INTERNAL FAULT DETECTION IN THREE PHASE TRANSFORMER USING MACHINE LEARNING METHODS

A Dissertation submitted in fulfillment of the requirements for the award of Degree
Of

MASTER OF ENGINEERING
IN
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Submitted by

Ravi Shankar Chauhan
Regd. No. 801341019

Under the Guidance of
Dr. Amrita Sinha
Assistant Professor, EIED

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Electrical and Instrumentation Engineering Department
Thapar University, Patiala
(Declared as Deemed-to-be-University u/s 3 of the UGC Act., 1956)
Post Bag No. 32, Patiala – 147004
Punjab (India)

DECLARATION

I hereby certify that work which is being presented in dissertation entitled, **"Internal Fault detection in three phase Transformer Using Machine Learning method"**, in partial fulfillment of the requirements for the award of degree of **Master of Engineering in power systems** at Thapar University Patiala, is an authentic record of my own work carried out undr the supervision of **Dr. Amrita Sinha, Assistant Professor (EIED).** The matter embodies in this dissertation has not been submitted for the awrd of any degree to any other university.

Date: 15/07/2015

Ravi

Ravi Shankar Chauhan
Reg.No. 801341019

It is certified that the above statement made by the candidate is correct and true to the best of my knowledge.

Dr. Amrita Sinha
Assistant Professor (EIED)
Thapar University, Patiala

Countersigned by:

Dr,Ravinder Agarwal
Professor and Head (EIED)
Thapar University, Patiala

Dr.S.S. Bhatia
Dean (Academic Affair)
Thapar University, Patiala

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Ravi Shankar Chauhan

Reg.No. 801341019

Email Id: Chauhanravi50@gmail.com

LIST OF ABBREVIATIONS

HV	High voltage
LV	low voltage
CT	Current Transformer
RMSD	Root mean square deviation
ABC	Artificial bee colony
OCR	Optical character recognition
SVM	Support vector method
LM	Linear model
USO	User specified Object
LLG	Double line to ground
LG	Line to ground
ANN	Artificial neural network
RMS	Root mean square

NOMENCLATURE

SN	Number of food sources
NP	Colony Size
Y	Star
S	Sensitivity
C	Rate of accuracy
C_{ij}	Confusion matrix

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ABSTRACT

The study of ABC (artificial bee colony algorithm) and four different machine learning methods has been explored for internal fault detection in three phase transformer using differential protection scheme. The half cycle window of differential current has been sampled at 1 kHz sampling frequency for classification of five operating conditions i.e. normal, magnetizing inrush, over-excitation, internal and external fault condition. 420 samples have been generated by modeling the differential protection scheme of Y-Y transformer and simulating different operating conditions usingsimpowersys of MATLAB/SIMULINK. The training and testing result shows that random forest method gives best result as compared to decision tree, linear model and support vector method.The k-fold cross- validation has been used for measuring the accuracy and sensitivity of random forest machine learning method. This gives the best result for classification of internal fault and other operating conditions.

CHAPTER-1

INTRODUCTION

1.1 GENERAL

The demand for a reliable supply of electrical energy for the exigency of modern world in each and every field has increased considerably requiring nearly a no-fault operation of power systems. Transformers are a class of very expensive and vital components of electric power systems. The crucial objective to mitigate the frequency and duration of unwanted outages related to transformer puts a high pointed demand on transformer protective relays to operate immaculately and predictably. The high pointed demand includes the requirements of dependability associated with no false tripping, and operating speed with short fault detection and clearing time.

Protection of large transformers is a very challenging problem in power system relaying. The protective system include devices that recognize the existence of a fault, indicates its location and class, detect some other abnormal fault like operating conditions and starts the inceptive steps of opening of circuit breakers to disconnect the faulty equipment of the power system.

Recent development in the field of digital electronics and signal processing made it possible to build microprocessor based relays which provide a viable alternative to the electromechanical and solid state relays. Microprocessor based relays use software for interpreting signals and implementing logic. With the advent of microprocessor various digital algorithms have been developed and successfully implemented for power transformer protection.

There are problems which are peculiar to transformer, which are not encountered in other items of power system. The major problems in transformer is the large magnetizing inrush 2 current, whose magnitude can be as high as internal fault current and may cause false tripping of the breaker. A common differential relay operating on the basis of measurement and evaluation of currents at both sides, primary and secondary side of the transformer can't avoid the trip signal during inrush condition.

Since the transformer inrush current is rich in second harmonic component therefore to avoid the needless trip by inrush current harmonic restraint logic together with differential logic is used in most of the fault detection algorithm in the digital differential protection of transformer. These methods utilize the fact that the ratio of the second harmonic to fundamental component of differential current under inrush condition is greater in comparison to that under fault conditions.

1.2 HISTORICAL BACKGROUND

A transformer is an electrical device that transfers electrical energy from one electrical circuit to another circuit while the circuits are inductively coupled to each other. Transformer transfers energy at step-down and step-up voltage according to the requirement. Transformer plays a very important role in electricity transmission. So, it is important for us that it should be kept safe from the different types of faults and hence the idea of protection of transformer got introduced.

The principle of transformer was introduced by Michael Faraday in year 1831. Transformer transfers electricity from low to high voltage and high to low voltage using two properties of electricity. In an electric circuit, there is magnetism around it. Whenever a magnetic field changes a voltage is induced.

Transformer is an electrical device used to transfer electric power from one electrical circuit at one voltage level to another voltage level usually from higher to lower. The standard voltage of high voltage transformer is 600 V to 5000 V. Transformers are basically used for security and metering in high voltage circuits in industrial applications and other technical applications.

1.3 THESIS OBJECTIVE

1. MATLAB/SIMULINK based Study of transformer in power system for different condition.
    a) Normal condition
    b) Magnetizing Inrush condition
    c) External fault condition
    d) Over-excitation condition
    e) Internal fault condition
2. Training and testing of data set obtained from the simulation with the help of four different machine learning methods.
    a) Random forest method
    b) Support vector method

c) Decision tree method
d) Linear model method

1.4 LITERAURE SURVEY

In the literature survey of protection of transformer, the key issue lies in discrimination between internal fault and other operating condition such as magnetizing inrush, over-excitation and external fault condition of transformer. It is natural that relay should operate in case of internal fault condition of transformer not in any other operating condition of transformer.

The transformer is major equipment in power system. It requires highly relative protective scheme. The protection of large transformer is important for overall protection strategy of power system. Differential protection is most common method of protection by comparing primary and secondary currents of transformer converting them to a common base. Differential protection is found to be more effective in identification of fault. Main challenge in differential protection is to differentiate internal fault with other operating conditions.

Digital differential relay has been improved significantly since its inception [1] and has been introduced in year 1988 for industrial application [2]. The phenomena of inrush current have been discussed since 1958 [3-8]. In case of magnetizing inrush, the second harmonic component in transformer is used for blocking differential relay to prevent maloperation. The ratio of second harmonic power spectrum to power spectrum of fundamental based on autoregressive process id used for identification of magnetizing inrush current [9-10]. Differential relay show the vector difference as differential quantity, while keeping the vector sum as restrain quantity [11].

The local transient saturation caused by decaying dc component in case of magnetizing inrush is the main cause of the maloperation in transformer differential protection [12].

Differential protection is done using artificial neural network which is used as pattern classifier [13] which differentiates among the magnetizing inrush, normal condition, over-excitation, internal and external fault condition in the transformer. ANN-based algorithms were implemented successfully as investigated by researchers [14-19] in many pattern recognition problems.

PSO (particle swarm optimization) trained artificial neural network based differential protection technique is used to train the feed forward to discriminate the different operating condition of transformer [20].

The protection of three phase transformer by wavelet packet is employed to explain certain features of differential current to discriminate between the different operating conditions and magnetizing inrush condition of transformer. Selection for optimal wavelet analysis which includes both the optimal number of levels of resolution and optimal mother wavelet is carried out by using minimum length description data criteria [21].

The method based on correlation for differentiate between magnetizing inrush and short circuit condition of differential current transformer protection using discrete wavelet is used to describe signals in term of frequency and time component. A coefficient of correlation is express relationship between wavelet energy coefficients at different scales of the signal resolution [22].

Power transformer protection using a multi-region adaptive differential relay is used to differentiate internal fault and disturbance based on the differential current trajectory and adopted weighting factors depending on the differential current locus in the relay characteristic. The traditional dual-slope differential characteristic relay is divided into three operating region with the corresponding weight factor [23].

Optimal smoothing factor of Probabilistic neural network is obtained with the help of PSO (particle swarm optimization). The PSO (particle swarm optimization) is used to obtain an optimal smoothing factor of Probabilistic neural network. It makes use of ratio of voltage-to-frequency and amplitude of differential current for determination of operating conditions of transformer [24].

The DWT (discrete wavelet transformer) and Probabilistic neural network (PNN) combination is used for discrimination between internal and external fault in transformer. The coefficients of first scale from DWT that can detect fault are investigated [25].

An advanced technique has been developed based on support vector machine (SVM) which provides effective discrimination between internal faults and other disturbances such as inrush current and over-excitation condition. The algorithm performance has been tested over a simulation data of 5422 cases and overall fault discrimination accuracy of more than 99% is achieved [26].

Artificial neural network (ANN) and support vector Machine (SVM) approach for locating fault in radial distribution system use the principal component analysis (PCA) technique and fault are classified according to their path combination of support vector classifiers and feed forward neural network (FFNN) [27].

A method based on the application of Clark's transform allows fuzzy logic to analyze operating condition of transformer such as inrush and over excitation [28].

GA trained ANN (artificial neural network) provides faster, accurate, more secured results as compared to back propagation trained ANN [29].

In an algorithm faulted phase protection and identification of windngs for the three-winding transformer using the IFLs, nine detectors and a rule are suggested. The algorithm accurately estimates the differences of IFLs and uses them to differentiate between normal operating conditions and internal windings fault. In addition, the algorithm can simply identify the faulted winding and its phase [30].

The magnetizing inrush current under unbalanced three phase parameters of one 500kV is carried out with statistical computing model of transformer magnetizing inrush current analysis on substation and the conclusion is: the unbalance short circuit impedance of transformer has little influence on the magnetizing inrush current, but great changes will occur in the magnetizing inrush current with the difference in three phase saturation characteristics. Such change will influence the normal operation condition of transformer and its protection still need further study [31].

The Artificial Bee Colony (ABC) algorithm [49] is a recently developed bio inspired algorithm. ABC is inspired by honey bee's food searching behavior. ABC search process required three control parameters i.e. number of food sources SN, it is also equal to number of onlooker bees or employed bees, number of iterations and limit (number of trials after which a food source is considered to be abandoned) [49].

In this work we explore four different methods of machine learning classification model to classify the different types of faults conditions in three phase transformer. 420 samples of differential current has been generated using sim power simulation software under different operating conditions. Since some of the considered features may have higher importance than others in predicting the faults, the feature importance is determined by use of artificial bee colony algorithm. The accuracy and sensitivity of different machine learning methods is measured by the help of K-fold cross validation. Basically with this thesis we are making an identification of different operating conditions of transformer which help relay to trip only at the time of internal fault condition in transformer and not in other operating conditions of transformer.

1.5 ORGNISATION OF DISSERTATION

The thesis structure is organized as follows:

Chapter-1 gives a brief over-view of need of transformer protection, detection and classification of fault condition, thesis objective and literature survey.

Chapter-4 covers a brief discussion on transformer protection and fault.

Chapter-3 covers a brief a discussion on the four different machine learning methods, artificial bee colony algorithm.

Chapter -4 covers the use of MATLAB/SIMULATION to develop model of transformer at different operating condition of transformer through which the sample of differential current data is generated by simulation model of transformer.

Chapter-5 covers the methodology and prediction model, implementation of four different methods of machine learning to get the test results.

Chapter-6 covers future scope and conclusion.

