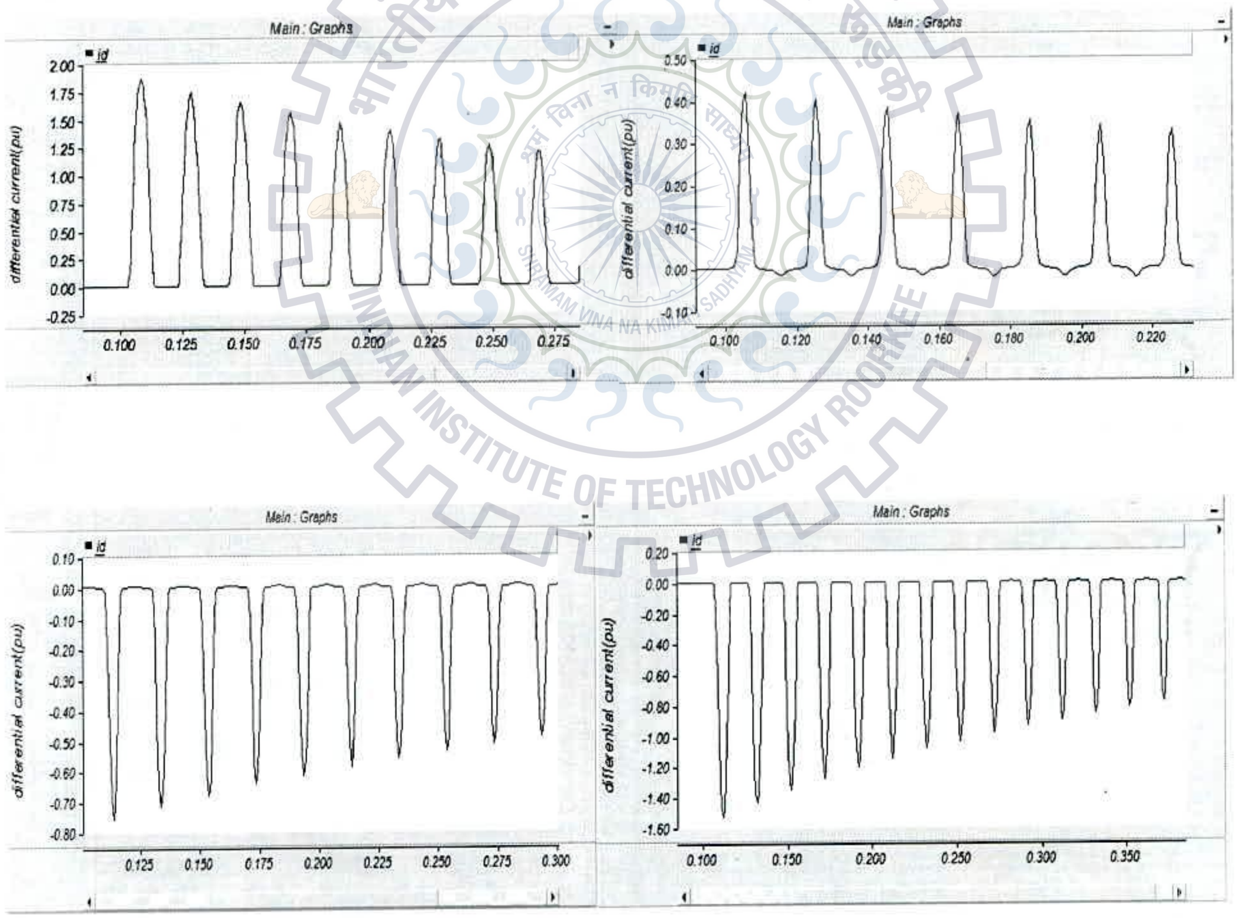


Fig 2.5: Differential current waveform under inrush condition at switching 0, 60, 90, 120, degree

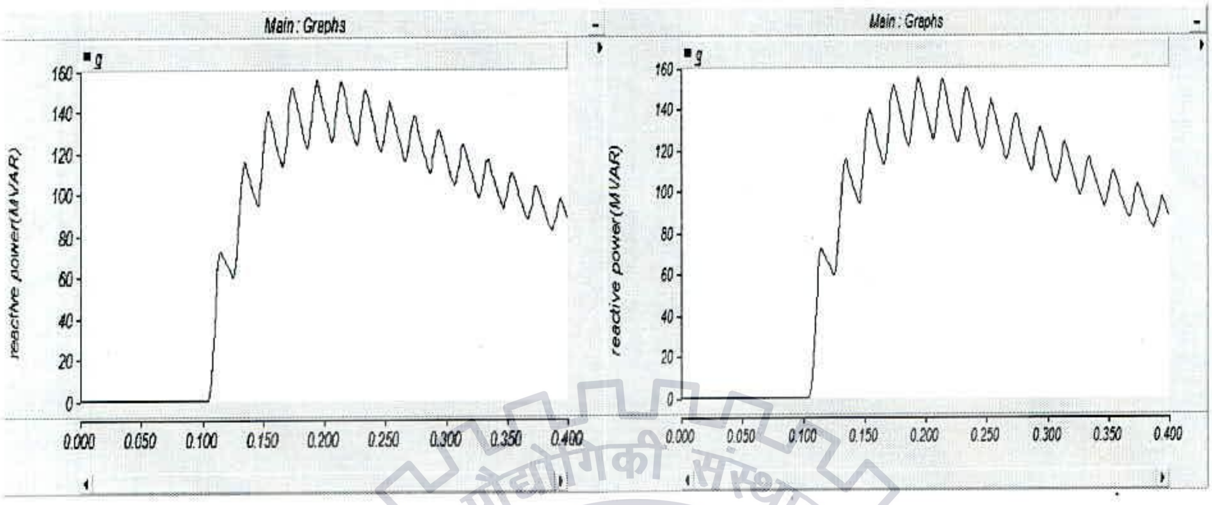


Fig 2.6: Differential reactive power waveform under inrush condition at switching 90,180

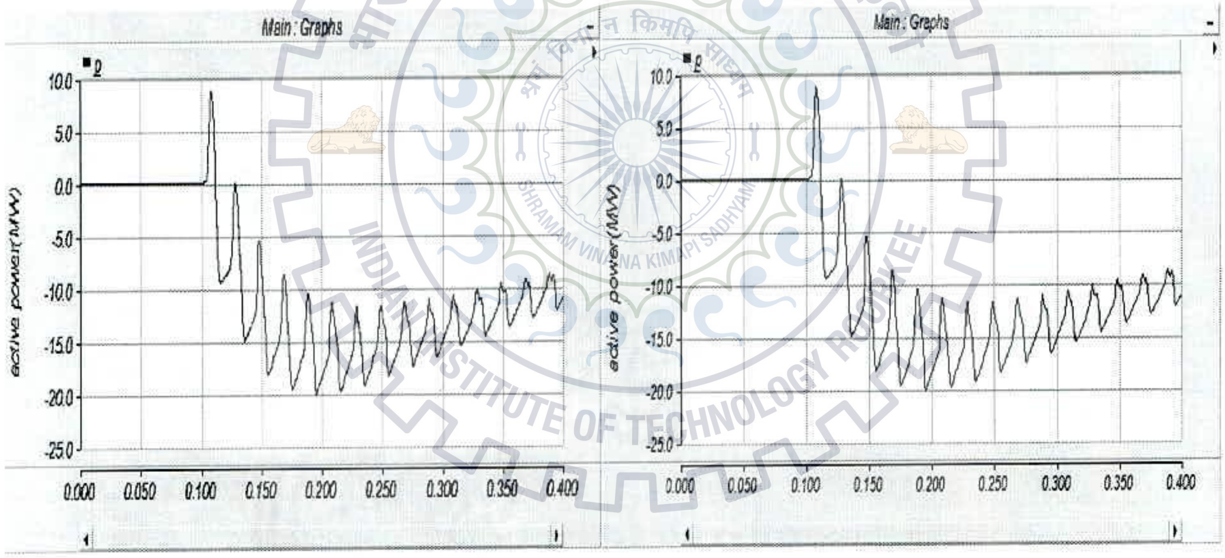


Fig 2.7: Differential active power waveform under inrush condition at switching 90,180

2.4 Overexcitation condition

Itcan occur when the transformer is lightly loaded and line capacitance are more prevailing that can result in increased voltage on the transformer. As we know that Transformer operates at the slightly lower than the saturation to achieve the max flux density required, a little change in the flux can push to the transformer in saturation, thus as flux is proportional to the voltage/frequency ratio any increase in v/f ratio will increase in flux.This condition occurs when the rated V/F ratio exceeds 1.1.

$$B=\mu_0 H \qquad \text{....... (2.1)}$$

B = is the flux density, μ_0=relative permeability of the transformer core, H =magnetic field intensity

$$\emptyset=B.A \qquad \text{....... (2.2)}$$

Ø=flux measured, A=area of the transformer core

$$E=4.44f\emptyset N \qquad \text{....... (2.3)}$$

E=EMF induced in the winding of the transformer,F=supply frequency, N= no of the turns in the winding

Hence certain conditions are to be maintained to restrict overexcitation

1. Applied voltage should not exceed the rated voltage by more than 110%
2. The frequency should not be lower than 95% of the rated frequency

Distortion occurs in the waveform that represents the harmonics present in the waveform as overexcitation condition is rich in third harmonics. This can cause the heating inside the transformer and large exciting current to distinguish this case it can be done by two ways

1. Measuring third harmonic to fundamental ratio
2. By checking more than one peaks in half cycle of the of the differential current waveform
3. By over fluxing relays which measure the rated voltage to frequency ratio.

