DESCRIMINATION OF INRUSH CURRENT FROM INCIPIENT FAULTS USING MULTI LAYER PERCEPTRON NEURAL NETWORK

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Abstract-
Dissolved gas analysis (DGA) is one of the most useful techniques to detect the incipient faults of power transformer, because of its high sensitivity to small amount of electrical faults. However, the identification of the faulted location by the traditional method is not always an easy task due to the variability of gas data and operational natures. Incipient fault detection in transformers can provide early warning of electrical failure and could prevent catastrophic losses. To develop transformer incipient fault detection technique, a transformer model to simulate internal incipient faults is required. The DGA is exploited for fault classification tools implementation using the artificial intelligence techniques. The multi-layer perceptron neural network (MLPNN) is applied for decision making. The paper presents a comparative study on one hand for the choice the most appropriate DGA method and to resolve the problem. This approach has the advantages of high accuracy. The other advantage is that the model is practically applicable and may be utilized for an automated power transformer diagnosis.

I.INTRODUCTION

Large power transformers are probably the most important equipment in an electrical system. Correct diagnosis of their incipient faults is vital for safety and reliability of an Electrical network. An in-service transformer is subject to electrical and thermal stresses, which can break down the insulating materials and release gaseous decomposition products. Overheating, partial discharge and arcing are three primary causes of fault related gases. There are many interpretative methods based on DGA to diagnose the nature of transformer deterioration.[1] Stability and reliability of a power system in depend upon the condition of power transformers. Essential devices as power transformers are in a transmission and

distribution system. The wide varieties of electrical and thermal stresses often age the transformers and subject them to incipient faults. Whose failures and damage may cause the outage of a power system. If an incipient failure of a transformer is detected before it leads to a catastrophic failure, predictive maintenance can be deployed to minimize the risk of failures and further prevent loss of services.[4] To monitor the serviceability of power transformers, many devices have evolved, such as Buchholz relays or differential relays. But the main short coming of these devices is that they only respond to the severe power failures which require removal of equipment from the service. Thus, techniques for early detection of the faults would be very valuable to avoid outages. In industrial practice, dissolved gas analysis (DGA) is a very efficient tool for such purposes since it can warn about an impending problem, provide an early diagnosis, and ensure transformers maximum uptime.[10] To find out the incipient faults, DGA is a prevailing method with periodically samples which test the insulation oil of transformers to obtain the composition of the gases dissolved in the oil due to the breakdown of the insulating materials inside. Diverse diagnostic criteria were developed for identification of the possible fault types by Rogers ratios method and Doernenburg ratios method This may improve and computerize

transformer fault diagnosis. The aim of this paper is applied the proposed combination method to solve the problem of the conflict between the Roger sand Doernenburg DGA methods, and utilized multi-layer perceptron (MLP) to incipient fault identification and localization in transformers and to choose the most appropriate gas signature. In this study, three DGA methods are employed as the inputs of the extended MLPNN classifiers for fault classification the Rogers ratios, the Doernenburg ratios and the proposed ratios combination.

II.POWER TRANSFORMER FAILURES

Damages to the power transformer can be caused by different stresses, which are due to overheating, open circuits and short circuits. The major focus of power transformer protection is short circuits because open circuits do not present a particular hazard. Short circuit protection includes internal and external faults.

External faults occur outside the protection zone of the transformer and include:

- over voltage
- Overloads
- under frequency

Internal faults occur within the transformer protection zone. The internal faults can be divided into two groups:

1. Incipient faults develop slowly and may develop into major faults such as phase-to-ground faults or three phase faults if the cause is not detected and corrected. Incipient faults can be divided into three groups:
   - Overheating
   - Over fluxing
   - Overpressure
2. Active faults – caused by the breakdown in insulation which creates a sudden stress. The active fault occurs when the current flows from one phase conductor to another such as phase-to-phase and phase-to-ground. These faults may occur suddenly and they require fast action by protective relays. Active faults:

   - Turn-to-turn short circuits.
   - Phase-to-phase short circuits.
   - Phase-to-ground short circuits.
   - Tank faults.
   - Core faults.

III.MAGNETIC INRUSH CONDITION

For the purposes of the discussion, inrush current is described as the magnitude of instantaneous current drawn by a line-frequency power transformer at the time the core is energized; it's of short duration, often milliseconds .Under a combination of certain conditions, inrush current can be measured at many times the rated load current. High inrush current is a time-dependent phenomenon caused by a coincidental set of circumstances that must occur simultaneously at the moment of switch ON. Inrush current is a problem, because it interferes with the operation of circuits as they have been designed to function. In a digital world, there is a zero tolerance for power interruptions. Some effects of high inrush include nuisance fuse or breaker interruptions, as well as arcing and failure of primary circuit components, such as switches. High inrush currents also necessitate over sizing of fuses or breakers, which complicates other aspects of approvals testing and may compromise protection on other vital components. Another side effect of high inrush is the injection of noise and distortion back into the mains.