CHAPTER-2

TRANSFORMER PROTECTION AND FAULT

2.1 TYPE OF FAULTS ENCOUNTERED IN TRANFORMER

The faults encountered in transformer can be placed in two main groups.

(A) External fault
(B) Internal fault

2.1.1EXTERNAL FAULT

In case of external fault, transformer must be disconnected if other protective devices meant to operate for such faults, fail to operate with in a predetermined time. For external faults, time graded overcurrent relays are employed as back –up protection. Also in case of sustained overload condition, transformer should not be allowed to operate for long duration. Thermal relays are used to detect overload conditions and give an alarm.

2.1.2 INTERNAL FAULT

The primary protection of transformer is meant for internal faults. Internal faults are classified into two groups.

1. Short circuits in transformer windings and connections:-these are electrical faults of serious nature and are likely to cause immediate damage. Such faults are detectable at the windings terminals by unbalances in voltage or current. This type of faults includes LG(line to ground) or LL (line to line) and interturn faults on H.V and L.V windings

2. Incipient faults:-.initially, such faults are of minor nature but slowly might develop into major faults. Such faults are not detectable at the winding terminals by unbalance in voltage or current and hence, the protective devices meant to operate under short circuit conditions are not capable of detecting this type of faults, such faults include poor electrical connections, core faults, and failure of the coolant, regulator faults and bad load sharing between transformers.

2.2 DIFFERENTIAL PROTECTION

Differential protection of large transformers is employed for protection against internal short circuits but it is not capable of detecting incipient faults.figure2.1.shows the schematic diagram of differential protection for star-delta transformer. The current direction and voltage polarity of CT shown in figure are for a particular instant. The convention for marking the polarity for lower CT's and upper CT's is same. The end at which current is entering has been marked as positive. The current leaving end is leaving has been marked negative.

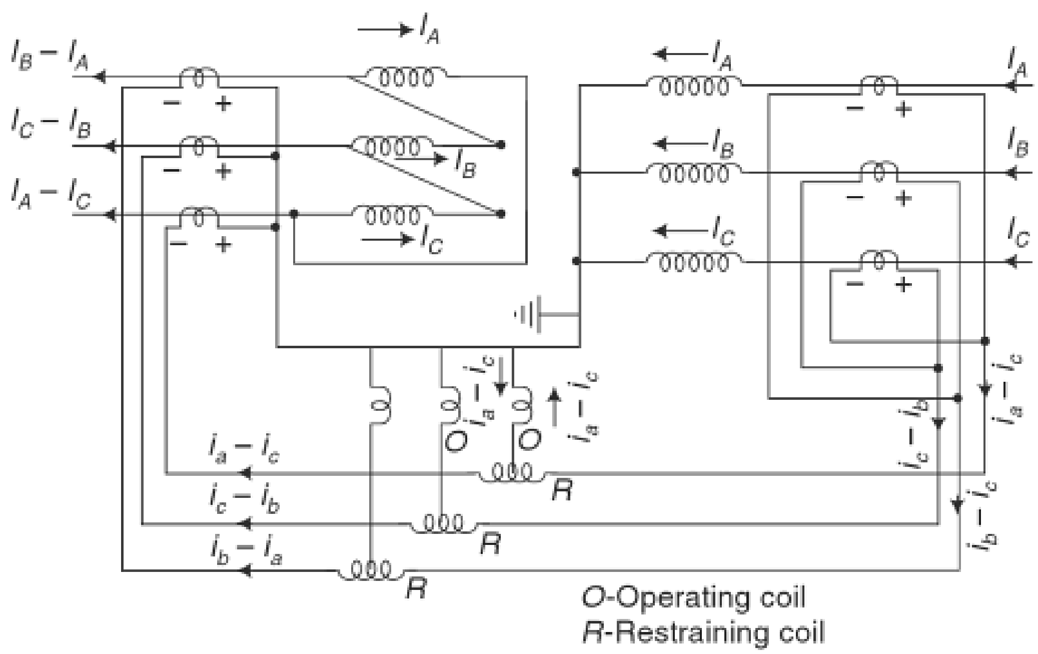


Fig2.1.schematic diagram of differential protection of transformer

In case of normal and external fault condition the connections are made in such a way that the current flowing in the operating coil of the relay due to CTs of primary side is in opposition to current flowing due to the CTs of the secondary side .Consequently, .if a fault occurs on the winding the relay does not operate, the induced voltage polarity of the CT of the secondary side is reversed. Now the currents in the operating coil from CTs of both sides are in the same direction and cause the operation of the relay. The matching currents is supply in the operating winding of relay, the CT which are on the star side of the transformer are connected in star. In case of star-delta connected transformer there is a phase shift of 30^0 in the currents. Also the above mentioned CTs connections also correct this phase shift .Moreover, Zero sequence current flowing on the star side of transformers does not produce current outside the delta on the other side. Therefore, the zero sequence current should be eliminated from the star side. This condition is also fulfilled by CTs connection in delta on the star side of the transformer.

The settings of relay for transformer protection are kept higher than those for alternators. The typical value of alternator is 10% for operating coil and 5% for bias. The corresponding values for transformer may be 40% and 10 % respectively. The reasons for a higher setting in the case of transformer protection are.

(1) A transformer is provided with on load tap changing gear. The CT ratio cannot change with varying transformation ratio of the power transformer. The CT ratio is fixed and it is kept to suit the nominal ratio of the power transformer .therefore, for taps other than nominal, an out of balance current flows through the operating coil of the relay during load and external fault conditions.

(2) Under no-load condition of transformer, there is no –load current in the relay. Therefore, its setting should be greater than no load current.

2.3 PROTECTION AGAINST MAGNETIZING INRUSH CURRENT

When an unloaded transformer is switched on, it draws a large initial magnetizing current which may be several times rated current of transformer. This initial magnetizing current is called magnetizing inrush current. This inrush flow in primary winding of transformer, the differential protection will see this inrush current as internal fault. The harmonic contents in magnetizing inrush current are different than those in usual fault current .the dc component varies from 40 to 60% ,second harmonic 30 to 70 % and the third harmonic 10 to 30% . The third harmonic and its multiples do not appear in CT leads as these harmonic circulate in the delta windings of transformer and delta connected CT’s on the star side of transformer .As second harmonic in the inrush current than in fault current, this feature can be utilized to discrimination between a fault and magnetizing inrush current.

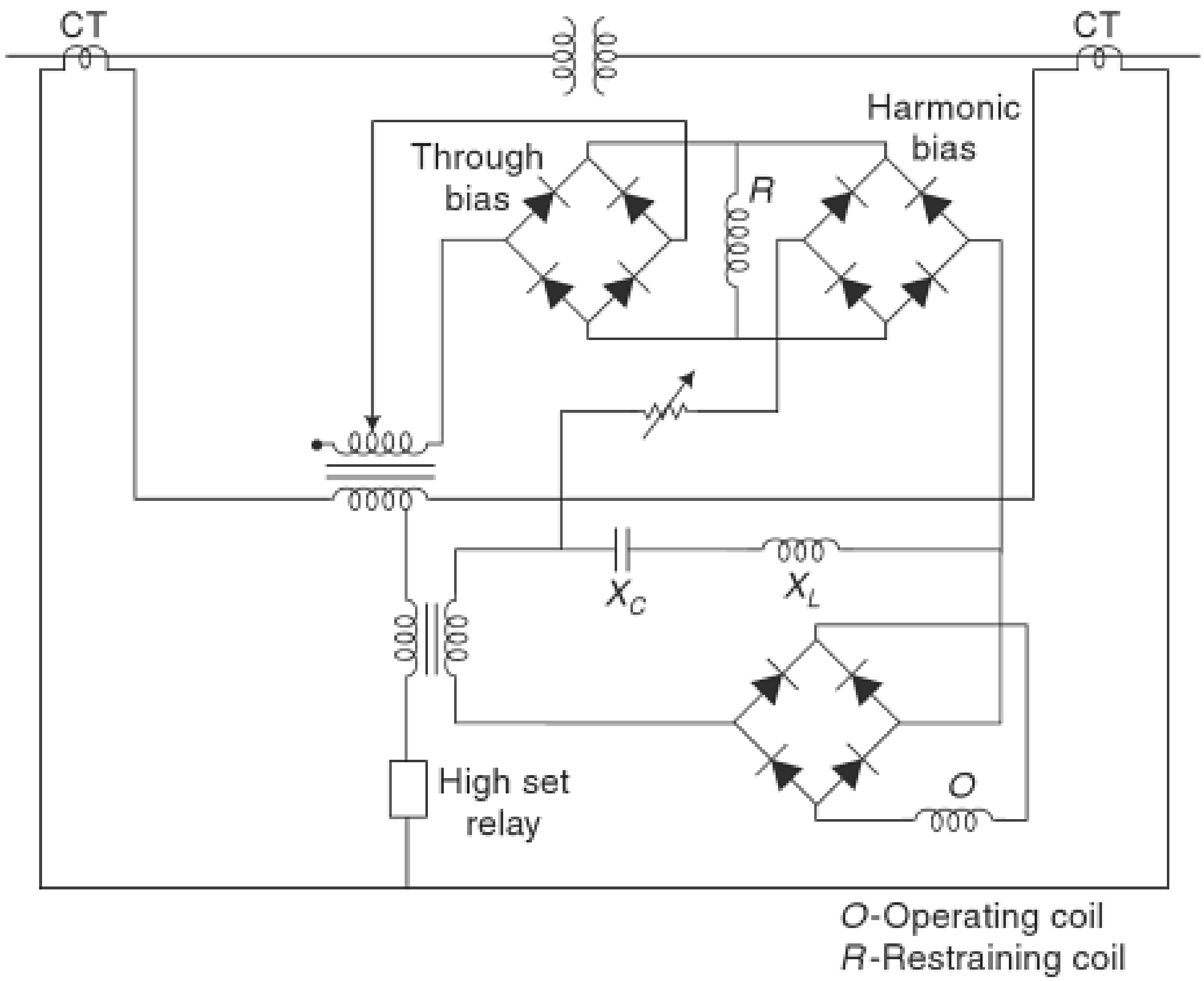


Fig 2.2 Schematic diagrams of harmonic restraint relay

Fig 2.2 shows a high speed biased differential scheme incorporating a harmonic restraint feature. The relay of this scheme is made insensitive to magnetic inrush current. The operating principle is to filter out harmonics from the differential current, rectify them and add them to the percentage restraint. Tuned circuit X_L and X_C allows only fundamental current frequency to flow through the operating coil. The dc and harmonics, mostly second harmonics in case of magnetic inrush current are diverted into restraining coil. The relay is adjusted so as not to operate when the second harmonic (restraining) exceeds 15% of the fundamental current. Two cycle is minimum operating time.

The dc offset and harmonics are also present in the fault current, particularly if CT saturates. The harmonic restraint relay will fail to operate relay will operate on the occurrence of an internal fault which contains considerable harmonics due to an arc or saturation of CT. to overcome this difficulty , an instantaneous overcurrent relay(the high set unit) is also incorporated in the harmonic restraint scheme. This relay is set above the maximum inrush current .it will operate on heavy internal faults in less than one cycle.

In an alternative scheme, known as harmonic blocking scheme, a separate blocking relay whose contacts are in series with those of a biased differential relay is employed. The blocking relay is set when second harmonic component is less than 15% of fundamental component.

2.4 OVER-EXCITATION PROTECTION

Over -excitation is normally of concern in generator-transformer units. Transforms are typically designed to operate just below the flux saturation level. Any further increase from the maximum permissible voltage level (or voltage/Frequency ratio), could lead to saturation of the core, in turn leading to substantial increase in excitation current drawn by the transformer When power transformers are over-excited, the leakage flux increases and these results in heavy hysteresis and eddy-current losses in non-laminated parts of the transformers. If the temperature rise, due to these losses, is excessive, the insulation and core laminations can be damaged and flashovers may occur. There are many causes of over-excitation:- Power transformers which are directly connected to a generator can be subject to over-excitation during the start-up or shut-down of the generator. Load shedding in systems supplied by overhead lines or cables, can cause excessive voltage rise which result in over-excitation of power transformers connected to these systems. Voltage rise in conjunction with low loads can occur in both generator and distribution stations.