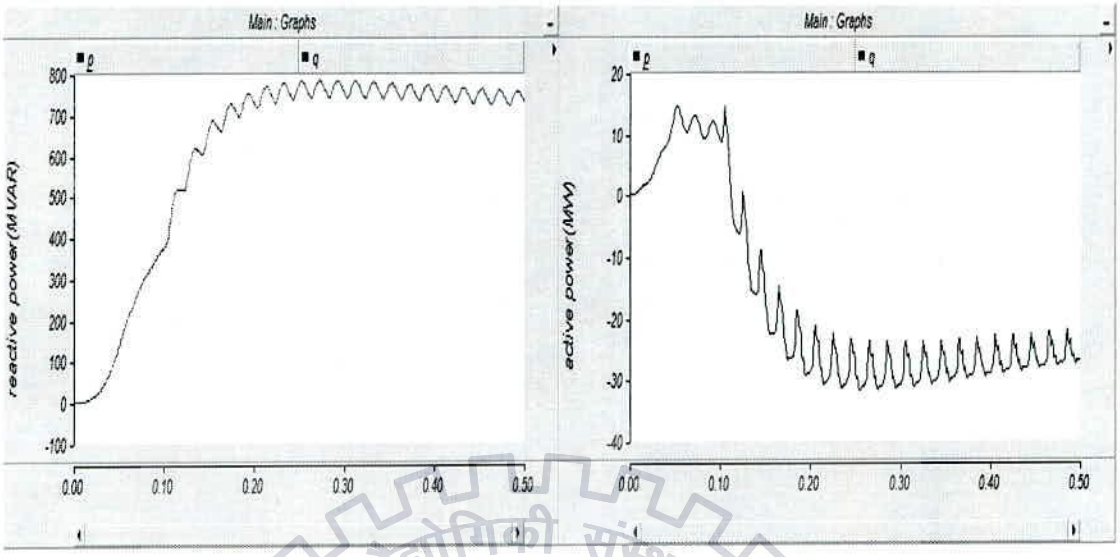


Fig 2.8: Differential reactive/active power waveform under overexcitation condition at 470KV (1.175pu)

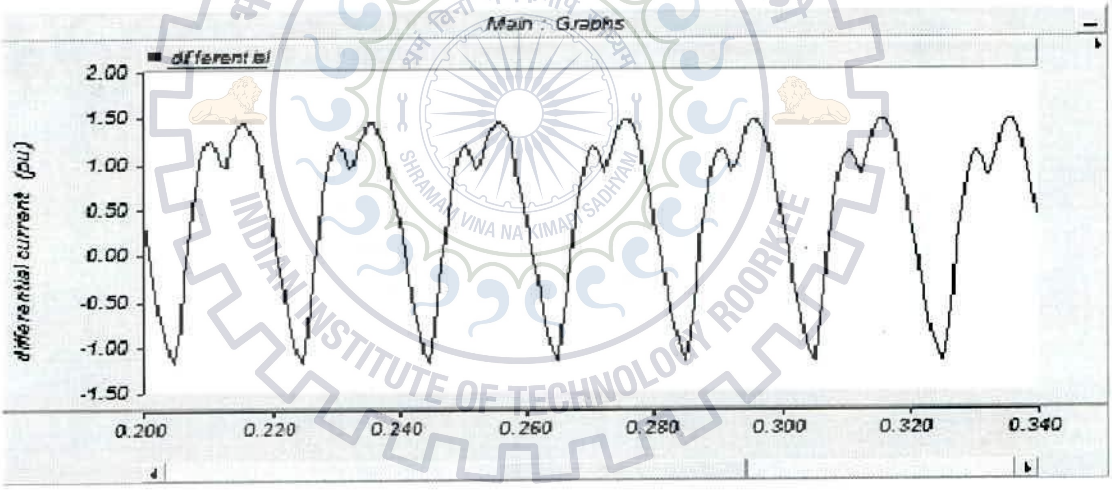


Fig 2.9: Differential current waveform under overexcitation condition at 580KV (1.45pu)

2.5 External fault condition

The fault which occursbeyond the protected zone is called the external fault, like fault occur in the bus bar short-circuits on the transmission lines are examples of external fault. The overvoltage on the transformer can cause the external fault.

For this type of fault case the differential current relay should not operate because in this case different current is still look alike same as the normal current. We need require to not tripping the transformer in this condition.

There are four types of external fault

1. Line to ground fault
2. Line to line fault
3. Double line to ground fault
4. Three phase fault

2.6 Internal fault condition

The fault which occurs inside the transformer is called internal fault this may be faults in the windings due to overheating and insulation breakdown. These types of fault are most severe they can cause huge damage to transformer and disturb the continuity of power supply. Hence differential relay must be operate for these types of faults and tripping is mandatory in case of internal fault.

2.6.1 Types of Internal fault

1. **Phase to phase fault** –The fault which occur from one of the winding to other is called Phase to phase fault

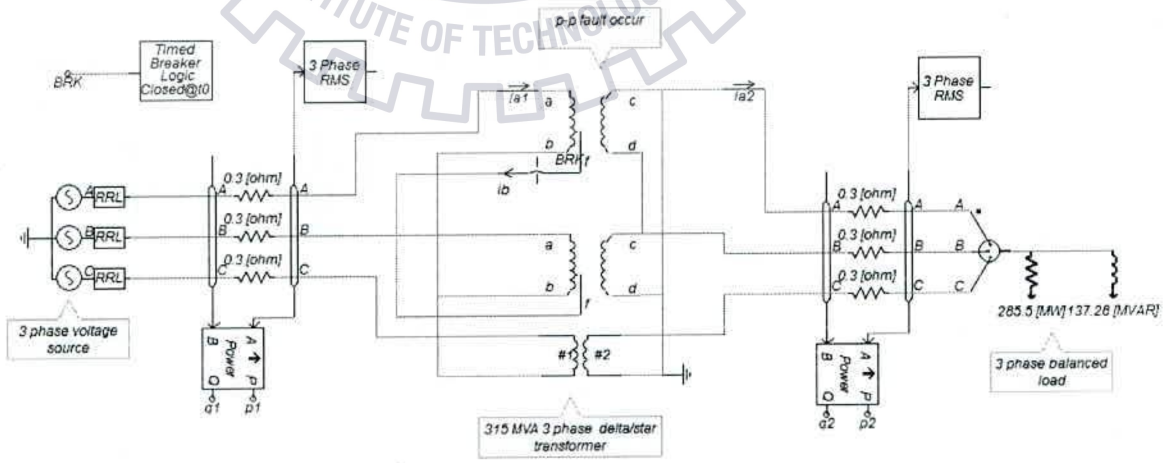


Fig 2.10: Simulation diagram of differential power model for Phase to phase fault of transformer

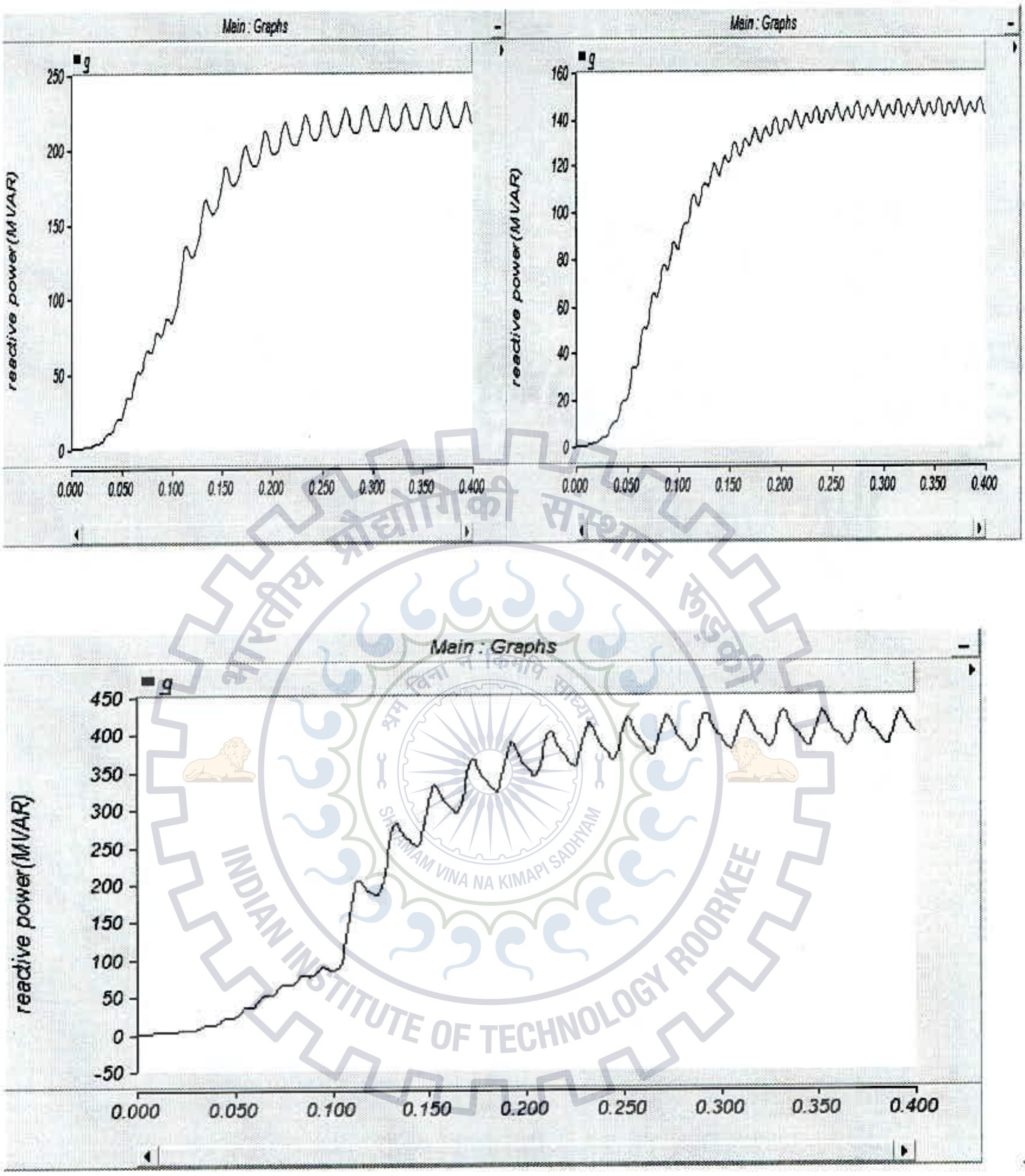


Fig 2.11: Differential l reactive power waveform under phase to phase fault condition at 90%, 98%, 75% fault location

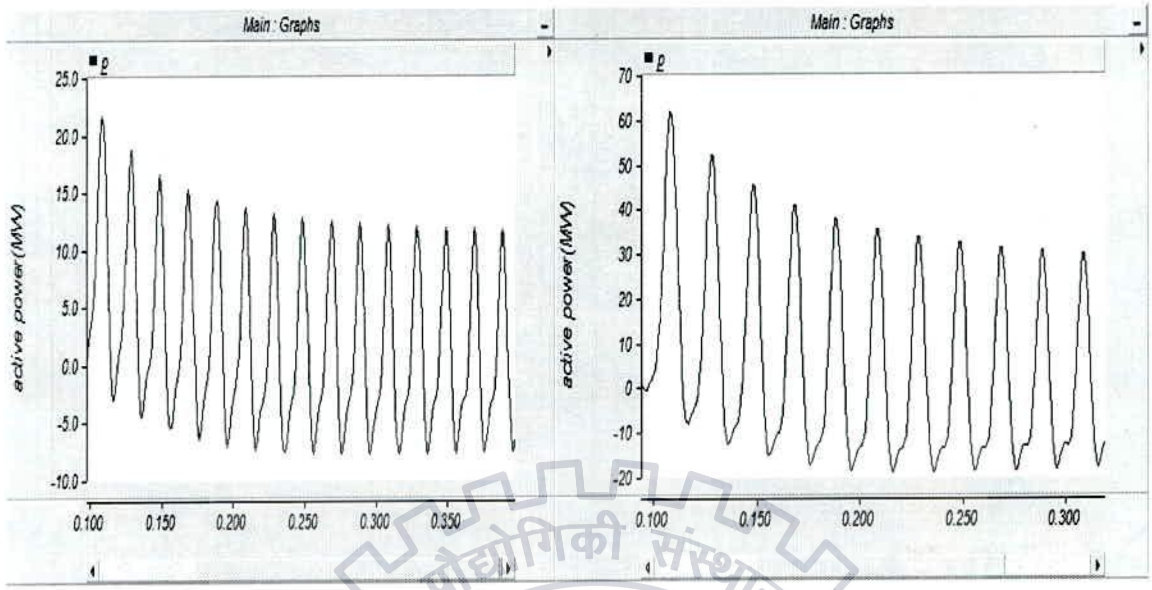


Fig 2.12: Differential active power waveform under phase to phase fault condition at 90%, 75% fault location