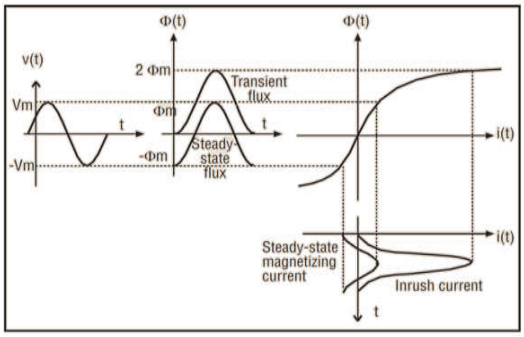


Fig-1 Graphical description of the inrush current phenomena

IV.PHYSICAL PROPERTIES OF INRUSH

Transformer inrush currents are drawn by the high saturation of the iron core during the switching-in of the transformer. Fig-1 illustrates a graphical description of the inrush current phenomenon, while Fig.- 2shows that remanence flux in the core at the moment of switch on increases inrush current. Flux is generated as the results of applied voltage; it is then cross-plotted with Φ-I characteristics to show the inrush current magnitude. This practice is shown for two cases: with and without resistance. The driving force of the inrush currents is the voltage applied to the primary of the transformer. This voltage forces the flux to build up to a maximum theoretical value of double the steady-state flux plus remanence. Therefore, the transformer is saturated and draws a large amount of current. Since the current is of short duration, no adverse effects occur to the transformer. However, the protective devices for overloads may falsely operate and disconnect the transformer.

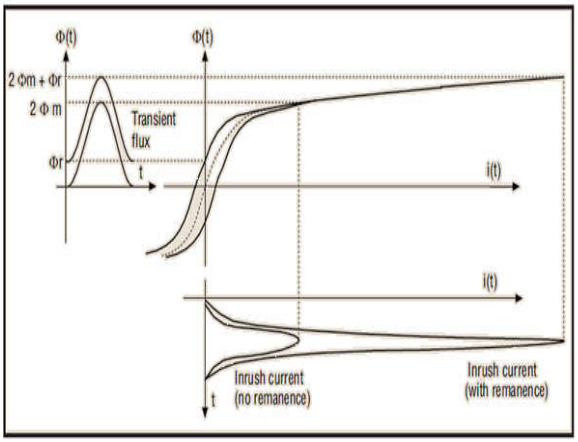


Fig- 2 Graphical description of inrush current phenomenon including permanence.

V.DIAGNOSIS OF INCIPIENT FAULT

1.Importance of power transformer incipient fault diagnosis

Power transformers are major power system equipment. Their reliability not only affects the electric energy availability of the supplied area, but also affects the economical operation of a utility. For example, the fault of a distribution transformer may leave thousands of homes without heat and light, and the fault of a step-up transformer in a power generation plant may cause the shutdown of the attached generation unit. Under the deregulation policy of electric systems, each utility is trying to cut its cost, and the prevention of accidental loss is much more important than before. The capital loss of an accidental power transformer outage is often counted in million dollars for output loss only, not to say the costs associated with equipment repair or replacement. Because of this economic incentive,

preventive tests and on-line monitoring are of benefit to predict incipient fault conditions, and to schedule outage, maintenance and retirement of the transformers.

2 Methodology of incipient fault diagnosis

The major concern of power transformer incipient faults is that they may decrease the electrical and mechanical integrity of the insulation system. This may progress to a point that the insulation cannot withstand transient overstresses caused by through-fault current (mechanical forces on windings) and electrical over voltages (temporary, switching or lightning). Incipient fault diagnosis is therefore closely related to insulation condition assessment.

2.1.Insulation condition assessment test

Insulation condition assessment test refers mainly to off-line routine tests, including measurement of insulation resistance (IR), dielectric loss factor (DLF), interfacial polarization(IP) using anomalous IR and frequency dispersion of capacitance, turns ratio (TR), winding resistance (WR), core ground resistance (CGR), and some excitation tests. These tests are applied to the whole transformer and thus are bulk measurements of the insulation condition. They can reveal some severe problems but may not find the incipient ones. Other tests examine paper or pressboard samples taken from transformers (and which must be replaced if the transformer is to be returned to service). These tests include measurement of the degree of polymerization (DP) and tensile strength (TS). Some relatively new methods, such as high performance liquid chromatography (HPLC) furan analysis, interfacial polarization spectra (IPS) using return voltage (RV) measurement, and analytical chemical techniques , are also used for the same purpose. These intrusive techniques are usually not favorable because the sampling process may damage the integrity of the insulation system, but may be necessary for very old transformers. The most favorable tests for power transformer insulation assessment are on-line types, including partial discharge (PD) monitoring and dissolved gas-in-oil analysis (DGA). These online tests are also the major incipient fault diagnosis methods.