Over –excitation of generator transformers can occur due to the following causes.

1. Running up or shutting down an alternator with A.V.R in service. The regulator will attempt to maintain normal voltage regardless of frequency, and hence at subnormal frequency, the connected generator transformer will be overexcited.
2. A similar effect to 1 above can occur if the alternator is started up with the manual control set inadvertently to a very high level of excitation, the AVR being out of service as per normal practice. The resultant voltage to frequency ratio will be in excess of normal value.

3. A deliberate attempt to export a large VAR component as an aid to system control results in an over fluxing condition in a transformer ,the control operation usually consists of leaving the AVR control normal but operating the tap changer to reduce primary turns which results in higher voltage per turn and hence ,an increase flux.
4. With the transformer connected to the bus, the bus voltage being greater than the rated value, operation of the tap changer over its full range as a maintenance operation can also produce over fluxing conditions.

CHAPTER-3

ABC ALGORITHM AND MACHINE LEARNING

3.1 GENERAL

Machine learning classification models have been widely used in protein structure prediction such as 2D and 3D structure prediction [32,33], fold recognition [34, 35, 36], solvent accessibility prediction, disordered region prediction [37, 38, 39], binding site prediction [40], trans membrane helix prediction [41], protein domain boundary prediction [42], contact map [43, 44, 45], functional site prediction, model generation [46], and model evaluation [47, 48]. The machine learning classification models to predict native or native like structure in the absence of its true native state using six physical and chemical properties and reports how far a structure is from its true native. Total surface area, Euclidean distance, total empirical energy, secondary structure penalty, residue length, and pair number are the physical and chemical properties used for predicting the native Protein sequences are taken from protein structure prediction center (CASP) and protein data bank (RCSB). The root mean square deviation (RMSD) of each structure lies between 0Å to 6Å space. Since some of the considered features may have higher importance than others in predicting the native structures, artificial bee colony (ABC) algorithm is used to determine the feature importance. The features are used by four machine learning models namely decision tree, random forest, SVM (support vector machine), and linear model for the prediction of protein structure in absence of its true native state. The accuracy of best predictive model is using K-fold cross validation.

3.2 ARITIFICAL BEE COLONY (ABC)

The Artificial Bee Colony (ABC) algorithm is a recently developed bio inspired algorithm ABC is inspired by honey bee's food searching behavior. Here, food source of honey bees is known as solution of the problem. The quality of food source is considered as fitness value. There are three types of honey bees i.e. scout bees, onlooker bees and employed bees. There are equal number of onlooker bees and employed bees. Employed bee's searches for the best fitness value (i.e. Food source) and get the information about its quality. The searching of onlooker bees are depend upon the information collected by employed bees. Onlooker bees are stay in the hive only. Scout bees randomly search for the new food sources. ABC search process required three control parameters i.e. number of food sources SN, it is also equal to number of onlooker bees or employed bees, number of iterations and limit (number of trials after which a food source is considered to be abandoned) [49]. The pseudo-code of the ABC is shown in Algorithm 1.

3.2.1 ALGORITHM 1 Artificial bee colony algorithm

Parameters Initialization

While Stopping condition is not met do

Step1: Generate new food sources (Employed phase)

Step2: Updating food sources (Onlooker phase).

Step3: Discovering new food sources randomly (Scout phase).

Step4: Remember best food source.

End While

Return the best solution.

3.3 FEATURE IMPORTANCE USING ABC ALGORITHUM

The ABC is used to find the importance of each feature. The weight given to each feature is defined in eq. (1). The parameters for the ABC are the colony size (NP=50; [50], number of food sources (SN=NP/2), dimension of the problem (D=30), limit D*SN [51] and the termination condition (number of iterations = 2000). The average weight of five different runs obtained for each feature is described in Table V. The average weight of F7, F1 and F9 are highest and all they belong to phase A current. F25, F23, F27 and F26 have the lowest weights and all they belong to phase C current. As the weight given to each feature is significant, all the features are selected for the experiment.

$$\text{Obj fun} = \min\left(\sum_{j=1}^{N}\sqrt{Fi - \sum_{j=1}^{n} wj.Pt,j}\right)\ldots\ldots\ldots\ldots\ldots\ldots \quad (1)$$

Where, N is number of instances in training set, F is the fault class, n defines the number of features and w is the weight defined in the range of (25 to 60) given to each feature.

3.4 MACHINE LEARNING METHODS

Machine learning is subfield of computer science that evolved study of pattern recognition and computational learning theory in artificial intelligence. Machine learning explores the study and construction of algorithm that can be learning from to make the prediction on different data set. Such type of algorithm operates by building a model from example inputs in order to make the data driven prediction or decision rather than strictly static program instruction.

Machine learning is related to computational statistics that specialize in prediction-making.it is strong mathematical optimization. Machine learning is employed in a range of computing tasks where designing and programing explicit algorithm is infeasible. Application includes spam filtering, optical character recognition (OCR), search engines and computer vision. Machine learning is sometimes conflated with data mining although that focuses more on exploratory data analysis. Machine learning and pattern recognition can be viewed as two facts of the same field. The four different method of machine learning are as follows: - Decision tree method, Random forest method, Support vector method, linear model method

3.4.1 DECISION TREE METHOD

Decision tree method uses a decision tree as a predictive tree as a predictive model which maps observations about an item to conclusion about the item's target value. It is one of the predictive modeling approaches used in statistics, data mining and machine learning. Tree models where the target variable can take a finite set of values are called classification trees. In these tree structure ,leaves represent class labels and branches represent conjunction of features that lead to those class labels .decision tress where the target where the target variable can take continue values (typically real numbers) are called regression. In data mining a decision tree describes data but not decision rather the resulting classification tree can be an input for decision making.

3.4.2 RANDOM FOREST METHOD

Random forest method is ensemble learning method for regression, classification and other tasks. These methods are operated by constructing a multitude of decision tree at training time and outputting the class that is the mode of the classes (classification) or mean prediction (regression) of the individual trees. Random forest methods correct for decision trees' habit of overfiting to their training set.

The random forest algorithm was developed by Leo Breiman and Adele Cutler."Random Forests" is their trademark. This method combines Breiman's bagging idea and the random selection of features, introduced independently by Ho and Amit and Geman in order to construct a collection of decision trees with controlled variance.

The selection of a random subset of features is an example of the random subspace method, which, in Ho's formulation, is a way to implement classification proposed by Eugene Kleinberg. In the field of machine learning the goal of statistical classification is to use an object's characteristics to identify which class (or group) it belongs to.

3.4.3 SUPPORT VECTOR METHOD

Support vector machine learning is supervised learning model associated with learning algorithm that analyze data and recognize pattern used for classification analysis. An SVM (support vector machine) learning algorithm builds a model that assign new examples into one category or the other, making it a non-probabilistic binary linear classifier, An SVM model is a representation of the examples as points in space, mapped so that the examples of the separate categories are divided by a clear gap that is as wide as possible. New examples are then mapped into that same space and predicted to belong to a category based on which side of the gap they fall on.

In addition to performing linear classification, SVM can efficiently perform a non-linear classification using what is called the kernel trick implicitly mapping their inputs into high-dimensional feature spaces.

3.4.4 LINEAR MODEL METHOD

Linear model method is a family of model-based learning approaches that assume the output y can be expressed as a linear algebraic relation with the input attributes x1, x2. Linear model uses linear models to carry out regression, single stratum analysis of variance and analysis of covariance. A linear model achieves this by making a classification decision based on the value of a linear combination of the characteristics. An object's characteristics are also known as feature values and are typically presented to the machine in a vector called a feature vector.

CHAPTER-4

MODELLING AND SIMULATION OF TRANSFORMER

4.1GENERAL

The name MATLAB stands for Matrix Laboratory. MATLAB was written originally to provide easy access to matrix software developed by the LINPACK (linear system package) and EISPACK (Eigen system package) projects.

MATLAB is a high-performance language for technical computing. It integrates computation, visualization, and programming environment. Furthermore, MATLAB is a modern programming language environment: it has sophisticated data structures, contains built-in editing and debugging tools, and supports object-oriented programming. These factors make MATLAB an excellent tool for teaching and research.

MATLAB has many advantages compared to conventional computer languages (e.g., C, FORTRAN) for solving technical problems. MATLAB is an interactive system whose basic data element is an array that does not require dimensioning. The software package has been commercially available since 1984 and is now considered as a standard tool at most universities and industries worldwide. It has powerful built-in routines that enable a very wide variety of computations. It also has easy to use graphics commands that make the visualization of results immediately available. Specific applications are collected in packages referred to as toolbox. There are toolboxes for signal processing, symbolic computation, control theory, simulation, optimization, and several other fields of applied science and engineering.

In addition to the MATLAB documentation which is mostly available on-line, we would recommend the following books: [52], [53], [54], [55], [56], [57], [58], and [59]. They are excellent in their specific applications.

Simulink is a graphical programming environment for modeling, simulating and analyzing multi-domain dynamic systems. Its primary interface is a graphical block diagramming tool and a customizable set of block libraries. It offers tight integration with the rest of the MATLAB environment and can either drive MATLAB or be scripted from it. Simulink is widely used in automatic control and digital signal processing for multi-domain simulation and Model-Based

Design .The systematic testing tool TPT is marketed as a way to perform a formal verification and validation process to stimulate Simulink models but also for use during the development phase where the developer generates inputs to test the system. By the substitution of the Constant and Signal generator blocks of Simulink, Math Works claim that the simulation becomes reproducible.

Sim Events is used to add a library of graphical building blocks for modeling queuing systems to the Simulink environment, and to add an event-based simulation engine to the time-based simulation engine in Simulink.

4.2 MODELLING AND SIMULATION OF TRANSFORMER.

Transformer outage has severed technical and economic consequences for the network, so implementing fast relaying algorithms is a challenge. Therefore, modeling of various types of internal transformer faults is the objective of this. This introduces a proposed approach to model internal incipient winding faults in three-phase three-winding transformers using. The User Specified Object (USO) is used for building the transformer model under fault conditions. The proposed models have the ability to change the transformer impedance matrices in a simple manner to satisfy the internal fault conditions. The internal faults in the three-windings are simulated and tested. The results show that proposed approach is able to represent the internal faults in the three-phase three-winding transformers accurately.

Large transformers are a class of very expensive and vital components of electric power systems. Since it is very important to minimize the frequency and duration of unwanted outages, these are a high demand imposed on power transformer protective relays. Protection of large power transformers is a very challenging problem in power system. The measurements of transformer abnormal conditions, especially for internal faults, are seldom available, the information needed for the investigation of protective relays improvement may be exclusively achieved The electrical faults of transformers are classified in two types: external and internal faults.

External faults are those that occur outside of the transformer: overloads, overvoltage, over-fluxing, under frequency, and external system short circuits. Internal faults are those that occur inside of the transformer: winding phase-to-phase, phase-to-ground, winding inter-turn, over-fluxing, and etc. About 70-80% of transformer failures are caused by internal faults. Several papers have introduced methods for modeling winding faults in transformers

Three phase 220/6.3 KV, 24 MVA (Star-Star) transformer has been used to produce the required testing and training pattern for different operating conditions of transformer is simulated with the help MATLAB/SIMULINK .Different power system model of three phase transformer for different operating condition are shown in the following figure.4.1, 4.2, 4.3, 4.4, 4.5.