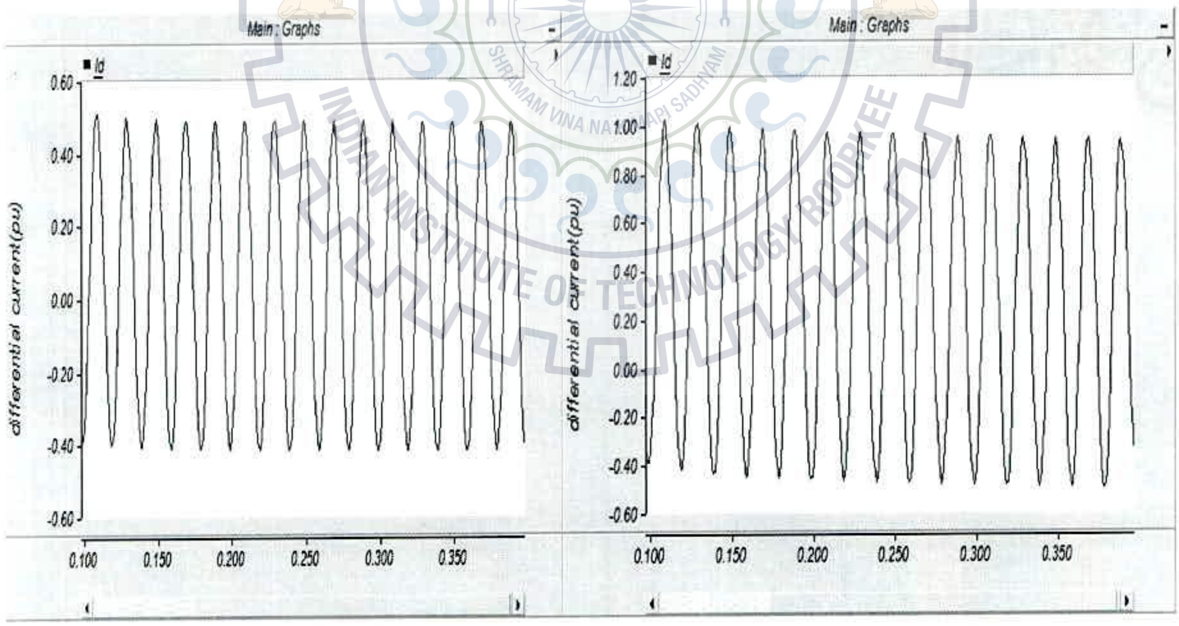


Fig 2.13: Differential current waveform under phase to phase fault condition at 98%, 90 fault locations

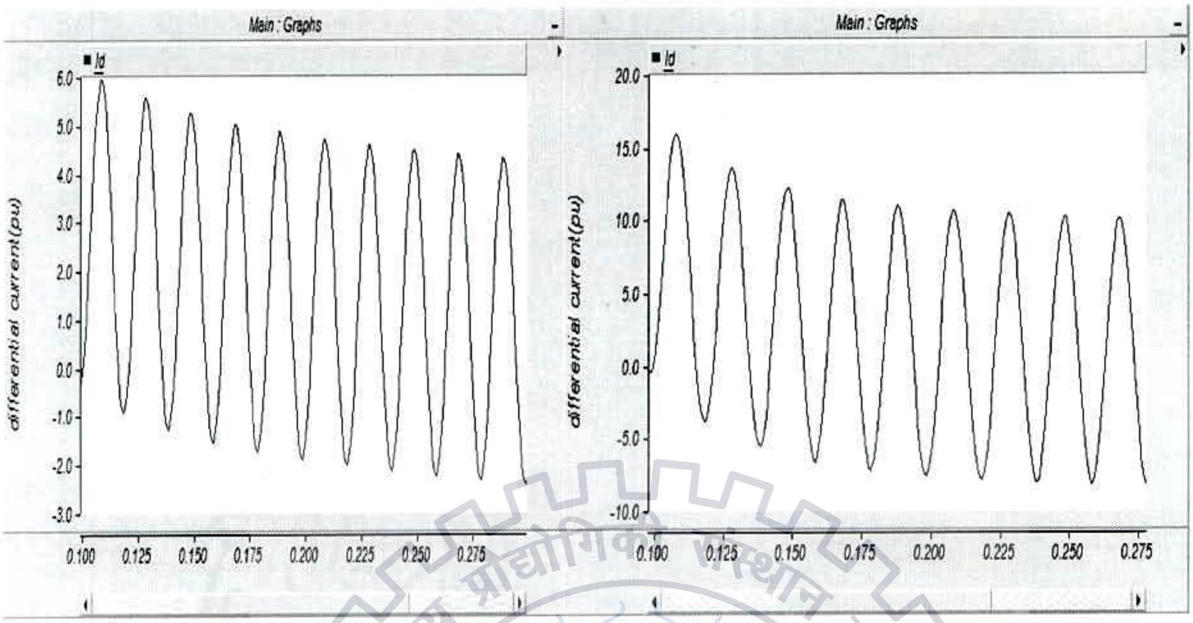


Fig 2.14: Differential current waveform under phase to phase fault condition at 75%, 25% fault location

2. **Phase to ground fault**-The fault which occur from one of the winding to ground is called Phase to ground fault.

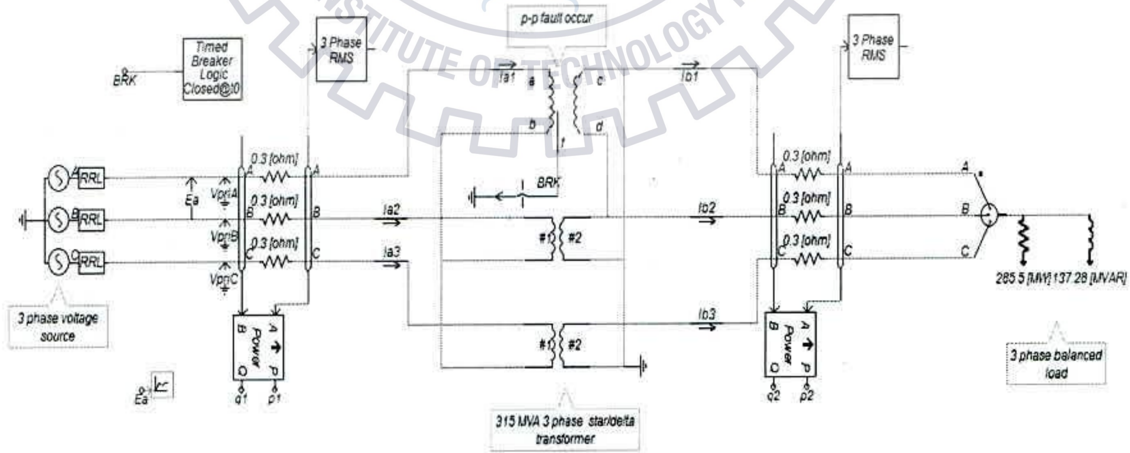


Fig 2.15: Simulation diagram of differential power model for Phase to ground fault of transformer

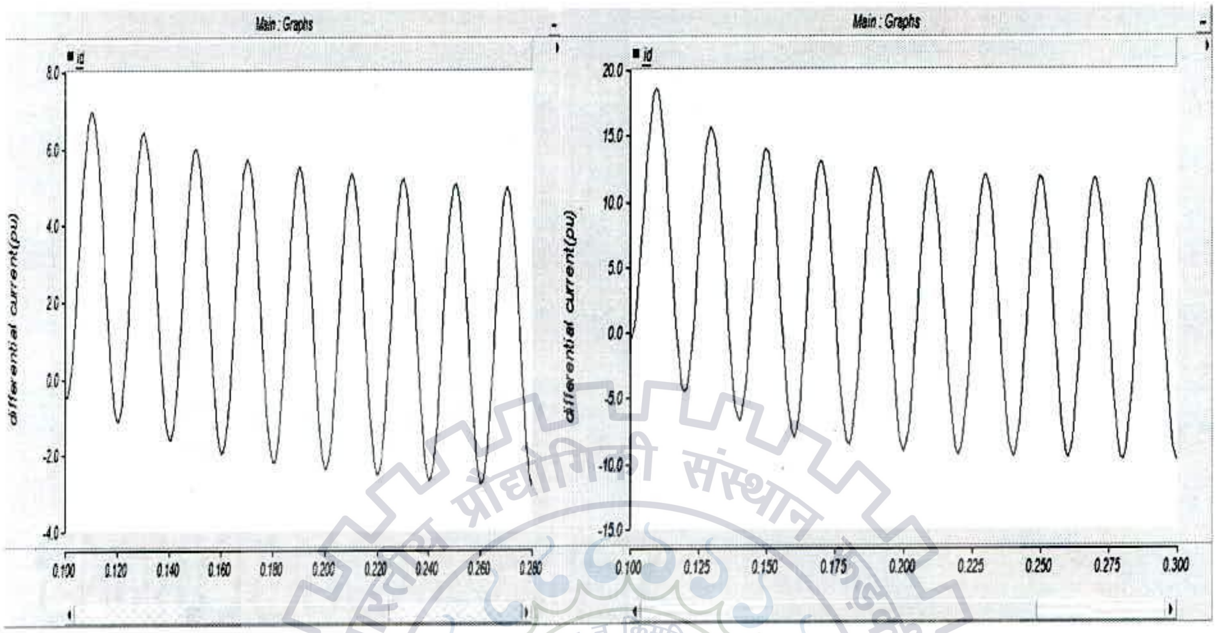
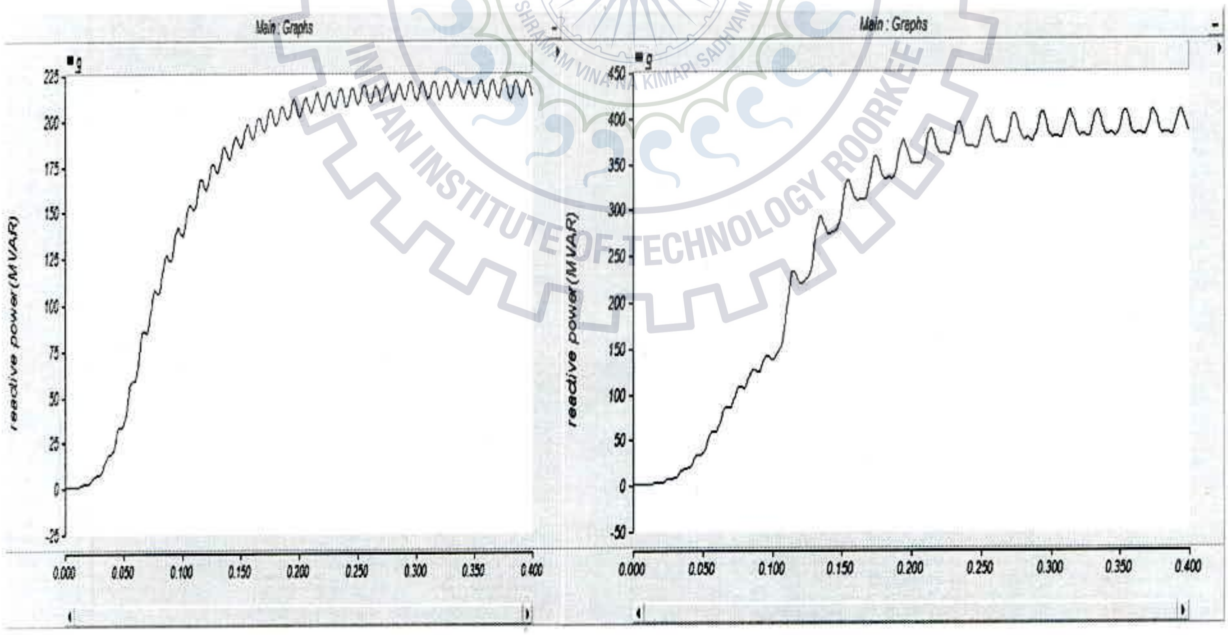


