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Incipient Fault Protection Using Artificial Intelligence Techniques

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Abstract

In the field of incipient fault protection, various sources can cause failures, such as lightning, switching transients, mechanical imperfections, and chemical breakdown. To guard against these errors, Buchholz relays and pressure relief devices have been utilized. However, in recent years, preventive health measures have gained more attention. One popular approach is the implementation of the Dissolved Gas Analysis (DGA) system, which detects incipient faults by analyzing the gases dissolved in the transformer oil. In this context, the use of artificial neural networks (ANN) and artificial neural networks combined with expert systems (ANNEPS) has shown promise for power transformer protection against incipient faults using DGA. Power transformers, especially large oil-filled ones, are commonly subjected to DGA for identifying and diagnosing early-stage faults. By analyzing the dissolved gases and employing interpretation systems, such as (ANNEPS), unexpected failures can be prevented. The objective of this research is to identify internal problems within transformers, and an (ANN) structure has been specifically developed for this purpose. The ANNEPS approach combines the outputs of ANN and expert systems to ensure rapid and accurate identification of various types of transformer failures. By comparing the results of both computational methods, a reliable assessment can be made, enhancing the effectiveness of incipient fault protection strategies. Overall, the combination of (DGA) and advanced techniques like (ANN) and (ANNEPS) provides a robust approach to detect and prevent incipient faults in power transformers. These methods offer improved accuracy and promptness in identifying transformer failures, ultimately contributing to the reliability and efficiency of power systems.

1. Introduction

Uncertainty in the electrical system causes equipment damage or even machine failure in response to abnormal system needs such as short circuits on electricity system components (line, bus, etc.). A safety mechanism shields the grid from the harmful effects of these aberrant system needs. 'Protection' is that the science, art and talent of establishing and applying relays and fuses to give greatest sensitivity to unpleasant and undesired situations. The art of protective relaying has always relied on thorough understanding of the systems and objects being protected, as well as their behaviour under abnormal settings. Related devices including tool transformers, communication lines, and others are included in this discussion, as well as their technologies, designs, and operations. Manufacturing companies and utilities have struggled with improving relay visibility for decades. Relay reliability has two major aspects: dependability (that is connected to the amount a relay will function well) and safety (which relates to "the degree of confidence a relay won't work erroneously") [1].Modern complex power systems are frequently operated close to their own limits, so a security that fails to function or excursions erroneously can cause significant problems, up to and including a total blackout. A small number of utilities have thus adopted complex and costly architectural measures to guard against the aforementioned eventualities. Therefore, protective equipment is a crucial component of power grids. Higher identification capacity, communication skills, adaptable capacity, and boosters that form a part of the integrated substation control system are all characteristics searched for in protective measures. The development of electronic security has made it possible to put these ideas from security systems into practice [1] [2].

Since the days of Demo and electromechanical equipment, advancements in power system security have progressed to the point where sophisticated microprocessor-based algorithms are required to ensure its integrity. The use of electronic know-how to safeguard power grids is now widely accepted as a proven technique and, in certain instances, the best option for avoiding imminent security threats. Dedicated electromechanical or semiconductor-based technologies have historically proven useful in software applications. However, they have a few drawbacks, such as the inflexibility of self-testing centres and the lack of knowledge that comes with it. Cushioned instruments are used rather than hard wired programs to get around these difficulties. Thanks to advancements in microprocessor technology, programmable smart systems can now be mass-produced with ease for use in system management and security [3]. These relays' configurations are determined during the preliminary stages of an industrial or utility system's installation and commissioning. Modern power systems need an overview of relay configurations for evaluating effective coordination among different safety devices in the machine, but this is seldom done due to the tedious and labour-intensive nature of assessing of abuse. In addition, there is a massive amount of error data that has to be evaluated and categorized to each line terminal, primary safeguards, and secondary protections. Using AI techniques, we can quickly and easily address these concerns. The defense engineer's expert judgment might be included into the process via interactive use of various AI approaches [3, 4].

2. Proposed Models

2.1 DGA (Dissolved Gas Analysis) method

The dissolving gas concentration and gas mixture. Gas chromatography is used to determine the relative amounts of individual gases dissolved in oil. If we know the concentration of these dissolved gases, their production rates, the particular gas ratios, and the total combustible gases in the petroleum, we may use DGA methodologies to assess the condition of the transformers.