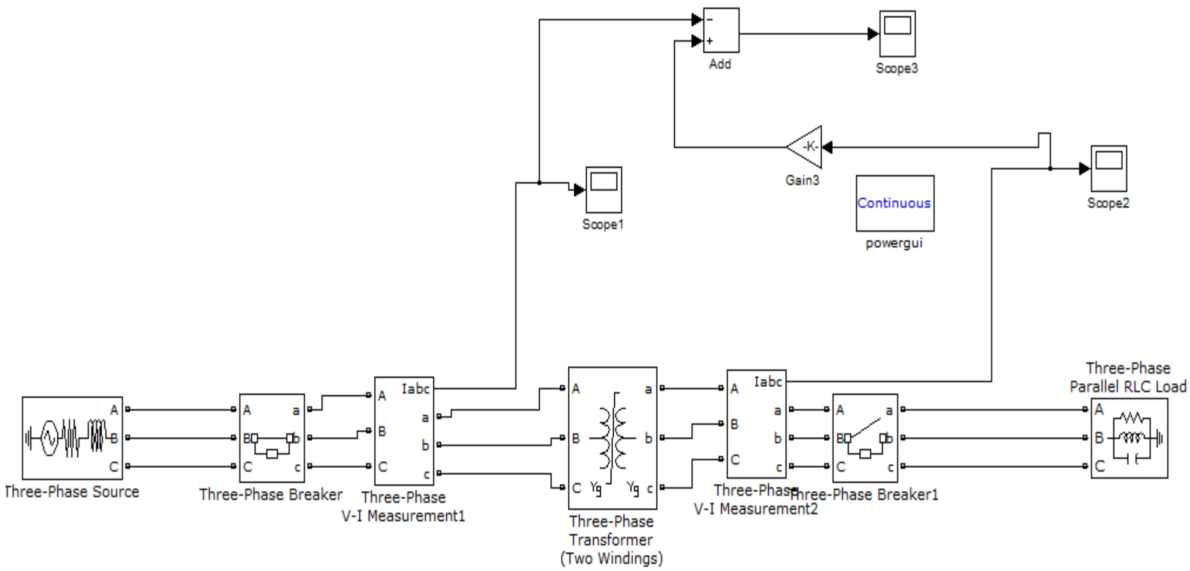


Fig4.1 simulated power system model for normal, magnetizing inrush and over-excitation

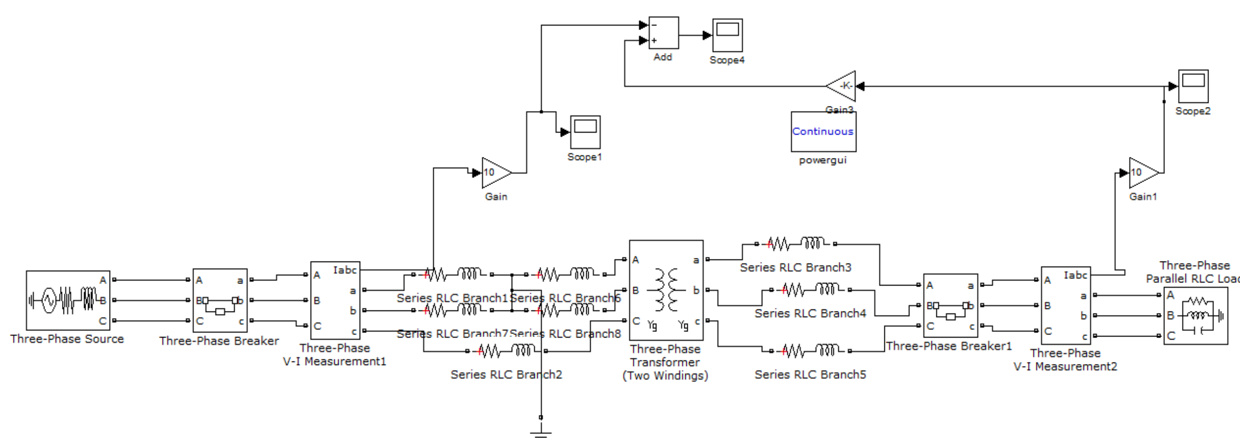


Fig4.2 simulated power system model for internal LLG fault of transformer.

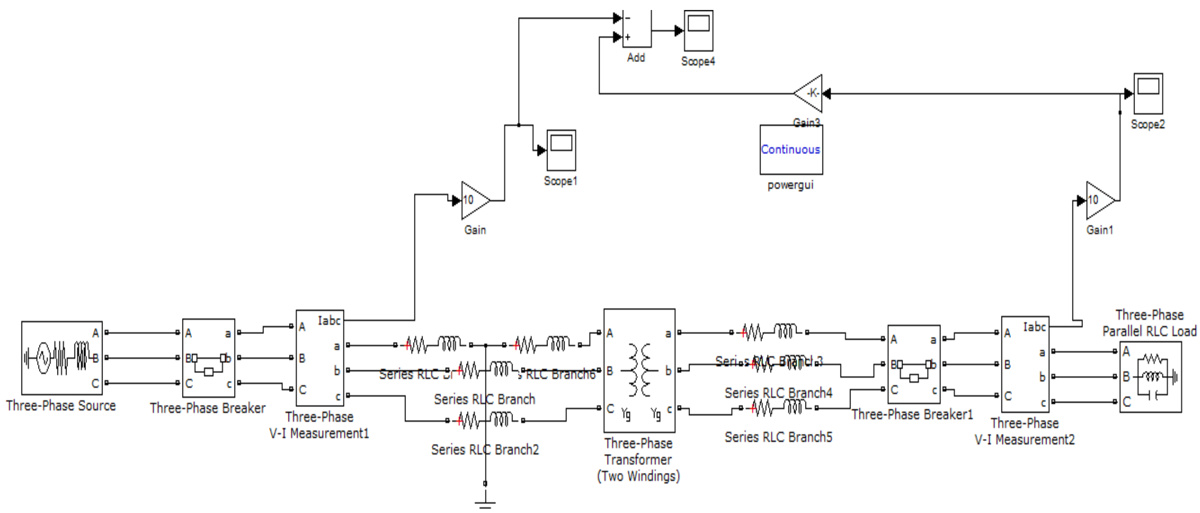


Fig4.3 simulated power system model for internal LG fault of transformer (primary side)

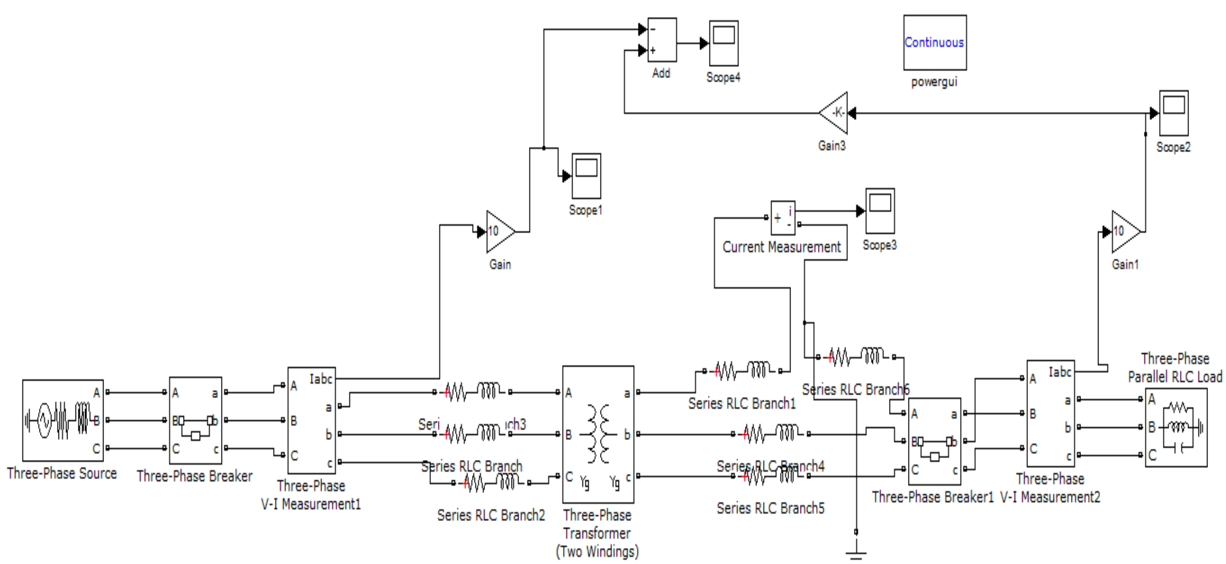


Fig4.4 simulated power system model for internal LG fault of transformer (secondary side)

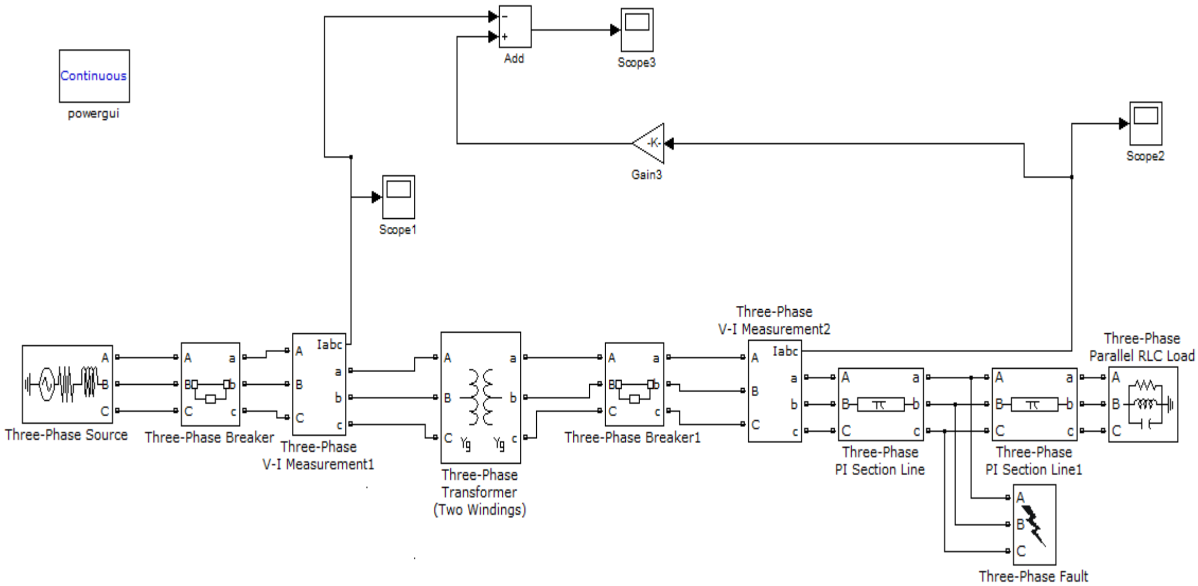


Fig4.5 simulated power system model external fault of transformer

4.3 SIMULATION RESULTS

4.3.1 FAULT SIMULATION

Power system model of transformer is simulated with different operating conditions of transformer such as normal condition, magnetizing inrush, over-excitation, internal and external fault conditions of transformer. Different types of internal fault is considered such as Line to ground fault in A,B,C phase in primary windings of transformer, similarly Line to ground fault in secondary windings of transformer ,Double line to ground faults, line to line faults . Different inception angles of 0^0, 30^0 ,60^0,90^0 are taken for simulation. In external fault condition we add a 100 km transmission line and fault is occurs 10%, 20%, 30% of transmission line .normal condition will be occurs one there is no fault in the transformer .magnetizing inrush condition will be occurs when secondary windings of transformer is open circuit .over excitation condition will be occurs at different voltage levels will be occurs. The general waveforms output will be coming with simulation of different model of transformer at different operating conditions of transformer are shown with brief discussion regarding the fault condition of transformer.