Fig 2.16: Differential current waveform under phase to ground fault condition at 50%, 25%fault location



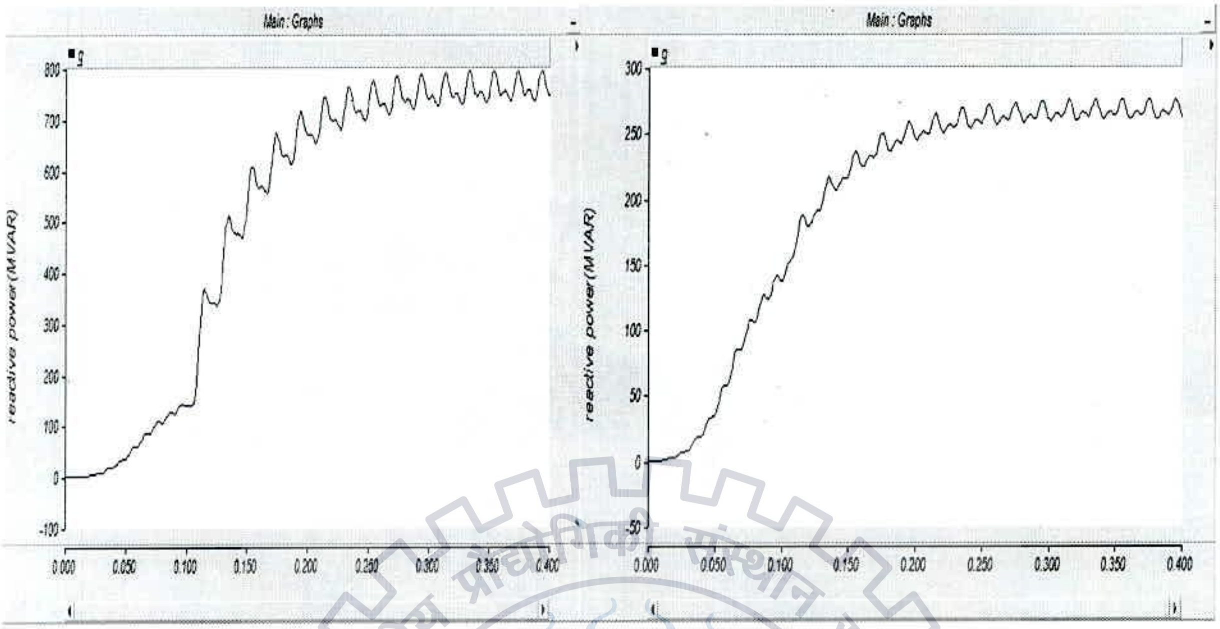


Fig 2.17: Differential reactive power waveform under phase to ground fault condition at 98%, 75%, 50%, 90 fault locations

3. **Interturn fault (turn to turn fault)**- the fault which occur in between the turns of the winding is called Interturn fault

2.7 Conclusion

Internal faults are very severe and dangerous there is always risk of fire it can damage the whole transformer and can cause instability to the system hence we need to concern about this fault and differential current relay should operate for this type of fault.

Chapter 3

ANN BASED METHODS FOR TRANSFOMER PROTECTION

3.1 Introduction

Harmonic restraint technique failed to protect the transformer because of the harmonic methods based on the threshold and that may vary from one transformer of one rating to another transformer of different rating hence it is not generalized [18,19].

This method failed due to modern power transformer which has high permeable and low reluctance core material that mostly decreases the amount of 3rd and 5th harmonic currents.

Hence literature says that waveform identification technique is most effective way to protect transformer may utilizing the intelligent methods like back propagation (BPNN), radial basis function neural network(RBFNN),support vector machine (SVM) for classifying different conditions including both fault and healthy cases [20,21].

3.2 BPNN (Back propagation neural network)

3.2.1 Introduction

Back propagation is multilayer feed forward network given by mcculloch and pitts. It consist of input layer, hidden layer and a output layer .fig 3.1 showing the architecture of BPNN .The no of input samples are the no of input layer whereas hidden layer is decided by empirically measuring the error at the time of training according to the data .Output layer consist of 1 neuron as we need to classify only between internal and inrush condition i.e. binary output, hence one neuron is sufficient to take that decision.

The function logsig generates outputs between 0 and 1 we also require to detect between inrush and fault case between 0 and 1and hence, the Output layer is taken as purelin linear layer because to give output between 0 and 1.Hidden layer has the tansign activation function and output layer has purelin as activation function. It contains more than one hidden layer.

3.2.2 BPNN architecture

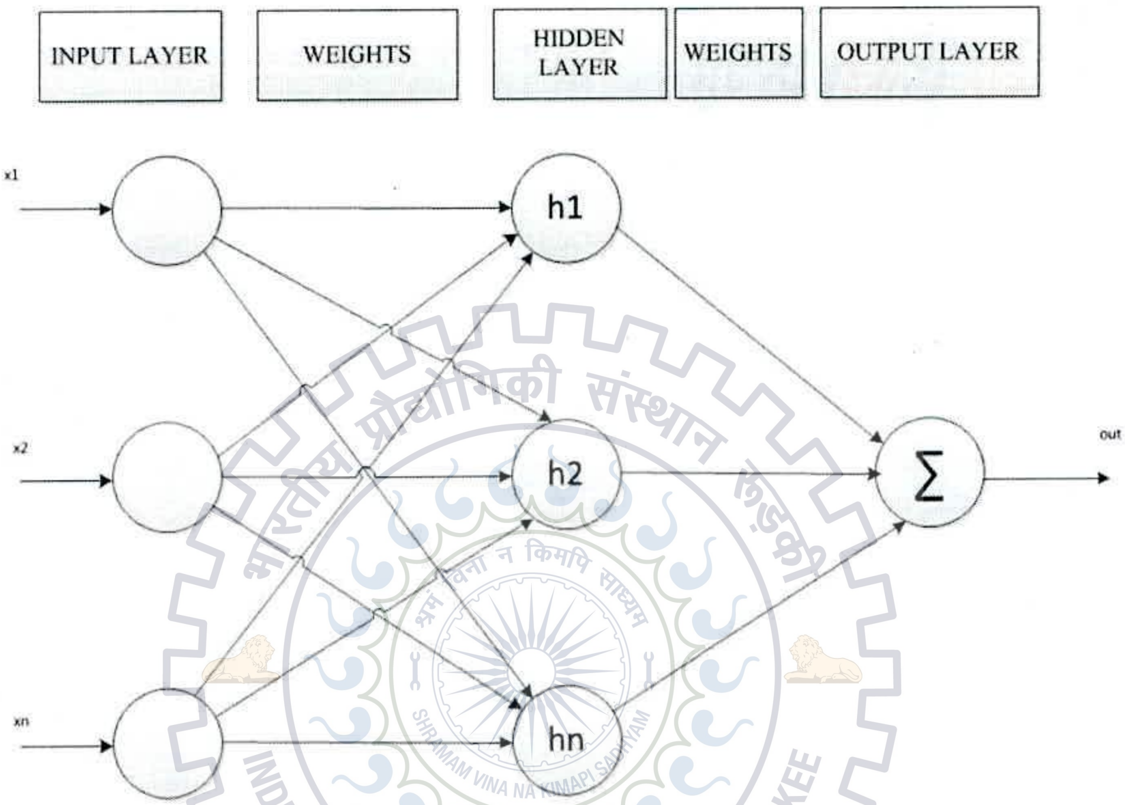


Fig 3.1: Back Propagation Neural Network Architecture

Training and testing

Before training a feed forward network, you must initialize the weights and biases. Weights are initialized by rand (twister) command or can be done by init.

input layer are the input samples values that is given to the BPNN network hidden layer neurons are decide by checking in which case the error is minimum (empirically by trial and error method) hence the convergence of the training will be faster and with higher accuracy

It trained by forward backward method the weights are updated by forwarding and then backward it again updates itself for the error minimization.The output layer consist of only 1 neuron because we need to get only two conditions to satisfy at the output i.e. inrush current and the internal fault current

The training algorithm used is levenberg marquart because it has the low error values and has faster convergence than any other method used

Hence $\frac{25ms}{800\mu s} = 25samples/cycle$

Training process for BPNN

1. Initialization of weights with randomly selecting initial values
2. Calculate the output for all input sampled valued
3. Calculate the mean squared error (MSE) and sum squared error (SSE), stop if MSE is below the desired values
4. Follow the loop till it reaches the MSE goal return to step 2 till the goal reaches or up to the, maximum iteration completed

$$err = \frac{1}{2}\left[\sum_{p=1}^{n}(d_{out} - out)^2\right] \qquad \ldots\ldots\ldots(3.1)$$

In eqn (3.2) err= the squared error, d_{out}= target output, *out*= actual output of the output neuron

Therefore the error, *err*, depends on the output. However, the output depends on the weighted sum of all its input:

$$out = f(\sum_{p=1}^{n} w_p i_p)$$

.... (3.2)

i= the number of input units to the neuron, w= weight the ith neuron, nonlinear sigmoid activation function, above relation in eqn (3.2) shows that is the output is purely the weighted sum of the input.