The three main DGA Methods listed in an ANSI/IEEE standard for diagnosis of issues in this process are Key gas evaluation, Dorenberg ratio procedure, and Roger ratio technique.

Table 1: The L1 norms of gases in-oil (concentration in PPM) from different sources[4].

sources	H2	CH4	C2H2	C2H4	C2H6	CO	CO2	TDGC
ANN and ANNEPS	102	122	2	52	67	205	2550	538
IEEE	104	124	36	55	68	350	2555	725
Double	105	105	8	105	65	255	----	615
General Electric measures	200	100	25	100	200	200	200	-----

Table 1 details the different standards used by various services. Except for C2H2, CO, and TDCG, all of the values used in the proposed methods were derived from IEEE (C57.104) benchmark values. For those three, we set numbers that are far lower than the IEEE (C57.104) average value to ensure that no suspect gets through the first screening process undetected. Detailed examples of the implemented recommendations are provided below.

2.2 . ANN Approach

Experts often use broad principles such as the Key gas assessment, Dorenberg ratio method, and Roger ratio process to narrow down potential issues with a system. Additional data, such as the fluctuation of dissolved gas information, the impact of environmental and loading variables on such data, and so on may all be included into a true identification process. As a result, AI methods will provide viable options to this complex problem [12, 13]. Within this strategy, a single ANN is developed for early-stage defect detection using a general-purpose output signal.

2.2.1. Incipient fault detection using ANN

In Figure 1, the proposed initial fault sensor model based on artificial neural network for power transformer is shown.

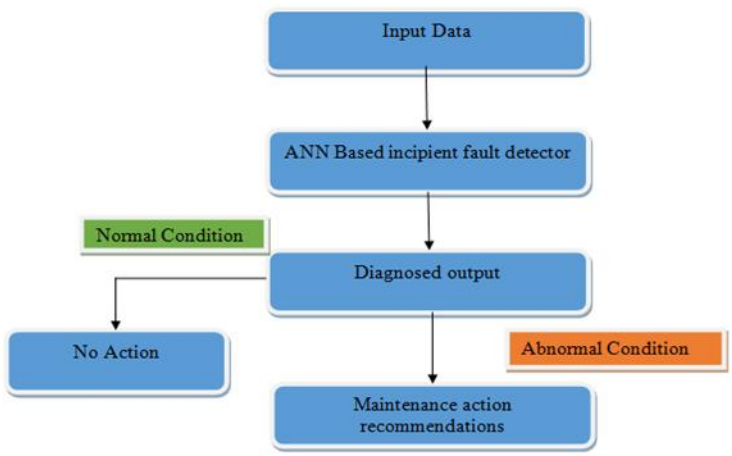

Figure 1: Power transformer protection model of ANN

2.2.2.Data for training and testing of ANN architecture

The software was taught to differentiate between five common workplace settings (Regular, OHO, CD, Corona, along with Arcing). Different power transformers' DGA test data under certain circumstances may be retrieved. For the purpose of reactivating the aforementioned five operational modes utilizing the (ANN) process, data on the gas evaluation of 103 evaluation samples have been collected. Because of this, in this paper get training data sets for various types of power transformers. Afterwards, the 103 sets of available data samples representing the five operational states of the power transformer are considered inputs for your (ANN) developed for the recommended technique. The system is taught to provide a binary output signalling if the supplied DGA test data sample is similar to ordinary, (OHO), (CD), (CORONA), and (ARCING) using these inputs. The software was taught to differentiate between five common workplace settings: Regular, Overheated Oil (OHO), Contact Discharge (CD), Corona, and Arcing. Different power transformers' Dissolved Gas Analysis (DGA) test data under certain circumstances may be retrieved [3,5].

For the purpose of reactivating the aforementioned five operational modes utilizing the Artificial Neural Network (ANN) process, data on the gas evaluation of 103 evaluation samples have been collected. These datasets originate from different sources, including:

Regular: Represents normal operational conditions with minimal gas concentration, obtained from well-maintained transformers.

Overheated Oil (OHO): Data collected from transformers where oil degradation due to excessive temperature has been observed, typically characterized by increased levels of methane (CH_4) and ethylene (C_2H_4).