4.3.2 NORMAL CONDITION

When there is no fault occurs in the transformer then we say that transformer is under normal condition. The differential current waveforms shown in fig4.5 that is coming from simulation of (star-star) three phase transformer is under normal condition shown in fig4.1 simulated power system model for normal condition of transformer

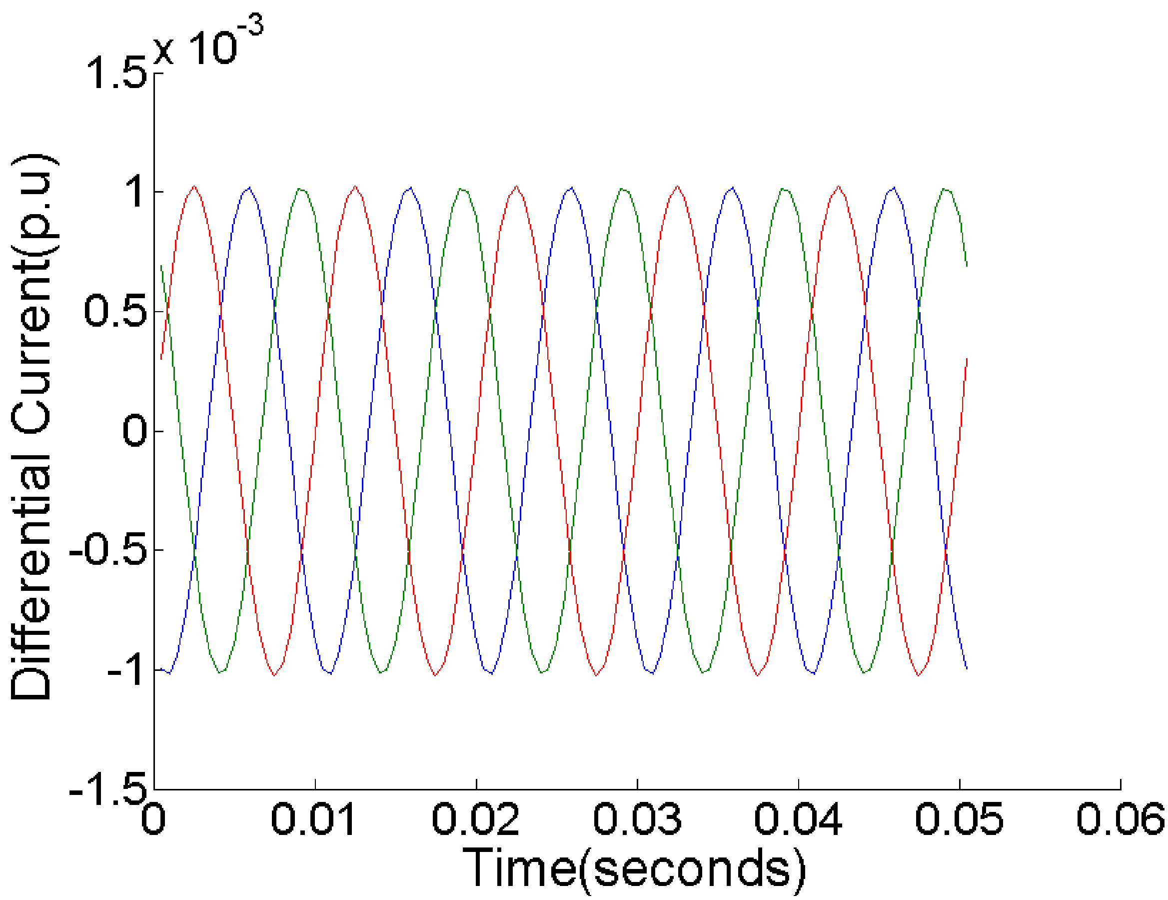


Fig 4.6 Normal condition of transformer (Differential Current)

4.3.3 MAGNETIZING INRUSH CONDITION

Magnetizing inrush condition is coming in the transformer when transformer is switched under no load condition. In the other words we are saying that at different voltage angles by closing the breaker connected the magnetizing inrush condition will be occurs in the transformer. The differential current waveform shown in Fig 4.6 is coming from simulation of power system model for magnetizing inrush condition of transformer shown in Fig 4.1

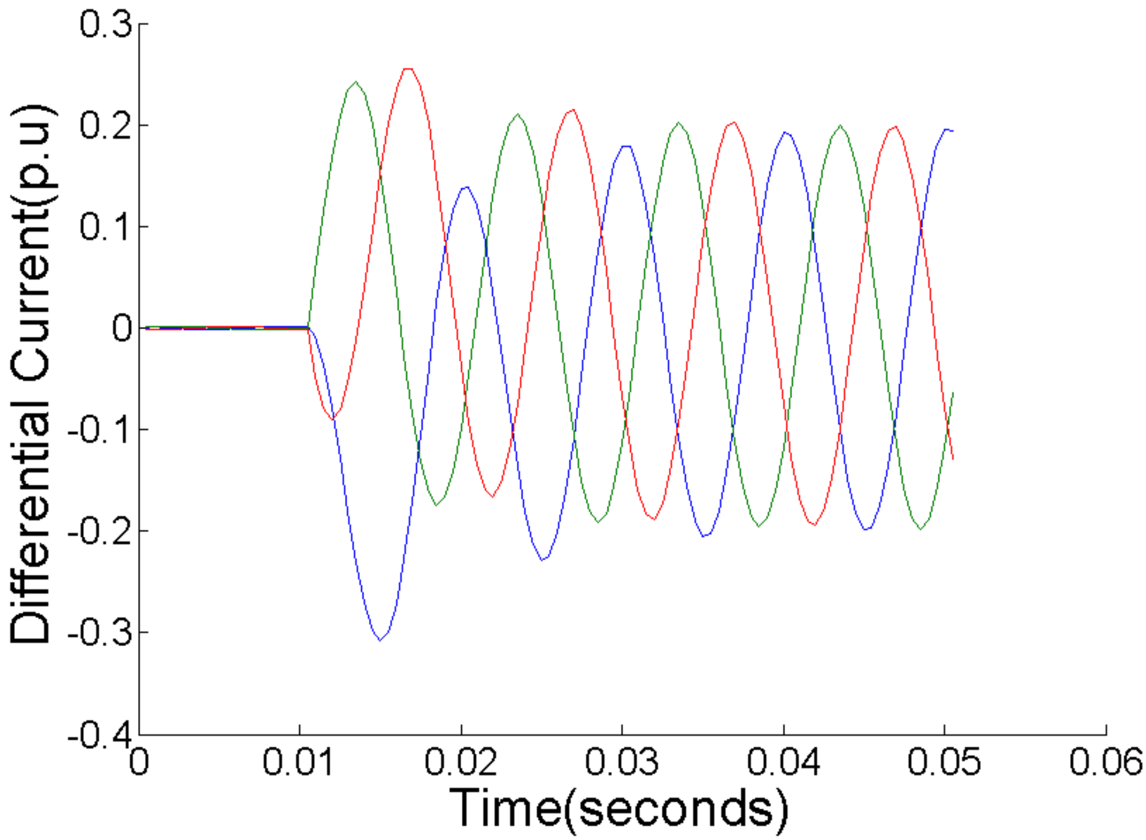


Fig 4.7 Magnetizing inrush condition of transformer (differential current)

4.3.4 OVER-EXCITATION

Over-excitation condition occurs in transformer at different over voltages. In other words we are saying that at different over voltage levels the over-excitation will be occurs in the transformer. The differential current waveform shown in Fig4.7 is coming from simulation of power system model for over-excitation condition of transformer shown in Fig 4.1

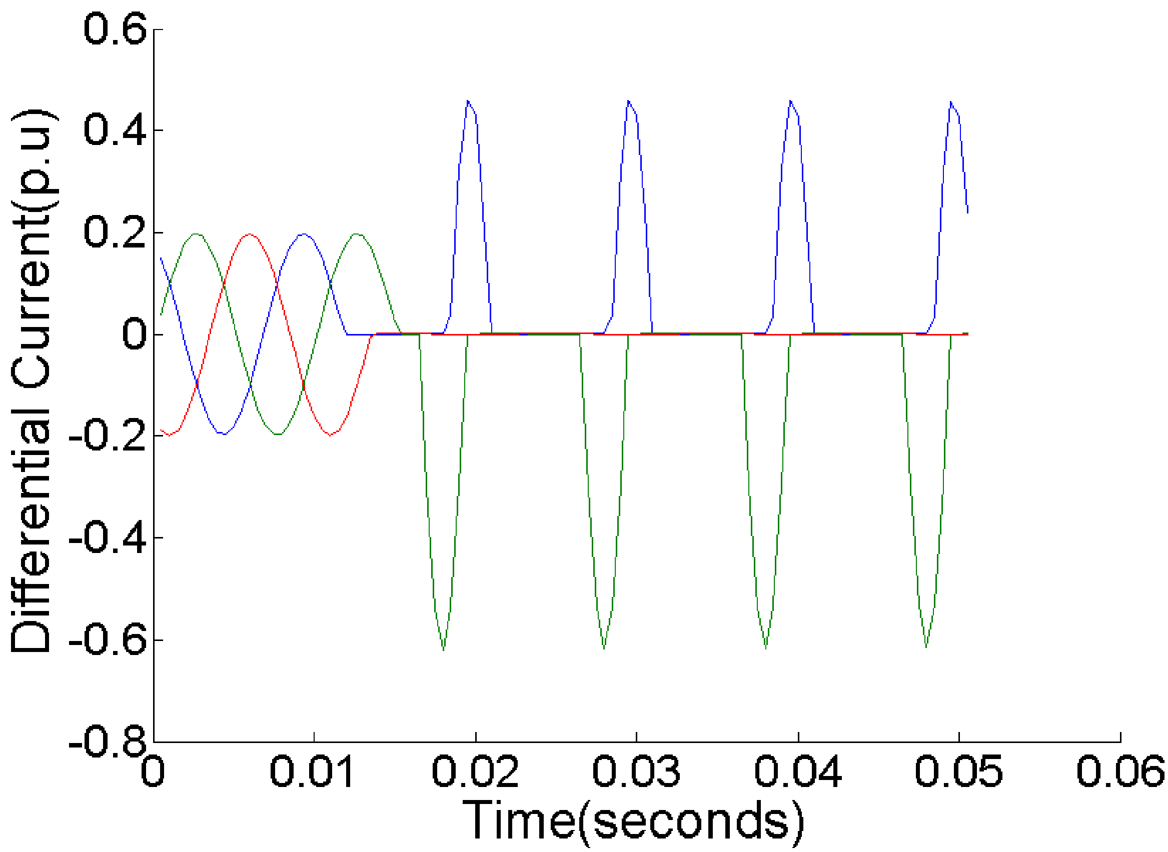


Fig 4.8 over-excitation condition of transformer (Differential current)

4.3.5 INTERNAL FAULT CONDITION

There are different types of internal fault such Line to ground, double line to ground fault are simulated in this at different phases such A,B,C phase in the primary winding as well as secondary winding of the transformer. Internal fault will be simulated at 10%, 20%, 30%, 40%, 50% faulty portion in different phases of transformer. The simulated waveform of differential current of one of the internal fault double line to ground fault are shown as in Fig4.9 which is coming from the simulation of power system model for internal fault (LLG) in fig4.2.