2.2 On-line partial discharge monitoring

Partial discharges (PD) are generated due to fault conditions related to moisture, cavities in the solid insulation, metallic particles, and gas bubbles and can eventually cause dielectric breakdown. A significant increase either in the PD level or in the developing rate of PD activity can provide an early indication of an incipient fault condition. On-line PD monitoring methods generally fall into two categories: the electrical method and the acoustic method. According to the sensors they are using, both of them can be further classified into two sub-categories: non-intrusive monitoring and intrusive monitoring. Non-intrusive monitoring uses sensors installed outside the transformers, such as coupling capacitors, high frequency current transformers (HFCT), piezoelectric type accelerometers, etc. Intrusive monitoring must put the PD sensors inside the transformer and the implementation is thus more dangerous and expensive. For safety reasons, optical fiber sensors are more favorable than other types of sensors for intrusive PD monitoring. In electrical PD monitoring, the impulsive PD current is often measured directly through a capacitive coupling circuit or a high frequency current transformer (HFCT). The coupling capacitor can be a separate high-voltage PD-free capacitor attached to the transformer terminals, or use the bushing capacitance directly. The major problem with electrical PD monitoring is the handling of interferences. This can involve very complicated algorithms and may not always be solved in practical applications.

2.3 Dissolved gas-in-oil analysis (DGA)

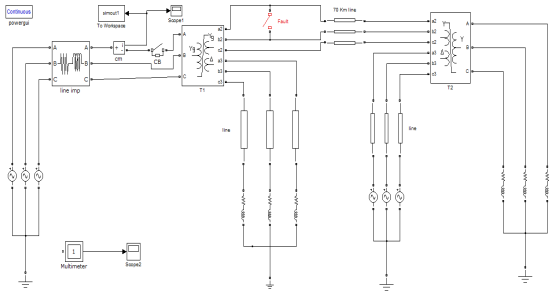
A more successful technique for on-line incipient fault diagnosis is dissolved gas-in-oil analysis (DGA). By “on-line” we mean the transformer does not need to be de-energized. This type of analysis includes the conventional DGA, which is based on routine oil sampling, and the modern technology of on-line gas monitors. Conventional DGA has been in practice for about thirty years, and

has gained tremendous success compared to other techniques. The main reason for this success is that the sampling and analyzing procedures are simple and inexpensive, and easy to be standardized. Many experiences have been gained from the process and several DGA standards have been set up. Major diagnostic gases have been identified as hydrogen (H2), ethane (CH4), methane (C2H6), ethylene (C2H4), acetylene (C2H2), carbon monoxide (CO) and carbon dioxide (CO2). An important problem with conventional DGA methods, however, is over reliance on experts. Since transformers of different size, structure, manufacturer, loading and maintenance history may have different gassing characteristic, they need to be considered differently in most cases. DGA is thus often referred to as "art" instead of "science".

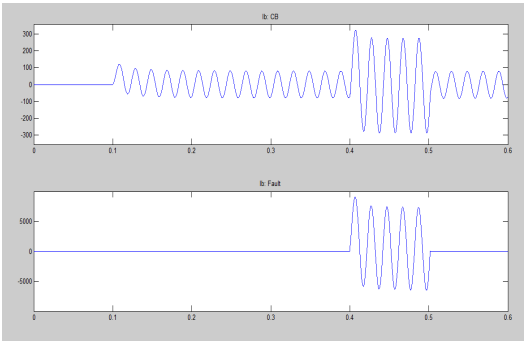
2.4 Combination Of DGA And Acoustic Method

Combining the use of DGA and acoustic methods often leads to successful diagnosis and location of PD type fault. The procedure is to identify the PD fault first using DGA, and then find the location of PD using acoustic method.