First for the training purpose we need to form the training, matrices i.e. input matrix or the target matrix. Then from this data to make input matrix we form the Hilbert matrix from the data available from PSCAD. Input matrix represent the one cycle the sampled values whereas target defines the desired output corresponding to that row of the input matrix

$$\begin{bmatrix} i_1 & i_2 & . & i_{25} \\ i_2 & i_3 & . & i_{26} \\ . & & & \\ . & & & \\ i_{50} & . & . & i_{75} \end{bmatrix} \begin{bmatrix} w_1 \\ w_2 \\ . \\ . \\ w_{50} \end{bmatrix} \begin{bmatrix} t_1 \\ t_2 \\ . \\ . \\ t_{50} \end{bmatrix} \qquad \text{.......... (3.3)}$$

In the same way we make the input matrix for the both the cases for internal fault and for the inrush case until all the elements up to 3cycles have been used.This way we form the matrix for one of the case of inrush and internal fault current. For thetraining purpose we need to make as much patterns for the testing of the transformer

The complete training matrix contains both inrush and internal fault case. The complete input matrix will consist of 1040 patterns and corresponding 1040 targets values given to the input matrix in which 540 patterns are for inrush and remaining are for fault case

These includes patterns for in inrush sympathetic, inrush at no load with different switching conditions and with remanant flux and fault includes phase to phase and phase to ground fault at different fault location.

The training matrices was built in such a way that BPNN was trained to give output as '0' For inrush and '1' for internal fault case

3.2.3 The Training Algorithm for ANN

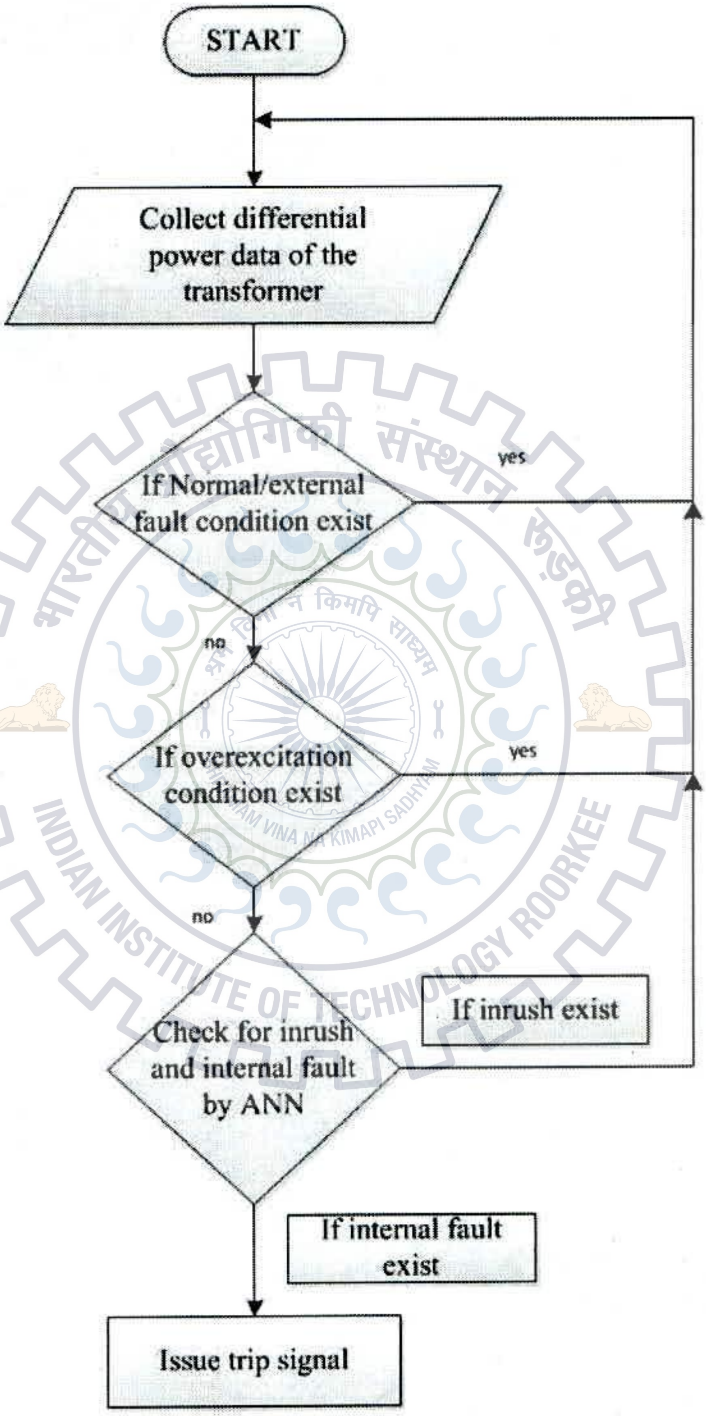


Fig 3.2: Flow chart of ANN based algorithm

Out of the five operating conditions of the transformer the normal and external fault were differentiate by comparing the peak to peak values for the two cycles and also by comparing sampled values for each cycle.Overexcitation condition can be distinguish by measuring voltage to frequency ration v/f these can be done by over fluxing relays and by comparing 3^{rd} harmonic content to the fundamental ratio.

The main problem comes in discriminating the internal fault and inrush case these two are classified by BPNN using ANN technique

These two conditions properties come same in case of light internal fault and inrush. Internal fault for less than 2% of the shorted windingand those of inrush both respond the same hence it's difficult to discriminate between the two hence we used ANN for successfully classified and initiate a trip signal in case of internal fault occur on the system.

When the internal fault is classified properly we need to initiate a trip signal by opening the CB to protect the transformer from further damage.

During the testing of the BPNN the if the output come as $y \geq 0.5$ it will take as '1'and if less than $y<0.5$ it will take as '0'.hence '1'is recognized as fault '0' as inrush.Training algorithm chosen is LM method because of fastest convergence and memory reduction features,Gradient decent (GD) method is also popular but it is slower[22-25]

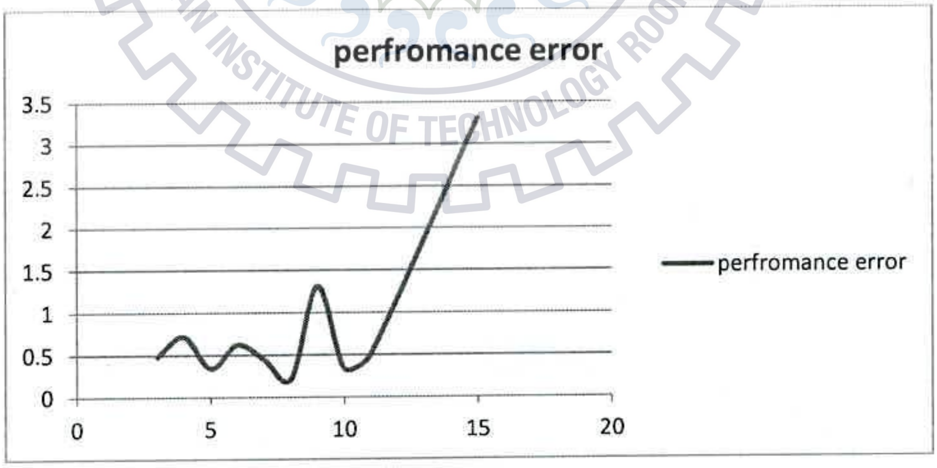


Fig 3.3: Showing the error value at different hidden layer neurons

Table 3.1: fault classification accuracy in case of BPPN taking different parameters

Different cases in which transformer tested	Active power 25 samples	25s/c (50 input neurons)	25 s/c (850 features)	25s/c (1400 features)
Fault Classification accuracy	91.667	96.1538	98.360	**99.33**

$$Classification\ accuracy = \frac{true\_positives + true\_negative}{length\_of\_the\_testmatrix}$$

$$Classification\ error = \frac{false\_positives + false\_negative}{length\_of\_the\_testmatrix}$$

3.3 RBFNN (Radial basis function neural network)

3.3.1 Introduction

RBFNN has the Gaussian based function it consist of an input layer ,one hidden layer and one output layer hidden layer of radial basis uses kernel as the activation function[13]

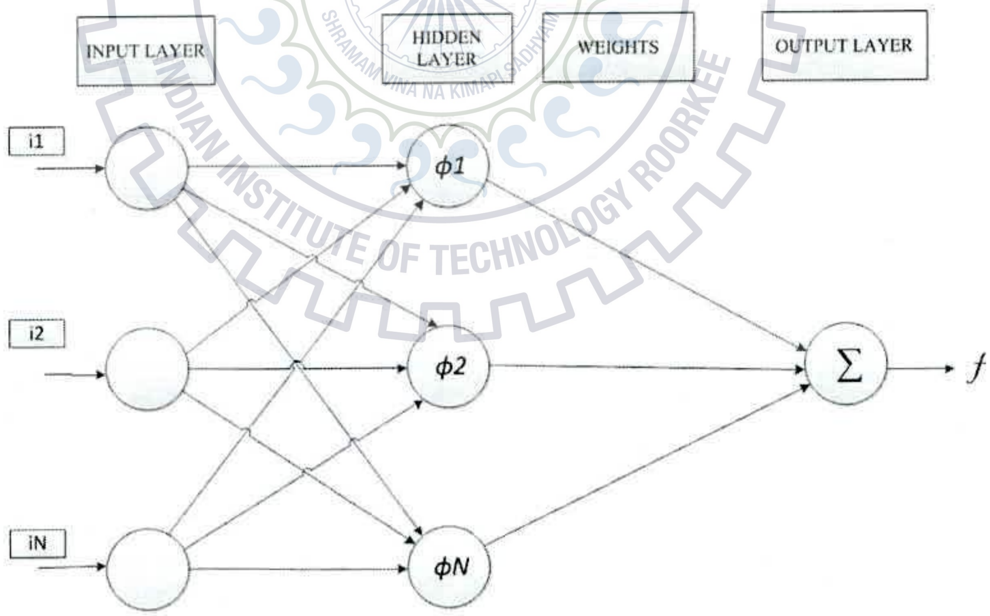


Fig 3.4: Back Propagation Neural Network Architecture

Training and implementation

The connected between the hidden layer and output consist of weights, as it was not in BPNN.

$$\phi_i = \exp\left(-\frac{1}{2}\sum_{i=1}^{n}\left[\frac{x_i - c_i}{\sigma_{ji}}\right]\right)^2 \qquad \text{................(3.4)}$$

In equation 3.4, x is the input variables and c is center and σ is the phase width

Performance in RBFNN

1. Centers are selected to minimize the total distance between data and centers(LOCATION of centers are determined by the clustering technique)
2. Width factor
3. Activation function at hidden layer

   Determining weights between the hidden and output layer (Weights can be determined by the pseudo inverse method)

   Width factor can be determined by fixed center method

   $$\sigma = \frac{D_{\max}}{\sqrt{2.\zeta}}$$

   $D_{\max}$ = max distance between the centers

   ζ =no of centers

Training is very time consuming it takes if the goal is smaller it takes more time to get completed as its displays results, MSE at every iteration it take more time [25-30].