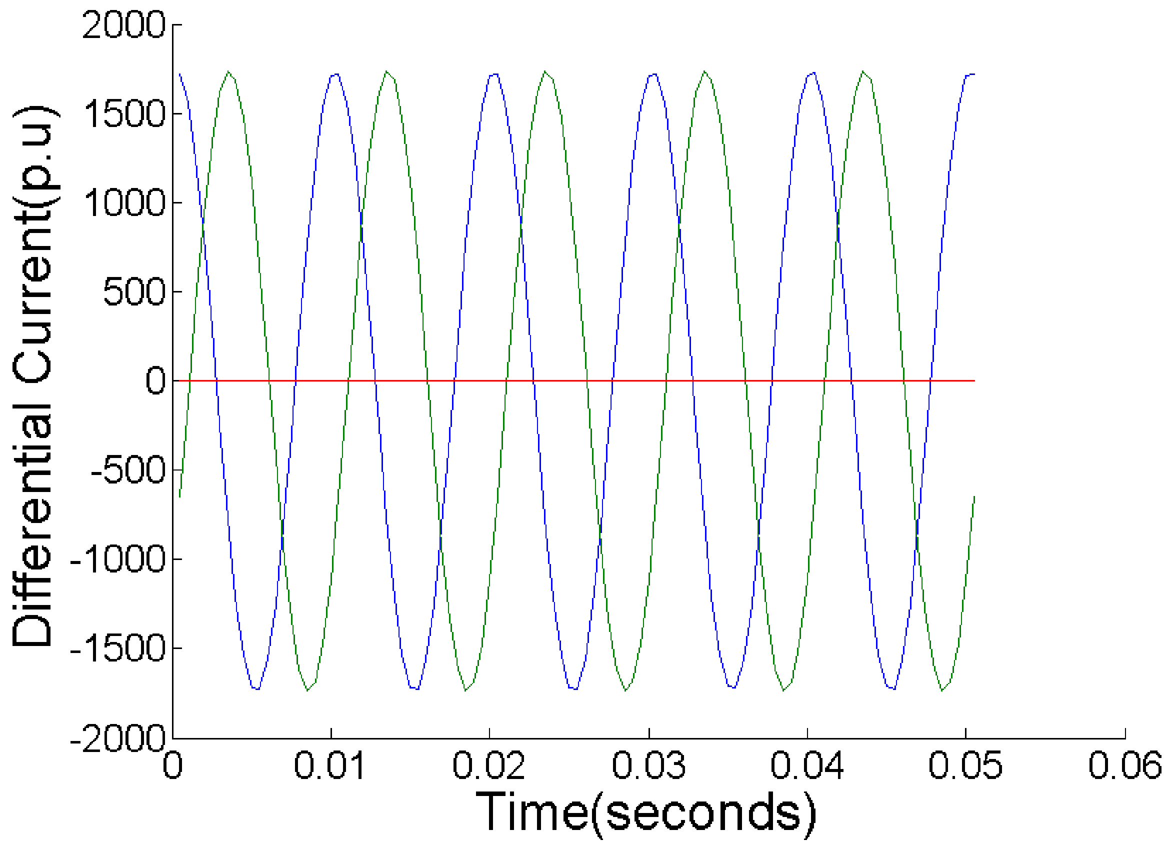


Fig 4.9 internal fault (LLG) condition of transformer (Differential current)

4.3.6 EXTERNAL FAULT CONDITION

External fault condition will occurs when there is some fault occurs at transmission line connected with transformer. In other words we are saying that when transformer is affected by some external disturbances like fault in the transmission line in any phase then this type of fault effect transformer. We are simulated the external fault condition of transformer at different length such as 10, 20,30,40,50 Km transmission line will be faulted. The simulated waveform of differential current of external fault condition of transformer is shown in Fig4.10 which is coming from the simulation of power system model for external fault shown in Fig 4.5.

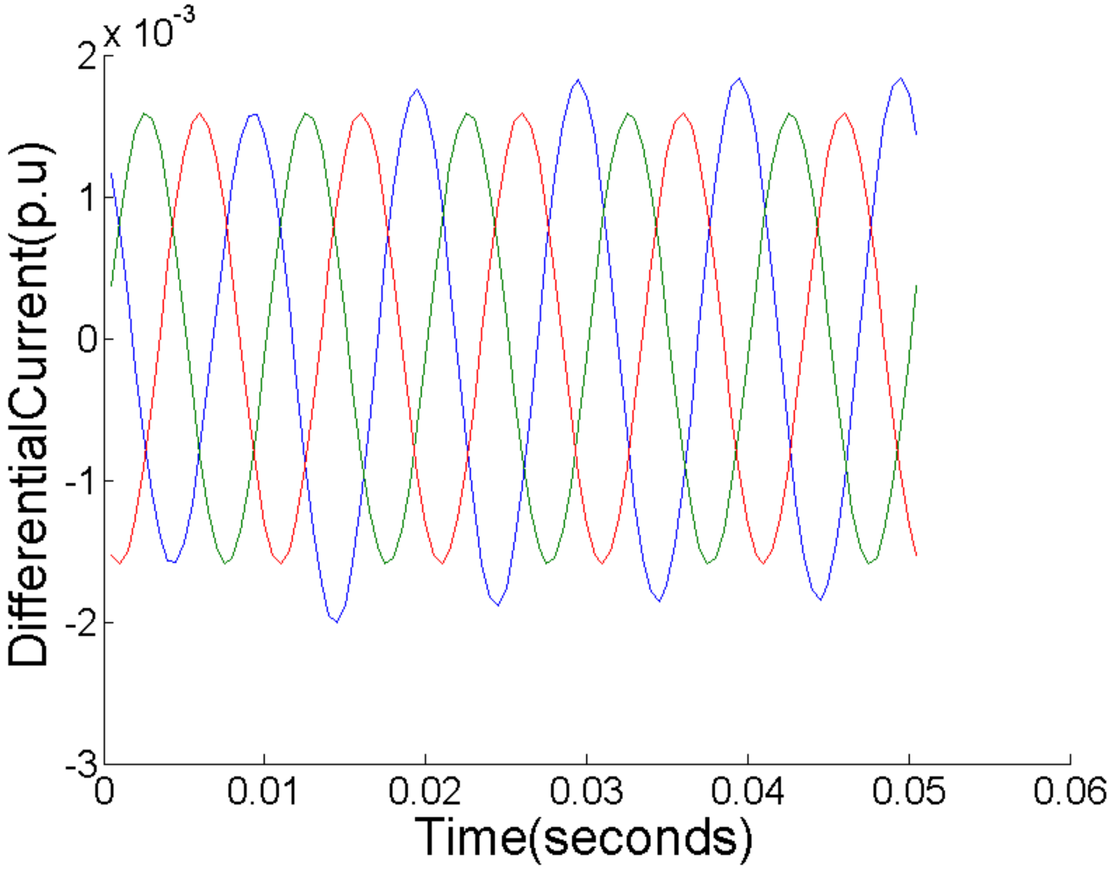


Fig 4.10 external fault condition of transformer (Differential current)

CHAPTER-5

TEST SYSTEM AND RESULTS

5.1 MODEL BASED DESIGN PROCESS

There are six steps to modeling any system.

- Define the system
- Identifying system components
- Modeling the system with equations
- Building the Simulink block diagram
- Running the simulation
- Validating the simulation results
- Running the simulation.

After building the Simulink block diagram, we can simulate the model and can analyze the results. Simulink allows us to interactively define the system inputs, simulate the model, and observe change in behavior.it allows quickly evaluation of the model.

5.2 SIMULATED SYSTEM

Three-phase 220/6.3 KV, 24MVA (star-star connected) transformer as shown in Fig. 4.1,4.2,4.3,4.4,4.5 has been used to produce the required test and training patterns. The simulation was done by means of Sim power systems (MATLAB) software. The combination of condition of system is shown in Table I. They involve inrush current and over excitation condition with different voltage angles and with different loads. The inputs to the network are samples taken from the waveforms generated by creating different operating conditions, they themselves define. There are total 420 simulations are generated for currents using sim power simulation (implemented in MATLAB) under different faults conditions. Table II describes description of features. The methodology and prediction model are describe in next step.

TABLE1: Dataset for classification of fault

Fault Class	**Fault Type**	F1	F2	F3 ….. F30
1.	Normal condition	0.001	0.001	0.001 ……0.000
2.	Magnetizing inrush	0.158	0.120	0.070……-0.108
3.	Over excitation	0.135	0.083	0.024…….-0.001
4.	Internal	-0.001	-0.001	-0.002…….-0.002
5.	External fault	-0.181	-0.208	-0.21…….-0.115

TABLE 2: description of feature

Feature	**Information**
F1 - F10	Current in A Phase.
F11 - F20	Current in B Phase
F21 - F30	Current in C Phase.

5.3 METHODLOGY

The methodology is described in Fig. 5.1. In the first step, collection of currents using sim power simulation under different operating conditions of transformer. Data cleansing is performed in step two that includes removal of missing values from the data set and removals of duplicates entries. In the third step, the importance of each feature is measure with ABC algorithm. Feature selection makes the prediction of model efficient and accurate. In the fourth step, decision tree, random forest, support vector machine and linear model were trained and tested on the data set with their default parameters. Fig.5.2 describes the prediction model. Finally, evolution of model is done on accuracy and sensitivity and robustness of the best predictive model is measure with K-fold cross validation.

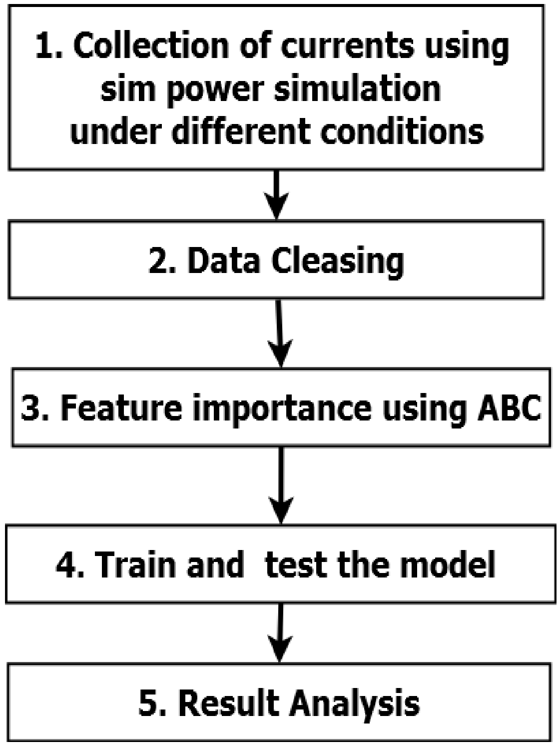


Fig5.1: Methodology used

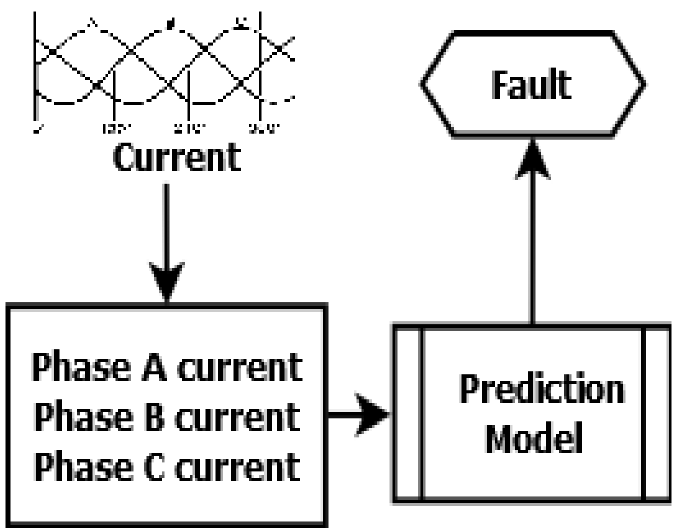


Fig. 5.2: Prediction model.

5.4 MACHINE LEARNING METHODS

In this thesis work, the four learning machine method are use (refer, Table 3) for prediction of fault in three phase transformer. Both the models are available in R open source software. R is licensed under GNU GPL. The models are presented below:

1. Decision Trees: In this model, an extension of C5.0 classification algorithms described by Quinlan [61].

2. Linear Models: linear models are used to carry out regression, single stratum analysis of variance and analysis of covariance [62].

3. Random forest is based upon the number of decision trees having random inputs [63].

4. SVM (Support Vector Machine) is a powerful classification model [64].

Table no IV represents the parameter settings of each machine learning models.