Contact Discharge (CD): Cases where electrical discharges occur between conductors in contact, leading to acetylene (C_2H_2) generation, commonly found in aging insulation materials.

Corona: Data from transformers experiencing partial discharges due to ionization of gas surrounding conductors, leading to the presence of hydrogen (H_2) and trace amounts of methane (CH_4).

Arcing: The most severe condition, where strong electrical faults produce significant levels of acetylene (C_2H_2) and hydrogen (H_2), indicating potential insulation failure [3].

Because of this, we are able to get training data sets for various types of power transformers. Afterwards, the 103 sets of available data samples representing the five operational states of the power transformer are considered inputs for the ANN developed for the recommended technique. The system is trained to provide a binary output signalling if the supplied DGA test data sample is similar to Regular, OHO, CD, Corona, or Arcing using these inputs [5].

2.2.3. ANN Architecture

In this research, we create and compare a number of ANN designs that are tasked with detecting early signs of malfunction. In addition, a wide range of assessments were performed, including anything from four to thirty-two participants and a single concealed layer. All data pertaining to the petroleum sample and the transformer should be included in the input. The gas in oil concentration and gas evolving rates of H_2, CH_4, C_2H_2, C_2H_6, CO, and CO_2 in an oil sample are important input data for defect detection. Important characteristics to consider when purchasing a transformer include the manufacturer, type, centre type, number of stages, number of windings, rated voltage, size (ability), with/without LTC, age, petroleum amount, water content, etc. The input signals used come from the proposed module and include everything that is relevant to a petroleum sample, i.e. the data from the compressed gas. That is to say, your ANN developed for the suggested technique would use as inputs 103 groups of available data samples covering five unique operational states of the power transformer. Eight different concentrations of gasoline are included in each data set. So, the ANN architecture uses inputs from 8 sets of neurons.

The most important challenge while creating an ANN is deciding how many hidden layers to use and how many volunteers to place in each layer. Multiple tests of varied sizes—from four to thirty-two participants—were also undertaken in this investigation. Extensive testing led to the conclusion that a hidden layer consisting of 8 participants produced the best results; this configuration was then selected for further investigation. The structure has 4 nerves that provide 5 horsepower (0 0 1 Regular, 0 1 tsp. OHO2 1 0 CD1 0 0 Corona plus 1 0 1 Arcing). Given its greater suitability for dealing with pattern recognition problems, a layered, feed-forward, back propagation network with a sigmoid activation function was used for this study.

2.2.4. Training and testing

In this research, we evaluate and create a number of (ANN) designs tasked with spotting early signs of malfunction. For the first stage, a single (ANN) structure is developed with one input layer of eight inputs, one hidden layer of five neurons, and one output of four outputs. Since then, we've experimented with a range of values for the buried layer's volunteer population, settling on somewhere around 32. Despite this, there was little progress being made in the quality of training and testing. Because of its superior identification accuracy and training rate compared to (ANN) enhanced by 8-16-4 and 8-32-4 architectures, an (ANN) based incipient fault sensor employing a single (ANN) structure as 8-8-4 has been selected for further evaluation to detect that the aforementioned flaws have been exploited. The log sigmoid activation function has been opted for. A value of 0.85 for the momentum variable was chosen. All data associated with a petroleum sample, such as dissolved gas data, must be included into the proposed system. If the sign matching to the actual operational condition of the (DGA) evaluation sample is supplied as the result of (ANN) training, then the training will be terminated and the whole data sample that was not used for training will be evaluated.

3.Results and Discussion

All simulation research in this study has been carried out using (MATLAB) 6.5 version tools, and all simulations have been run on an Intel Pentium IV calculating platform operating at a chip speed of 2.4 GHz. Table 2 and Table 3 provide the outcomes of simulated training and analysis applied to the (TNEB) 103 information sample using several (ANN) topologies. By analyzing them, we learn that the ideal outcome for its enhanced (ANN) structures is obtained after 1500 iterations, with a precision of around 99.99 percent.