Comparison and results

Table 3.2: showing effect of phase width on classification accuracy taking 15 sample/cycle (15 input neurons)

Spread width	15 sample/cycle (15 input neurons)	
	Performance goal (MSE) 1×10^{-5}	Performance goal (MSE)1×10^{-8}
25	80.55%	80.55
50	**99.44%**	87.10

Table 3.3: showing effect of phase width on classification accuracy taking 25 sample/cycle (50 input neurons)

Spread width	25 sample/cycle (50 input neurons)	
	Performance goal (MSE) 1×10^{-5}	Performance goal (MSE)1×10^{-8}
50	95.2%	**98%**
75	78.14%	86.8
100	73.4%	83.6
200	61.6%	76.4

Table 3.4: showing effect of phase width on classification accuracy taking 25 sample/cycle (15 input neurons

Spread width	25 sample/cycle (15 input neurons)	
	Performance goal (MSE) 1×10^{-5}	Performance goal (MSE)1×10^{-8}
150	72.667	98%
175	98	86.8
185	94	83.6
195	**98.667**	76.4

Table 3.5: showing effect of phase width on classification accuracy taking 25 sample/cycle (25 input neurons)

Spread width	25 sample/cycle (25 input neurons)	
	Performance goal (MSE) 1×10^{-5}	Performance goal (MSE)1×10^{-8}
100	73.6	77.2
150	82.2	85.2
175	86.8	88.8
185	79.2	84.2
200	85.2	87.8

In RBFNN with 15 input neurons max no of neurons taken as 1000 Number of neurons to add between displays is taken as 25 as shown below with total 510 training patterns and 150 testing patterns

Phase spread is taken as 195 performance goal is taken as 0.00001

Percentage Correct classification: 98.666667%

NEWRB, neurons = 0, MSE = 0.207612

NEWRB, neurons = 100, MSE = 0.000312267

NEWRB, neurons = 200, MSE = 5.19491e-005

NEWRB, neurons = 250, MSE = 1.18033e-005

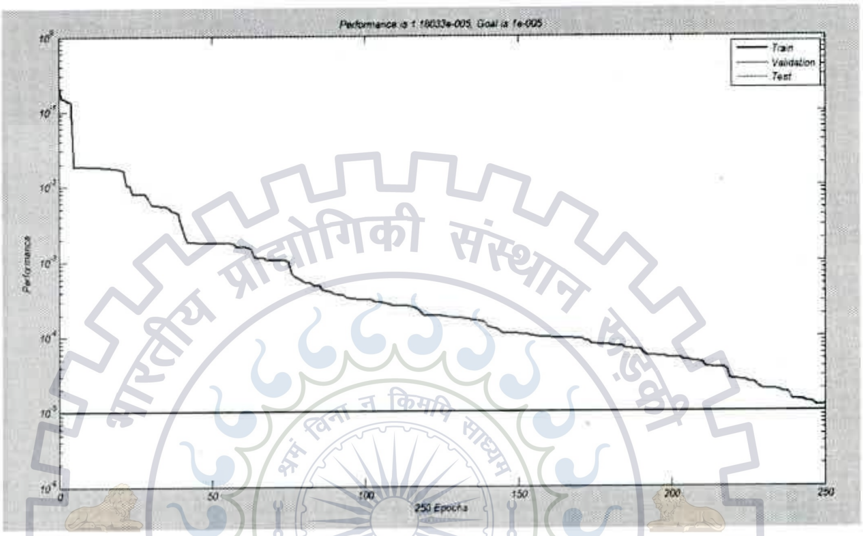


Fig 3.5: showing performance goal (MSE) in comparison no of epochs

In RBFNN with 50 input neurons max no of neurons taken as 1000 Number of neurons to add between displays is taken as 100 as shown below with total 850 training patterns and 250 testing patterns in which 100 patterns where of inrush and 150 patterns where od internal fault

Phase spread is taken as 50 performance goal is taken as 0.00001
Percentage Correct classification: 95.200000%
NEWRB, neurons = 0, MSE = 0.207612

NEWRB, neurons = 100, MSE = 0.095658, NEWRB, neurons = 200, MSE = 0.0190256

NEWRB, neurons = 300, MSE = 0.00174887, NEWRB, neurons = 600, MSE = 2.21108e-005

As the no of neurons are larger it takes larger time for training

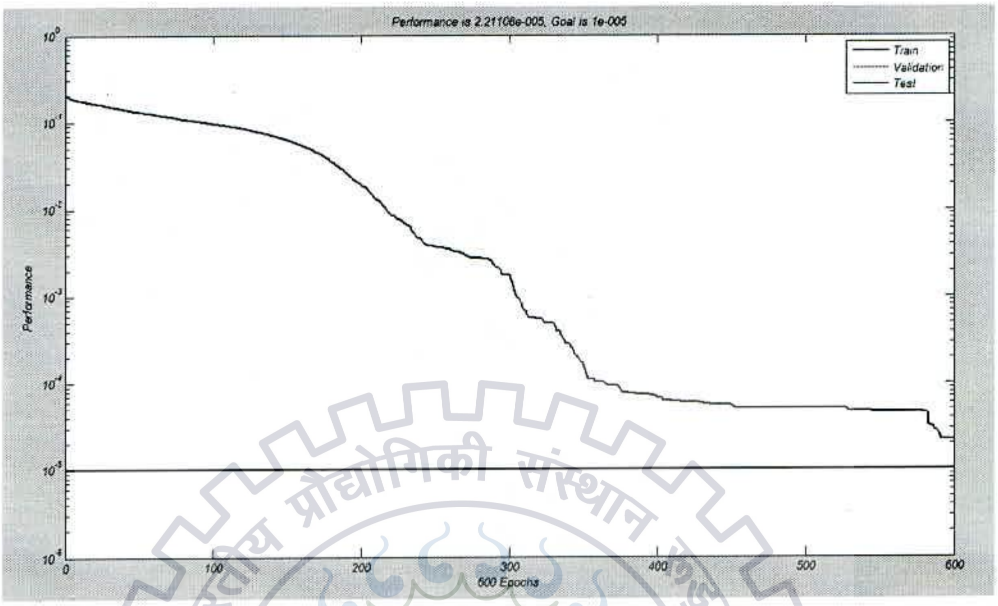


Fig 3.6: Showing performance goal (MSE) in comparison with no of epochs

3.4 Conclusion

In this chapter, algorithm based on discrimination of inrush and internal fault have been presented in BPNN and RBFNN the highest obtained from BPNN testing was 99.33% taking 25s/c (1400 features).and for that of RBFNN was 99.44% taking 15 samples /cycle and spread width as 50. Thus we can conclude that RBFNN has the better classifying capability than BPNN .RBFNN has advantages over BPNN like it uses only one hidden layer ,there is no problem for over fitting and local minima thus it responds well in case of classifying internal fault than BPNN.

Chapter 4

SVM BASED METHOD FOR TRANSFORMER PROTECTION

4.1 Introduction

The problems earlier arise was the problems of over fitting or local minima and SVM is the best tool to optimize this problem .SVM completely depends on the sets of the input data which can be called as support vectors.

SVM is the classification tool based on the separating of the hyperplanes it classifies both linear and nonlinear data sets by creating hyperplanes and constructing the margin to separate or classify data .when the data is nonlinear the data is transform into higher dimensional space

SVM is the supervised learning based on the statistical learning theory (SLT). If we had an n sets of data for that if we require n-1 hyperplanes to separate them is called linear classification. Linear classification was given by Vapnik in 1963 but later on in 1992 Vladimir N. Vapnik suggested the kernel methods to classify the nonlinear data [32-36].

4.2 Support vector machine implementation

4.2.1 There are four types kernel function associated with SVM these can be given by:

1. the linear function,
2. Polynomial function,
3. radial basis function (RBF) for kernel,
4. Sigmoid function.

In this chapter the radial basis kernel is utilized with the library for SVM (LIBSVM). The equation

for the radial basis kernel is given by:

$$K(\mathrm{u},\mathrm{v}) = exp(-\gamma\| \mathrm{u}-v\|^2), \gamma > 0$$

.. (4.1)

Where γ is the width of the kernel function

Some time γ may be taken as $\gamma = 1/2\sigma^2$, σ is the spread width, where u and v are the input values of the classes

There are two parameters which control the Radial basis kernel are Gama (γ) parameter and c cost parameter. They are used to control the generalization potential of the radial basis kernel. The values for c and γ are usually greater than zero. The memorizing procedure for SVM using radial basis kernel is given by[36-38].

1. Features scaling or normalization of the data to standardize the range of input variables (In this method all Features were scaled to values between 0 and 1).
2. Empirically obtained the best values of (C and γ).
3. Apply the best values of C and γ for dataset training.
4. After applying we can use those values on thetrained data to get maximum accuracy on the on the testing data.