TABLE 3: Machine learning classification model used

Model	Package	Tuning Parameter(s)	Ref.
Decision Trees	C50	window, model, trials	[61]
LM	Stats	None	[62]
Random Forest	Random Forest	mtry	[63]
SVM	e1071 nu	epsilon	[64]

TABLE 4: Parameter setting for machine learning models

Model	Parameter Setting
Decision Trees	Min Split = 20, Max Depth = 30, Min Bucket = 7
LM	Multinomial
Random forest	Number of tress is 500
SVM	Kernel Radial Basis

5.5 MODE OF EVALUITON

The performance of the prediction model is done on sensitivity and accuracy. Both the machine learning model uses the same formula given by

FAULT _ f (F1, F2... F29, F30)

The sensitivity and accuracy as a pair of (S, C) for measuring the performance of both the machine learning models. To determine the (S, C), a confusion or error matrix is formed showing the information about actual and predicted classifications done by a classifier. The diagonal elements of confusion or error matrix represent the number of objects for which the predicted label is equal to the true label, while off-diagonal elements are those that are mislabeled by the classifier. The higher the diagonal values of the error matrix, better the accuracy. If there is n number of classes then the value Cij of the confusion matrix of size n×n represents the number of patterns of class i predicted in class j. The classifier accuracy can be calculated as

$$\text{Accuracy} = \sum_{i=1}^{n} cii / \sum_{i=1}^{n} \sum_{j=1}^{n} cij \; \ldots\ldots\ldots\ldots\ldots\ldots\ldots \; (2)$$

However, the classification accuracy may show inaccurate results in a case when there is a high variance in the number of objects in the classes. Hence, this paper represents the accuracy of the classifier as a pair of values (S,C) where S is the minimum of sensitivities among all classes and C is the overall accuracy [65]. Sensitivity Si for the class i can be defined as the number of patterns correctly predicted to be in class i with respect to the total number of patterns in class i which is shown below [66].

$$S_i = cii / \sum_{j=1}^{n} cij \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \; (3)$$

Therefore, the sensitivity (S) of the classifier will be the minimum value of the sensitivities as shown in eq. (2) [66].

$$S = \min (S_i;\ i = 1, n) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \; (4)$$

The correct classification rate or accuracy (C) for the classifier is defined as in eq. (5) that is, the rate of all the correct predictions [66].

$$C = 1/n\sum_{i=1}^{n} Si \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.. \quad (5)$$

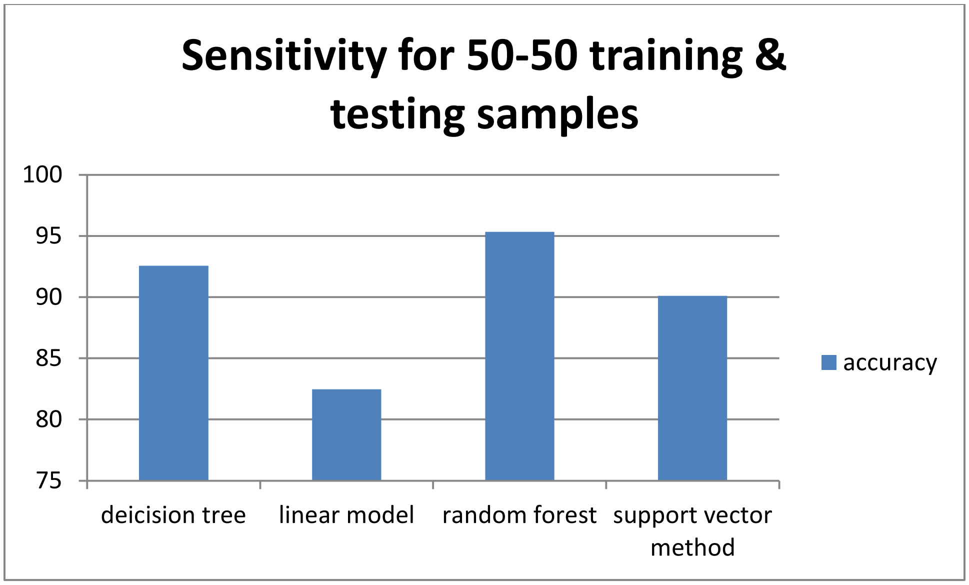
The robustness of best predictive model is measured with K-fold cross validation. In K-fold validation, the sample is divided into k equal number of partitions. Out Of k partitions, a single partition is used for test the model and the remaining. K-1 partitions are used for train the model. The process of K fold validation is repeated k times and average of k results to produce a single estimation. Here, K=10 (K-f old) cross validation is used.

5.5 TEST RESULT

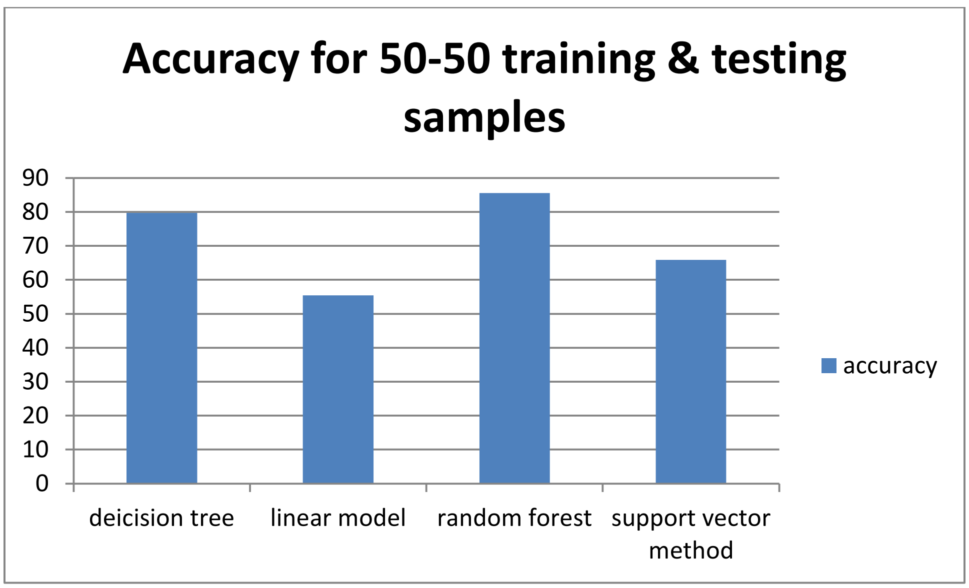
We analyze the prediction results of all the four machine learning classification models on testing dataset. All the four methods are run on their default parameters as shown in Table4. The accuracy is calculated using eq. (5) and is shown in Table5 for all the models on 50-50, 60-40, 70-30 and 80-20 training-testing partitions. It is evident that the random forest have highest sensitivity and accuracy pair of (0.81, 85.55%), (0.91, 90.12%), (0.93, 94.16%), (0.93, 95.35%) on the training-testing partitions respectively. Further, robustness of the random forest method is measure by use of 10-fold cross validation. Fig 5.3 and Fig 5.4 shows the sensitivity and accuracy respectively for the 10 folds. Cross validation results show a uniform performance in accuracy using random forest. The result validates that random forest machine learning models in the classification.

Table 5. Performance comparison of four machine learning method on different training-testing partitions in sensitivity and accuracy pair

Models	**Training - Testing Partition**			
	50-50%	**60-40%**	**70-30%**	**80-20%**
Decision Trees	(0.75, 79.68)	(0.79, 82.02)	(0.88, 91.97)	(0.90, 92.57)
LM	(0.52, 55.43)	(0.60, 63.74)	(0.69, 72.26)	(0.81, 82.47)
Random Forest	(0.81, 85.55)	(0.91, 90.12)	(0.93, 94.16)	(0.93, 95.35)
SVM	(0.63, 65.91)	(0.69, 77.72)	(0.80, 87.59)	(0.88, 90.11)

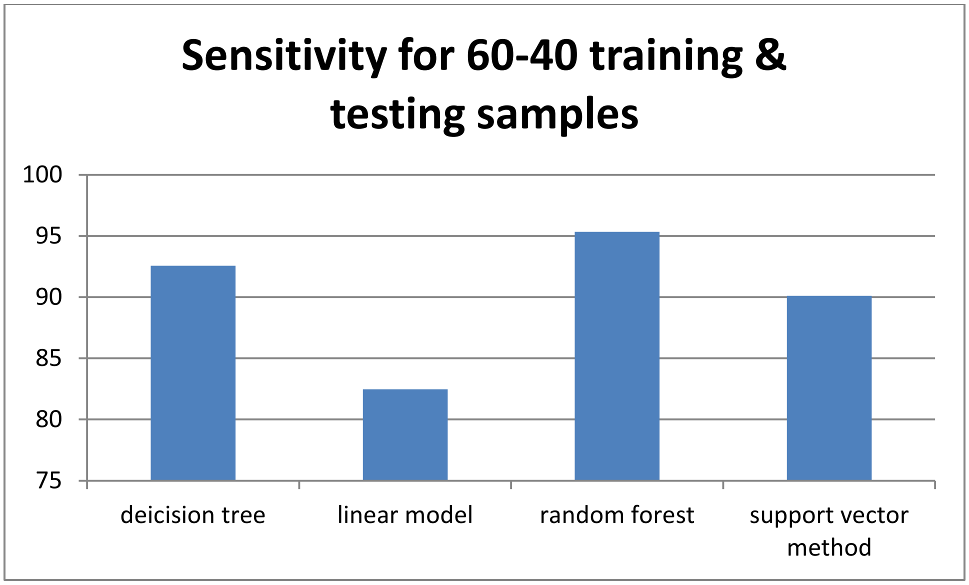


Sensitivity

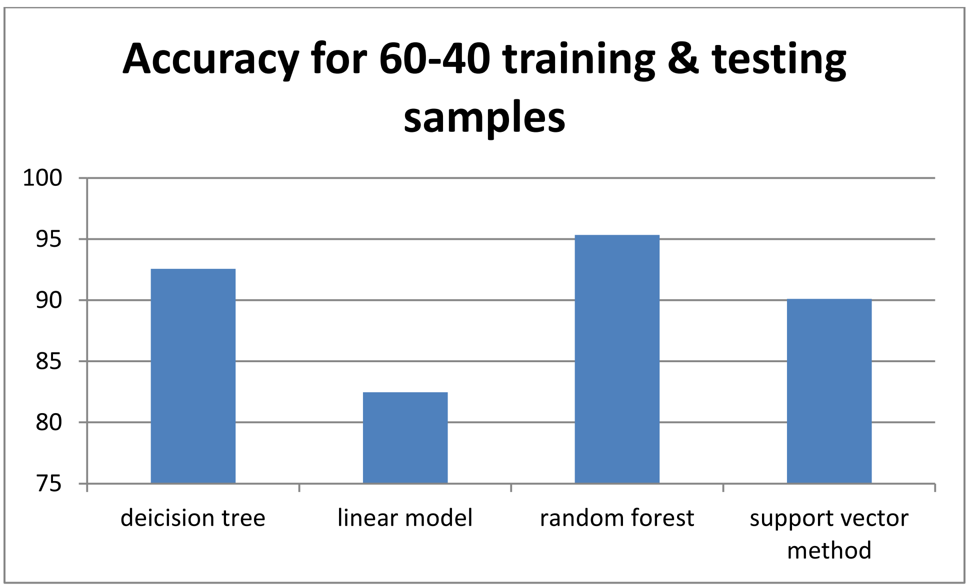


Accuracy

Fig 5.3 Sensitivity and accuracy for 50 -50 training and testing samples for different machine learning method