VI.SYSTEM ARCHITECHTURE



VII.ARCHITECHTURE DESCRIPTION



To obtain the required current signals for investigation of the merit of the proposed algorithm, a part of a power system consisting of a power transformer and relevant CTs with transmission lines on the both sides of the transformer are modeled using MATLAB SIMULINK. So the required current signals for a digital differential protection can be provided. The proposed power system consists of a 500-MVA and 400/230-kV transformer and the distributed model for the transmission lines is used. A long 400-kV line in parallel withthe transformer distorts the faulty current waveform. Different cases of inrush current and fault current are simulated. Different cases of inrush current are simulated by varying those major parameters that influencing the characteristics of this current. These parameters are the residual core flux of single phase transformers , the voltage angle of switching phase a, switching in the case of close or open secondary, the high or low power supply connected to transformer and knee of the core

magnetic characteristic. Different cases of fault currents are also simulated where the major factors affecting the characteristics of the current are considered. These factors include the type of fault and load condition. The results of application of the proposed algorithm for different conditions of inrush current have been summarized in Table II. This table shows the values of X and Y of different phases during shorter than a quarter a cycle following waveform distortion due to different inrush current. The first column of the table presents the remnant fluxes in thesingle-phase transformer core at instant of switching as percent of the rated flux.

VIII.PREPROCESSED DATA

Inrush Current (I_r)
1.0000 -0.0286 0.1267 2.2243

Fault Current (I_f)
0.1020 -0.4047 -0.1097 1.0000
Normal Current (I_n)
0.0179 1.0000 0.0982 0.7150

IX.RESULT OF SIMULATION

Inrush Current & Fault current
data_in =

0 .0179	1.0000	0.1020
1.0000	-0.0286	-0.4047
0.0982	0.1267	-0.1097
0.7150	2.2243	1.0000

X.PRPOSED ALGORITHM

MULTI LAYER PERCEPTRON NEURAL NETWORK

Basic Concepts Of MLP Neural Network

The neural network technique is used to recognize and classify complex fault patterns without much knowledge about the process, the used trials or the fault patterns themselves. A neural network consists of many simple neurons which are connected with each other. It has been recognized that one of the most widely used ANN structures of classification problems is multi-layer perceptron(MLP) with a back-propagation (BP) learning algorithm. This is useful when a diagnosis system must run in real time and must handle a lot of signals. Moreover, this neural network is robust, especially regarding noise . The MLP is a network organized in layers. Fig. shows the integral structure of the feed forward algorithm of the BP artificial neural network . The numbers of neuron in both input and output layer depend on the applied problem, while the number of neuron in the hidden layer is arbitrary and is usually decided by trial-and-error . The hidden layers have a particular activation sigmoid function, which we will call tangent sigmoid function. very neuron in a hidden layer calculates using the following equation:

$$s_j = f\left(\sum_{i=1}^{N} x_i w_{ji} + \theta_j\right)$$

where xi is the ith input to the net,wji is the weight of the connectionfrom input neuron i to hidden neuron j, hj is the bias of the θ jthhidden neuron, and f(.) is the activation function of the neuron. The output layer, each neuron is calculated by the followingequation:

$$y_k = g\left(\sum_{i=1}^{L} s_j w_{kj} + \theta_k\right)$$

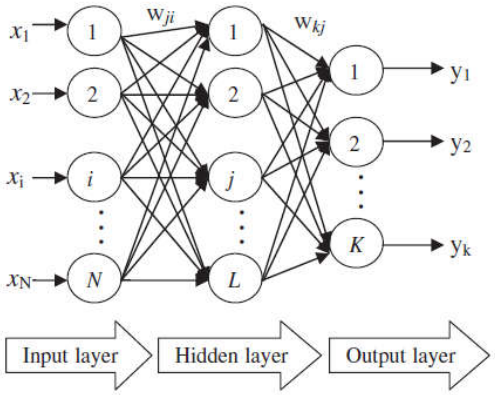


Fig- MLP network topology

where yk, the kth output of the net; Wkj, the weight of the connection from hidden neuron to output neuron k; hk, the bias of the kth output neuron and g() is the activation function of the neuron

XI.FAULTS CLASSIFICATION BY MLPNN

MLPNN in this study is implemented based on an expert database consisting of 175 actual gas sample numerical records collected from various transformers and their actual fault types are decided to use DGA methods interpretation and are confirmed by diagnostic experts of STEG during the maintenance of transformer. In this study, DGA fault types (one normal, six fault operating conditions) are used to verify MLPNN. The 135 data used for training and the 40 used for testing are summarized . The diagnostic outputs available to the proposed MLPNN are: (a) no fault; (b) partial discharge; (c) low energy discharge; (d) high energydischarge; (e) low temperature thermal fault T < 300 C; (f)medium temperature thermal fault 300 < T < 700 C; (g) high temperature thermal fault T > 700 C. The MLPNN fault classification is performed using the MLPNN approach for transformer diagnosis The process of MLPNN algorithm is divided into two phases:

Step 1: Generation of training data

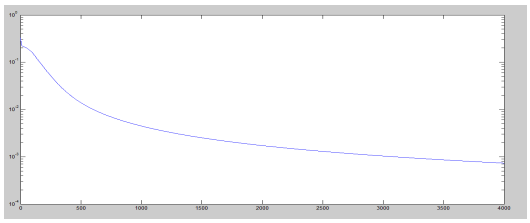
The training DGA data were used to represent the complicatedstructure to simplify the input variables of the MLP network.