Normalize is the scaling of the input features for the standardization of in dependent variables of the data. SVM calculate the distance between the points, all the values should be governed by the particular feature. The data should normalize so that each sets corresponds to the particular features

$$normtable(i,:) = \frac{(\mathrm{final(i,:)} - \mathrm{min(final(i,:))})}{(\mathrm{max(final(i,:))\text{-}min(final(i,:))})}$$

.... (4.2)

Normalize which make all the data of input sets in the rage of {0,1}

Model=svmtrain(training_label_vector, training_instance_matrix [, libsvm_options])

training_label_vector= is the desired target values

training_instance_matrix=in the hibert matrix form by the input sampled values

each cycle

LibSVM options

-g set gamma in kernel function (default 1/k). The k means the number of attributes in the input data

-c set the parameter C of C-SVC(Support vector clustering), epsilon-SVR, and nu-SVR (default 1)[31]

SVM type chosen is the C-SVC which is the regularized SVM standard algorithm.Probability estimates decides the output values which ranges from the {0, 1}

For normal and external fault case for discriminating between the operating conditions we measure the consecutive peaks of the waveform for each sample of the cycle
Like we have simulated on 25 samples/cycle on PSCAD with channel plot step time as 800 μs

Thus $\frac{20ms}{800\mu s} = 25 samples/cycle$

4.3 Results and comparison

Table 4.1: Fault classification based on the SVM taking 850 features (25samples/cycle)

Values of gamma in kernel function(γ)	γ=0.001	γ=0.01	γ=0.1	γ=1
Values of cost parameter				
c=0.01	80	80	88.4	92.8
c=0.1	80	84.4	88	92.8
c=1	80.8	84	88	94.6
c=10	87.6	84	**96.8**	94.2

Table 4.2: Fault classification based on the SVM taking 1400 features (25samples/cycle) (active power)

Values of gamma in kernel function(γ)	γ=0.01	γ=0.1	γ=1
Values of cost parameter			
c=0.01	84	83.667	94.33
c=0.1	84	83.667	94.66
c=1	84	86	**98.33**

Table 4.3: Fault classification based on the SVM taking 1400 features (25samples/cycle)

Values of gamma in kernel function(γ)	γ=0.01	γ=0.1	γ=1	γ=10	γ=100
Values of cost parameter					
c=0.01	71.33	85	94.33	97.66	98.33
c=0.1	73.33	84.66	95.66	97.66	98.33
c=1	73.33	89.66	96	98.33	**99.67**
c=10	80.00	96	98	99	**99.67**

Table 4.4: Fault classification based on the SVM taking 510 features (15samples/cycle)

Values of gamma in kernel function(γ)	γ=0.01	γ=0.1	γ=1	γ=10
Values of cost parameter				
c=0.01	80.66	83.33	84.00	90.667
c=0.1	80.66	83.33	83.33	90.667
c=1	83.33	83.33	87.33	94.00
c=10	83.33	84.66	94.00	**99.33**

Table 4.5: Fault classification based on the SVM taking 510 features (25samples/cycle) with 15 input samples

Values of gamma in kernel function(γ)	γ=0.01	γ=0.1	γ=1	γ=10
Values of cost parameter				
c=0.01	80	83.33	84	90.667
c=0.1	80.66	83.33	83.33	90.667
c=1	83.33	83	87.33	94
c=10	83.33	84.667	94	**99.33**

Table 4.6: Fault classification based on the SVM taking 510 features (25samples/cycle) with 50 input samples

Values of gamma in kernel function(γ)	γ=0.001	γ=0.01	γ=0.1	γ=1
Values of cost parameter				
c=0.01	80	80	86	89.2
c=0.1	80	82.4	92	89.2
c=1	86.8	96	93.2	**95.6**

4.2 Conclusions

In this chapter, SVM based algorithm have been used in which results have been compared and show that with reactive power, fault are classify more accurately than the active power the results show as to optimize the algorithm parameters ,proved that 25samples/cycle and by having c=10 and γ=100 getting the maximum accuracy of 99.67.

Chapter 5

COMPARISION BETWEEN ANN AND SVM

5.1 Introduction

Ann has some advantages and SVM has also some features which are better than SVM hence It is difficult to say which is better is depends on the type of data, thus in this chapter we discuss merits and demerits of these two methods and compare these methods with help of results.

Ann has two major disadvantages

1. Ann converges on the local minima it converges for its own bandwidth, Over fitting can occur in the ANN if it takes larger time for training
2. Response time of ANN is slower than SVM, training time is also larger

Two more advantages of SVMs are that that have a

1. Simple geometric interpretation and give a thin solution.
2. SVM gives the solution based on global values and solution is unique.

5.2 BPNN advantages and limitation

1. It is capable to detect internal fault in case of high permeable modern power transformer
2. It is faster compare to RBFNN and other methods
3. It is simple and quite easy to implement and can applied to any network

5.3 Multiple classifications algorithm and implementation

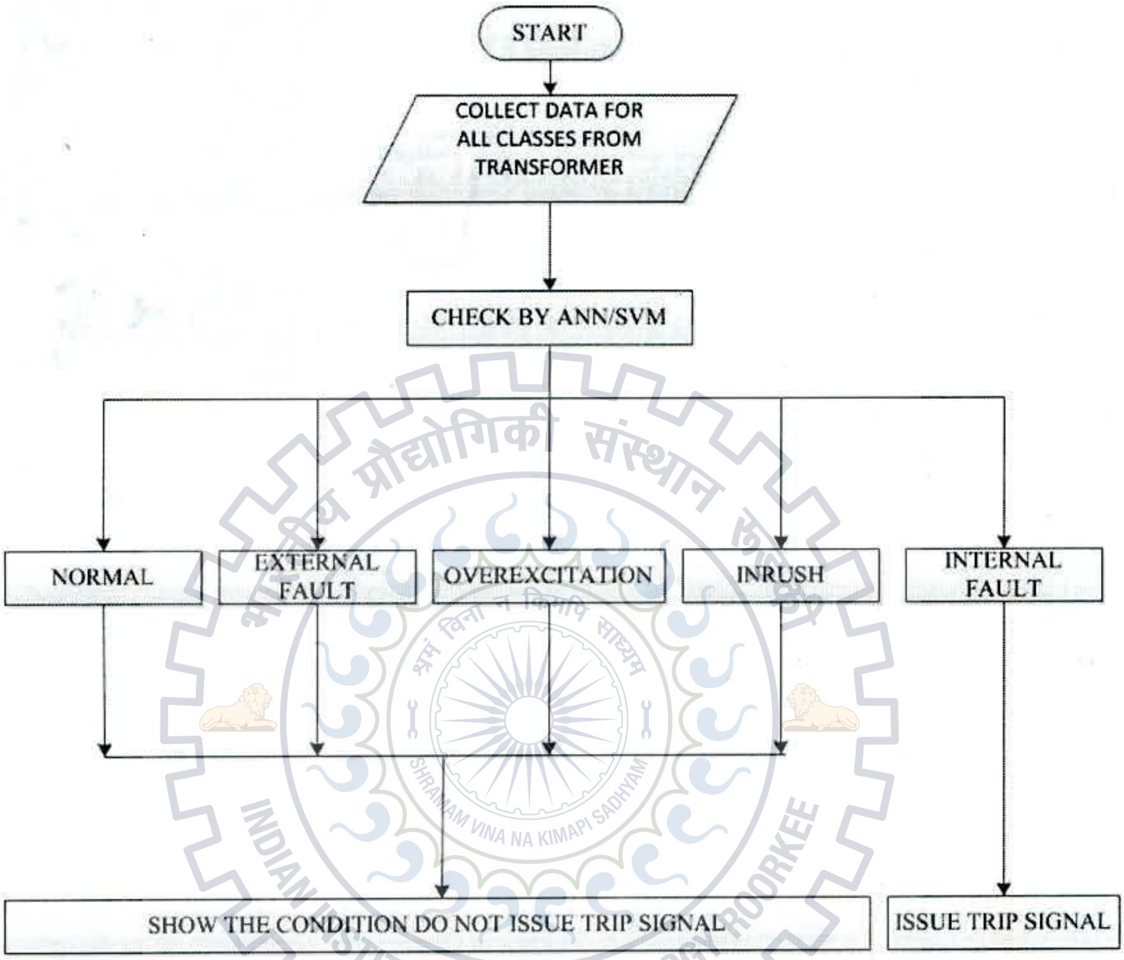


Fig 5.1: Flow chart of algorithm based on the multiple classification

The multiple classification performed as it has different conditions so we assigned different target numbers to the different conditions show in table 5.2

Table 5.2: Target output for the multiple condition classification

Normal condition	10000
External fault condition	01000
Over excitation condition	00100
Magnetizing inrush condition	00010
Internal fault condition	00001

Fig 5.1 showing algorithm for the multiple class classification in this case every condition is check by the ANN/SVM if the condition is internal fault trip signal will be issue to that and if that is other than internal fault it will show but not trip.

Table 5.3: fault classification accuracy in case of multiple classes

	Normal	External fault	overexcitation	Inrush current	Internal fault
BPNN	100	100	100	99.7143	**99.7143**
RBFNN	100	100	84.51	95.71	**99.142**
SVM	100	100	97.66	99.33	**99.66**

1. As it training utilizes local minima it can struck to a particular value
2. Selections of weights should be done properly if it not done it could struck at local minima or maxima
3. Parameters are selected empirically
4. Exact relation for output values is difficult

The learning process is time consuming and there is no exact rule for setting the number of neurons to avoid over-fitting or under-fitting, and, hopefully, making the learning phase convergent. To avoid these problems, a RBFN has been developed on theory of RBF for approximations. The RBFNs have only one hidden layer with a growing number of neurons during learning to achieve an optimal configuration

5.2 Conclusions

This chapter presents a comparison between the SVM and ANN methods to discriminate between all the conditions of the transformer the proposed algorithm was successfully able to classify inrush among the different conditions as the classification accuracy with BPNN was 99.7143%, RBFNN 99.143%, and that of SVM is 99.66%.thus here we can conclude that SVM proved as the most efficient method to protect the transformer from internal faults.

Chapter 6

Conclusions and Future Scope

6.1 Conclusions

In this dissertation several methods presented, some methods have disadvantages other method overcome that and prove as the best classifier .All the methods successfully overcome the disadvantages of harmonic based methods and has the generalization ability also .these methods can be implemented to any transformer .these methods are also stable in case of inrush with high magnitude and with the residual flux.

BPNN technique is faster and simple in implementation and calculation .but if the parameters are not selected properly it will trap to local minima and get poor accuracy problems. Thus we take different parameters to optimize the structure and the performance of the classifier.

To tackle the limitation of the BPNN, RBFNN has been introduced and it optimize the result more further. RBFNN technique we have also taken different parameters like spread width, different input neurons ,different samples/cycle to optimize the results .the disadvantages of these method was it take more time for training as it do not have iterative training.

The problem of RBFNN like iterative training and empirically selecting parameters has overcome in the SVM.SVM classifying data according to creating hyperplanes thus it has the faster response time better accuracy and independence of selecting parameter for optimization .SVM proved to be most successful in discriminating internal fault from inrush current and the literature have also say that SVM as the better classifier over ann.

6.2 Future Scope

As significant development has been made in the transformer protection and the new Novel techniques are coming to more accurate and precise and faster operation to protect

Transformers. I would like to discussed some developments in transformer protection can be carried out in future

1. To provide information about fault winding and classify weather which section of winding is effected by which type of fault.
2. To provide information about the fault location can be further improvements made in the proposed methods
3. More feature extraction tools can be used to get best results and faster operating time like by using genetic algorithm (GA) and particle swarm optimization (PSO).
4. A real time implementation of the proposed techniques to apply this in real world to get more knowledge about how the real transformer responds to fault situations.
5. Using different techniques to more improvise the features like wavelet transform and new unique methods.
6. Allowing more randomness to the transformer selection any rating and any type of configuration.