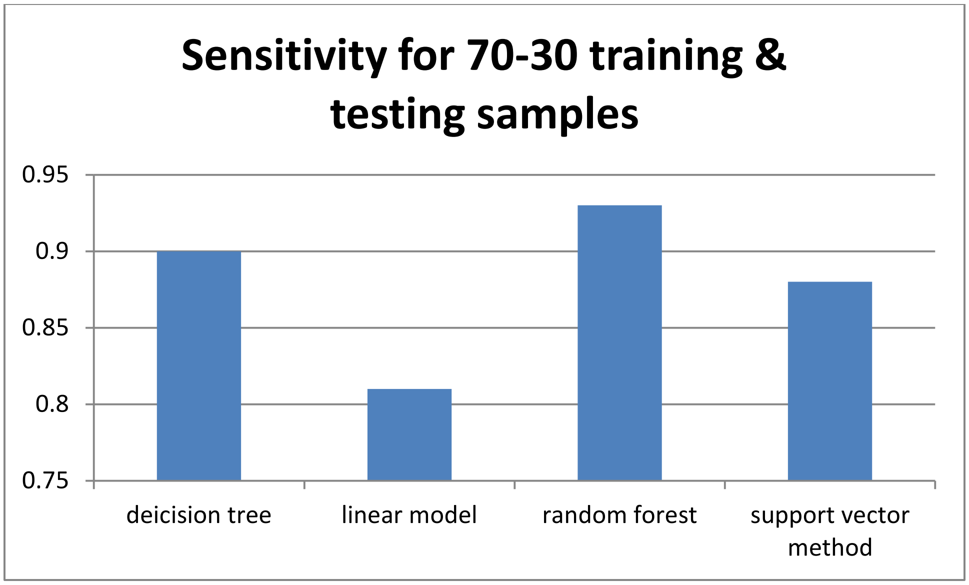


Sensitivity

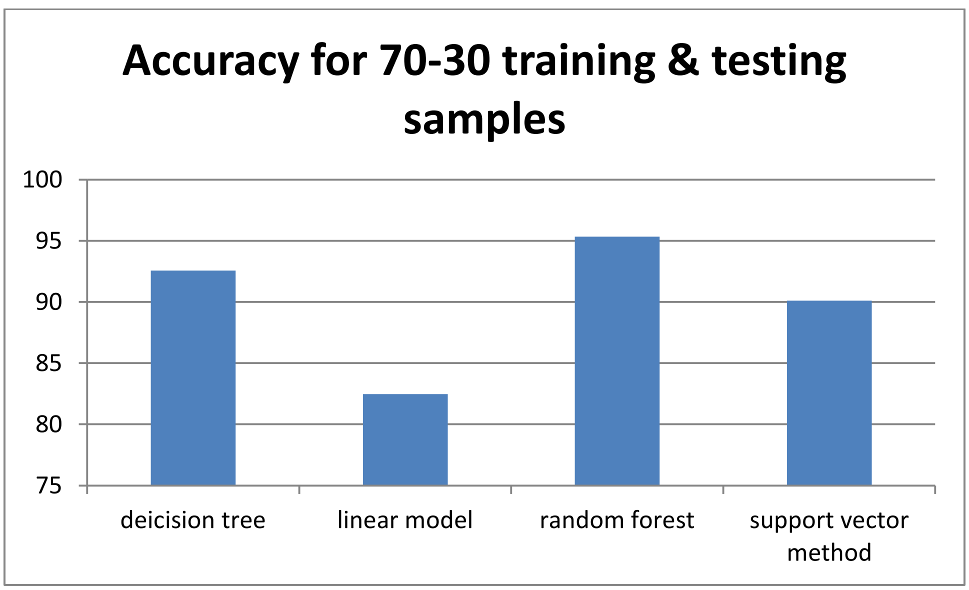


Accuracy

Fig 5.4 Sensitivity and accuracy for 60 -40 training and testing samples for different machine learning method

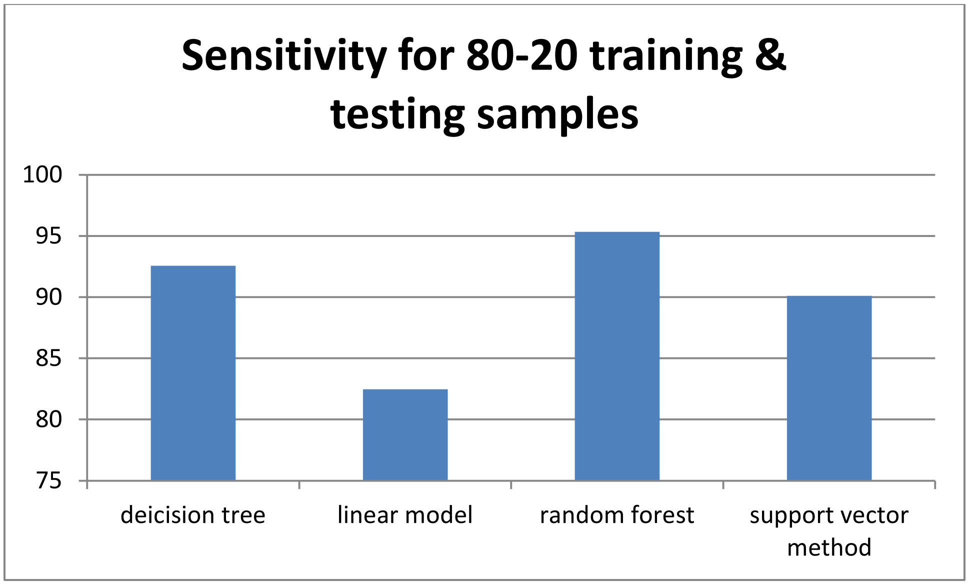


Sensitivity

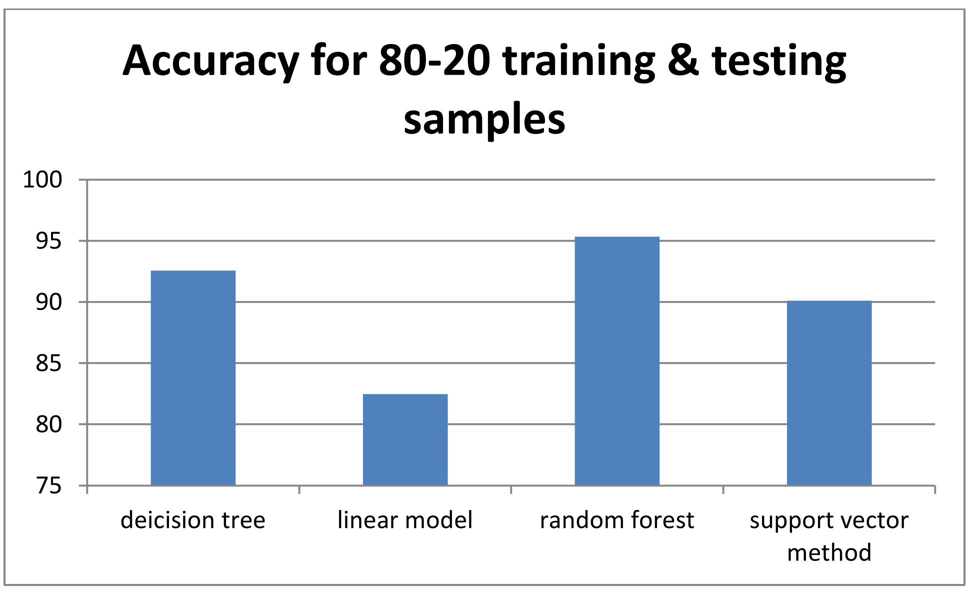


Accuracy

Fig 5.5 Sensitivity and accuracy for 70 -30 training and testing samples for different machine learning method



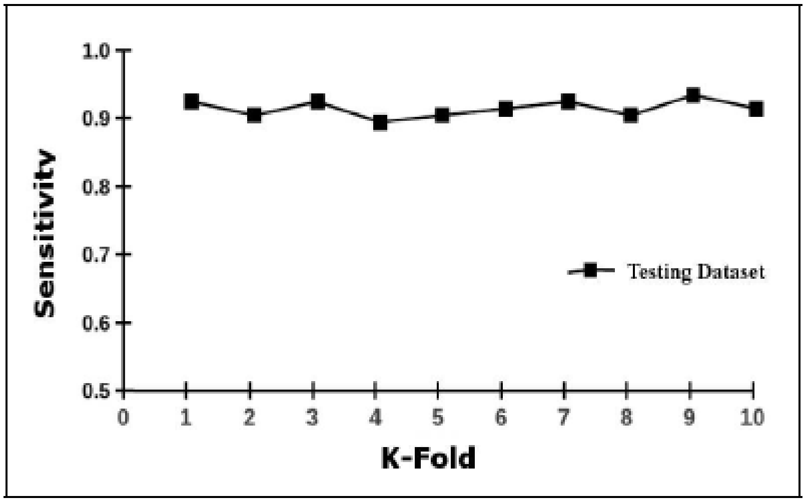
Sensitivity



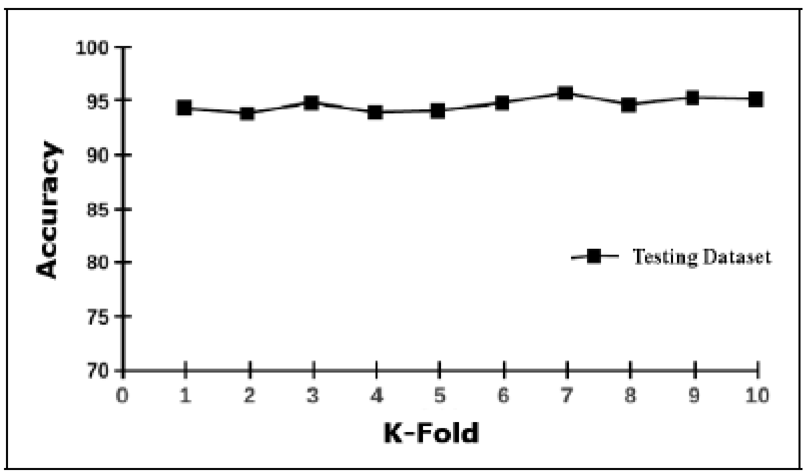
Accuracy

Fig 5.5 Sensitivity and accuracy for 80 -20 training and testing samples for different machine learning method

As we see from result that random forest method is best as compare to decision tree, linear model and support vector method so we apply k-fold validation to random forest



(A) Sensitivity



(B) Accuracy

Fig. 5.7: 10-fold cross validation of sensitivity and accuracy on training-testing dataset (70-30%) in the prediction of RMSD using random forest.

CHAPTER-6

CONCLUSION AND FUTURE SCOPE OF WORK

6.1CONCLUSION

In this work, three phase transformer is simulated with different operating conditions such as normal condition, magnetizing inrush, over-excitation, internal and external fault condition in MATLAB/SIMULINK. The four different machine learning method with 30 differential current samples to predict the internal fault in three phase transformer and also discriminate it with magnetizing inrush and over-excitation. Artificial Bee Colony (ABC) algorithm is used for feature importance. The robustness of best predictive model is measure by using K-fold cross validation. The performance of different machine learning method has been tested successfully for the classification of various cases. From the results obtained, following conclusion has been drawn.

- Out of four different machines learning methods the random forest method is the best method for training and testing the different sample of current to identify the internal fault in the transformer.
- Accuracy and sensitivity of random forest method is higher as compared to decision tree, linear model and support vector.
- The classification ability of the machine learning technique opens the door for smart relays for power transformer protection with very less operating time and desirable accuracy.

6.2 SCOPE FOR FUTURE WORK

In this work, we use only three phase (star-star) transformer for protection purpose. This work can be extended for different configurations of transformers using higher sampling frequency, full cycle data window and other computational methods to enhance the performance of machine learning methods. Based on this thesis, the following area of work is suggested for further exploration:

- ✓ This work can be compared with other classifiers like MFNN.
- ✓ Prototype modeling based on machine learning protection of transformer.
- ✓ Online testing of algorithm.

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APPENDIX

TRANSFORMER PARAMETERS

Parameters	Value
Nominal Power and Frequency	24 MVA, 50 Hz
Primary Side	V1=220 KV, R1=7.5132e-6 pu, L1=8e-7 pu
Secondary Side	V2=6.3 KV, R2=7.5132e-6 pu, L2=3.04e-3 pu
Magnetization Resistance	500 pu
Magnetization Inductance	500 pu

SOURCE PARAMETERS

Phase- to- phase RMS voltage (V) = 220e3

Phase angle of phase A (degrees) = 0

Frequency (Hz) = 50

Internal connection = Yg

X/R ratio = 7