Step 2: Establishing the MLP neural network

The artificial neural network contains three processes, whichare training, testing, and validation.

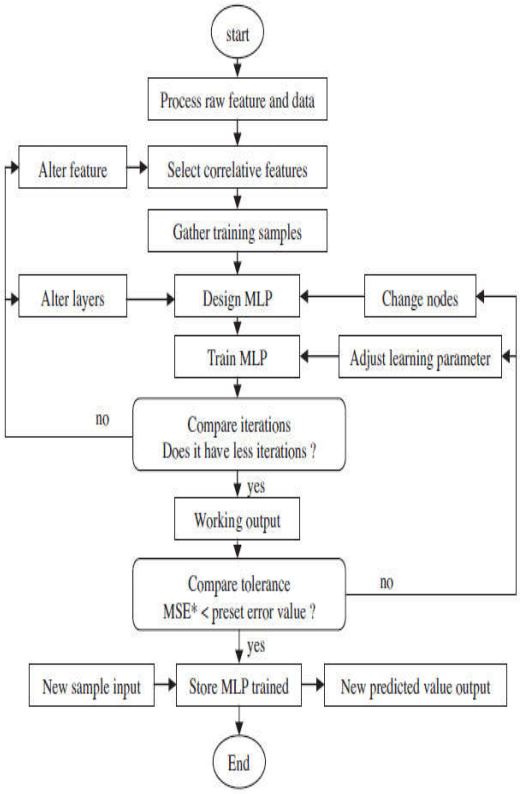
Therefore, the flowchart of proposed process with the DGA ontransformers to process the fault types classification.

XII.MLPNN IMPLEMENTATION



In this paper, multi-layer perceptron (MLP) neural network is used for identification on MATLAB platform. When constructing MLP networks, it is essential to choose a suitable transfer function and several essential parameters. For transfer function, the tangent sigmoid functions have been used widely in the past for complex problems. Therefore, the tangent sigmoid function is also used in this study. The structure of the MLP network is set to include an input layer whose the number of neurons is equal among the ratios for every gas signature, a three hidden layer types (single, two and three hidden layers).

XIII.FLOW CHART



XIV. TRAINED EPOCH DATAS

epoch = 1 mse = 0.32917
epoch = 2 mse = 0.30771
epoch = 3 mse = 0.28923
epoch = 4 mse = 0.27388
epoch = 5 mse = 0.26151

TO

epoch = 3995 mse = 0.00073361
epoch = 3996 mse = 0.00073339
epoch = 3997 mse = 0.00073317
epoch = 3998 mse = 0.00073295
epoch = 3999 mse = 0.00073273
epoch = 4000 mse = 0.00073251

XV.CLASSIFED RESULT FROM MLP

X_tst =

0.0179	**1.0000**	**0.0179**
1.0000	**-0.0286**	**1.0000**
0.0982	**0.1267**	**0.0982**
0.7150	**2.2243**	**0.7150**

Y =

0.9773	**0.0097**	**0.9773**
0.0174	**0.9705**	**0.0174**
0.0142	**0.0283**	**0.0142**

XVI.CONCLUSION

In this paper, the MLPNN has been adopted for fault classification of incipient faults for power transformers. The MLPNN based DGA methods are developed for fault diagnosis in power transformers. The training samples and testing data are used in fault diagnosis test. The performance of the proposed MLPNN ratios combination method has been compared with MLPNN based Rogers then Doernenburg ratios methods and found that, the MLPNN based the proposed combination method detects more accurately. The effectiveness of MLPNN fault diagnosis has been analyzed for single, two and three hidden layers, and the output layer with three and seven neurons. From the test results, we have demonstrated that the MLPNN model can be applied when the output layer have three neurons as well as when two hidden layers is used. These encouraging results show that this work can provide a feasible and effective way to early diagnosis the power transformer faults. The results obtained from the proposed MLPNN model were then compared with other artificial intelligence approaches (FL,KNN, PNN and RBF). The comparison with the different techniques leads to the observation that the proposed approach was successfully tested and provided better results. The proposed method has a large potential in practice. The MLPNN approach could provide a very useful and accurate tool to solve problems in power transformer diagnosis studies and management.

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