REFERENCES

[1]. H. K. Verma and G. C. Kakoti, "Algorithm forHarmonic Restraint Differential Relaying Based on the Discrete Hartley Transform," vol. 18, pp. 125–129, 1990.

[2]. H. K. Verma and A. M. Basha, "A microprocessor-based inrush restrained differential relay for transformer protection," pp. 13–18, 1986.

[3]. R. K. Bansal, B. K. Joshi, S. P. Singh, and R. N. Bandopadhaya, "Microprocessor based harmonic restraint differential protection scheme for a transformer," *Journal of Microcomputer Applications*, vol. 15, no. 2, pp. 169–176, Apr. 1992.

[4]. H. K. Verma and a. M. Basha, "Microprocessor-based comprehensive relaying scheme for power transformer protection," *Electric Power Systems Research*, vol. 19, no. 2, pp. 115–127, Aug. 1990.

[5]. JC Yeh, C.E Lin "Calculation and harmonic analysis of transient inrush currents in three-phase transformers," vol. 30, pp. 93–102, 1994.

[6]. A.M. Shah, B. R. Bhalja, and S. Member, "Discrimination Between Internal Faults and Other Disturbances in Transformer Using the Support Vector Machine-Based Protection Scheme," pp. 1–8, 2013.

[7]. T.-F. Lee, M.-Y. Cho and F.-M. Fang, "Features Selection of SVM and ANN Using Particle Swarm Optimization for Power Transformers Incipient Fault Symptom Diagnosis," *International Journal of Computational Intelligence Research*, vol. 3, no. 1, pp. 60–65, 2007.

[8]. M. Tripathy, R. P. Maheshwari, and H. K. Verma, "Particle Swarm Optimization Based Probabilistic Neural Network for Power Transformer Protection," *2006 IEEE International Conference on Industrial Technology*, vol. 4, pp. 568–573, 2006.

[9]. S. Ala, M. Tripathy, and a K. Singh, "Identification of internal faults in power transformer using symmetrical components and Park's plots," *Power Systems 2009 ICPS 09 International Conference on*, pp. 1–6, 2009.

[10]. M. Tripathy, R. P. Maheshwari, and H. K. Verma, "Radial basis probabilistic neural network for differential protection of power transformer," pp. 43–52.

[11]. M. Tripathy, R. P. Maheshwari, and H. K. Verma, "Optimal Probabilistic Neural Network," vol. 25, no. 1, pp. 102–112, 2010.

[12]. M. Tripathy, "Power transformer differential protection using neural network Principal Component Analysis and Radial Basis Function Neural Network," *Simulation Modelling Practice and Theory*, vol. 18, no. 5, pp. 600–611, May 2010.

[13]. Z. Moravej, D. N. Vishwakarma, and S. P. Singh, "Application of radial basis function neural network for differential relaying of a power transformer," *Computers & Electrical Engineering*, vol. 29, no. 3, pp. 421–434, May 2003.

[14]. Introduction to PSCAD® / EMTDC™ Manitoba HVDC Research Centre Inc.244 Cree Crescent, Winnipeg, Manitoba R3J 3W1 Canada page 57-65

[15]. Craig Muller, P.Eng.USER'S GUIDE on the use of PSCAD 211 Commerce Drive, Winnipeg, Manitoba, Canada R3P 1A3 February, 2010 - Version 4.2.1, fifth printing.

[16]. Introduction to PSCAD and Applications Training Course Presented by the Manitoba HVDC Research Centre Prepared by: Dharshana Muthumuni Date: August 2005 Revision: 3 Date: March12, 2007

[17]. www.xianelectric.com/dzyb/download/Tans11-15.pdf?

[18]. M. Rasoulpoor and M. Banejad, "A correlation based method for discrimination between inrush and short circuit currents in differential protection of power transformer using Discrete Wavelet Transform: Theory, simulation and experimental validation," *International Journal of Electrical Power & Energy Systems*, vol. 51, pp. 168–177, Oct. 2013.

[19]. S. R. Samantaray and P. K. Dash, "Decision Tree based discrimination between inrush currents and internal faults in power transformer," *International Journal of Electrical Power & Energy Systems*, vol. 33, no. 4, pp. 1043–1048, May 2011.

[20]. Howard B. Demuth Mark Hudson Beale Martin T. Hagan Neural Network Toolbox™ User's Guide R2013a

[21]. M. Tripathy, "Neural Network Principal Component Analysis based power transformer differential protection," *Power Systems 2009 ICPS 09 International Conference on*, vol. 18, no. 5, pp. 600–611, 2009.

[22]. E. a. Mohamed, a. Y. Abdelaziz, and a. S. Mostafa, "A neural network-based scheme for fault diagnosis of power transformers," *Electric Power Systems Research*, vol. 75, no. 1, pp. 29–39, Jul. 2005.

[23]. L. M. R. Oliveira and a. J. M. Cardoso, "Application of Park's power components to the differential protection of three-phase transformers," *Electric Power Systems Research*, vol. 83, no. 1, pp. 203–211, Feb. 2012.

[24]. M. Ã. Geethanjali, S. M. R. Slochanal, and R. Bhavani, "PSO trained ANN-based differential protection scheme for power transformers," vol. 71, pp. 904–918, 2008.

[25]. V. Duraisamy, N. Devarajan, D. Somasundareswari, a. A. M. Vasanth, and S. N. Sivanandam, "Neuro fuzzy schemes for fault detection in power transformer," *Applied Soft Computing*, vol. 7, no. 2, pp. 534–539, Mar. 2007.

[26]. H. Han, W. Hou-jun, and D. Xiucheng, "Transformer Fault Dignosis Based on Feature Selection and Parameter Optimization," *Energy Procedia*, vol. 12, pp. 662–668, Jan. 2011.

[27]. M. Moscoso, G. J. Lloyd, K. Liu, Z. Wang, and A. Grid, "Improvements to Transformer Differential Protection – Design and Test Experience," vol. 1, no. 5.

[28]. H. Balaga, D. N. Vishwakarma, S. Member, and A. Sinha, "Numerical Differential Protection of Power Transformer using ANN as a Pattern Classifier," pp. 1–6, 2010.

[29]. M. Geethanjali, S. M. Raja Slochanal, and R. Bhavani, "PSO trained ANN-based differential protection scheme for power transformers," *Neurocomputing*, vol. 71, no. 4–6, pp. 904–918, Jan. 2008.

[30]. M. Tripathy and S. Ala, "Optimal Radial Basis Function Neural Network power transformer differential protection," *2009 IEEE Bucharest PowerTech*, vol. 25, no. 1, pp. 102–112, 2009.

[31]. Chih-Chung Chang and Chih-Jen Lin, LIBSVM: a library for support vector machines, 2001. Software available at http://www.csie.ntu.edu.tw/~cjlin/libsvm.

[32]. L. V. Ganyun, C. Haozhong, Z. Haibao, and D. Lixin, "Fault diagnosis of power transformer based on multi-layer SVM classifier," *Electric Power Systems Research*, vol. 74, no. 1, pp. 1–7, Apr. 2005.

[33]. A. M. Shah, B. R. Bhalja, and S. Member, "Discrimination Between Internal Faults and Other Disturbances in Transformer Using the Support Vector Machine-Based Protection Scheme," pp. 1–8, 2013

[34]. Z. Li and Z. Xie, "Transformer Fault Diagnosis Based on Rough Sets and Support Vector Machine," *2012 Asia-Pacific Power and Energy Engineering Conference*, pp. 1–4, Mar. 2012.

[35]. M. Bigdeli, M. Vakilian, and E. Rahimpour, "Transformer winding faults classification based on transfer function analysis by support vector machine," *IET Electric Power Applications*, vol. 6, no. 5, p. 268, 2012.

[36]. A. M. Shah and B. R. Bhalja, "A new approach to digital protection of power transformer using support vector machine," *2011 24th Canadian Conference on Electrical and Computer Engineering(CCECE)*, no. 1, pp. 11–14, May 2011.

[37]. S. Fei and X. Zhang, "Fault diagnosis of power transformer based on support vector machine with genetic algorithm," *Expert Systems with Applications*, vol. 36, no. 8, pp. 11352–11357, Oct. 2009.

List of Candidate's Publications

[1] V.Pratap, R. P. Maheshwari and M. Tripathy "**Intelligent methods to distinguish between Inrush and Internal Fault current of Power Transformer**," IEEE Indian. Conf.,(INDICON),IIT Bombay section & IEEE India council, 2013

APPENDIX

The technical specifications of 315 MVA Power Transformer obtained from the MP electricity board Jabalpur, India is given as follows

THE TECHNICAL SPECIFICATIONS OF 315 MVA POWER TRANSFORMER

S.No	Parameter	Value
1.	MVA rating of transformer	315 MVA
2.	Primary secondary side rated voltage	400/220 KV
3.	Rated frequency	50HZ
4.	No of phases	3
5.	Connection type	Delta/star
6.	No load losses	75KW
7.	Load loss(at normal tap)	405KW
8.	Reactance per phase at normal tap	
	HV winding	12.5%
	LV winding	45%
9.	Regulation at full load and 75^0c temperature	
	i. Unity power factor	1 %(approx.)
	ii. 0.8 power factor	8.2 %(approx.)
10.	Positive sequence impedance (ohms) on rated base MVA and current and frequency At 75^0c temperature	
	HV winding	12.5%±10 %tolerance
	LV winding	30%±15 %tolerance
11.	Over fluxing capability of transformer at over fluxing factor	Period in seconds
	1.70	Few cycle
	1.60	Few cycle
	1.25	60

	1.10	continuous
12.	Magnetising current at normal tap and frequency	
	85% of the rated voltage	0.1% of rated current
	100% of the rated voltage	0.3% of rated current

The technical specifications of 150 and 180 MVA Power Transformer obtained from the Xian Electric Engineering Co., Ltd Xian, chinais given as follows[17]

S.No	Parameter	Value
1.	MVA rating of transformer	150 MVA
2.	Primary secondary side rated voltage	220/121 KV
3.	Rated frequency	50HZ
4.	No of phases	3
5.	Connection type	Delta/star
6.	No load losses	110KW
7.	Load loss(at normal tap)	498KW
8.	Reactance per phase at normal tap	
	HV winding	14.47%
	LV winding	24.65%

The technical specifications of 180 MVA Power Transformer obtained from the Xian Electric Engineering Co., Ltd Xian, china is given as follows

S.No	Parameter	Value
1.	MVA rating of transformer	180 MVA
2.	Primary secondary side rated voltage	121/15 KV
3.	Rated frequency	50HZ
4.	No of phases	3
5.	Connection type	Delta/star
6.	No load losses	77.4KW
7.	Load loss(at normal tap)	478KW
8.	Reactance per phase at normal tap	
	HV–LV winding	10.5%