Table 2: Training Results of Incipient fault detector using (ANN)

ANN Architecture	No of Iterations	Time (Seconds) takes for Convergence	Error	Accuracy (%)
8-10-4	1500	8	0.0051	99.56
8-20-4	1600	18	0.0072	99.67
8-32-8	1600	28	0.0069	99.16

Table 3: Testing Results of Incipient fault detector using (ANN)

Condition	ANN Model	Output 1 (Actual)	Output 1 (Target)	Output 2 (Actual)	Output 2 (Target)	Output 3 (Actual)	Output 3 (Target)	Output 4 (Actual)	Output 4 (Target)	Error
Normal	**8-8-4**	**0.0135**	**0**	**0**	**0**	**0.0002**	**0**	**1**	**1**	**0**
OHO	**8-8-4**	**0.0127**	**0**	**0.0035**	**0**	**0.989**	**1**	**0.0002**	**0**	**0.011**
CD	**8-8-4**	**0.0008**	**0**	**1**	**1**	**0.0118**	**0**	**0**	**0**	**0**
Corona	**8-8-4**	**1**	**1**	**0**	**0**	**0**	**0**	**0.021**	**0**	**0**
Arcing	**8-8-4**	**0.9985**	**1**	**0**	**0**	**0.0023**	**0**	**1**	**1**	**0.0015**

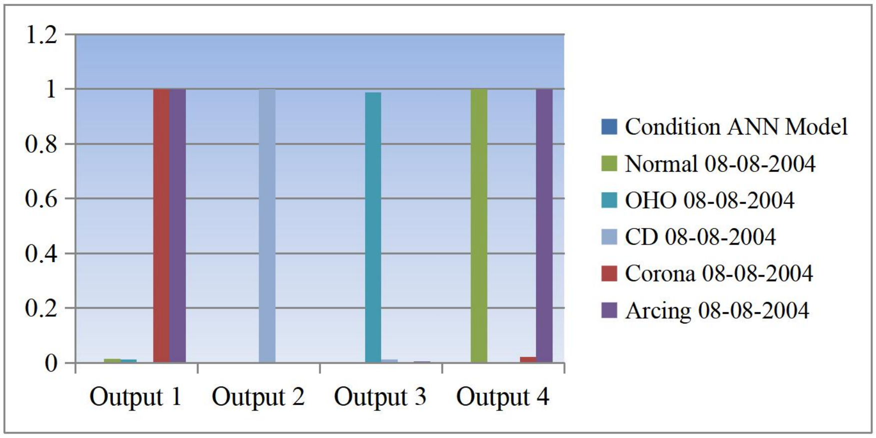

Figure 2: Results of Incipient fault detector using ANN

Based on the projected findings, the ideal result for 8-8-4 architecture may be obtained after 1500 iterations with an error of 0.0057 percent and an accuracy of 99.43 percent. Also, this proposed (ANN) drastically lowered the time needed for convergence to 9 minutes, whereas the 8-16-4 and 8-32-4 (additional two upgraded ANNs) designs needed 16 and 25 minutes, respectively, to reach virtually the exact same accuracy. Therefore, 8-8-4 incipient error prevention was selected as the ANN-based method for the proposed system. The results show that the method has been performing well for various types of energy transformers. The accuracy of the (ANN) based proposed technique was higher than that of the results produced using conventional methods like the Rogers ratio procedure since (ANN) is a powerful tool for pattern categorization. However, the (ANNEPS) method has been finalized to achieve even better outcomes. To identify early-stage faults in electrical transformers, an enhanced (ANNEPS) method using (DGA) technique is discussed below.

3.1 ANNEPS Approach

The safety measures used to guard transformers are shown in Figure 2. This proposed (ANNEPS) electrical system design relies on the aforementioned Standard fault Identification Transformer for safety purposes. The expert system's knowledge base is built on the knowledge-based principles (EPS) formula, which includes (IEEE) and IEC standards updated with new code, gas and ratio period boundaries. The (ANNEPS) module's specialized system consists of a number of analytical modules that, among other things, make use of a knowledge base and an inference engine.

Experts use methods as a guiding concept. Additional data, such as the variability of dissolved gas information, the influence of environmental and loading variables on such data, and so on, can be factored into a real identification process. As a result, advanced AI methods will provide viable solutions to this complex problem.

In particular, if (ANN) and (EPS) have been combined, the self-learning and mapping capabilities of (ANN) and the Experience knowledge established principles shall provide best options.

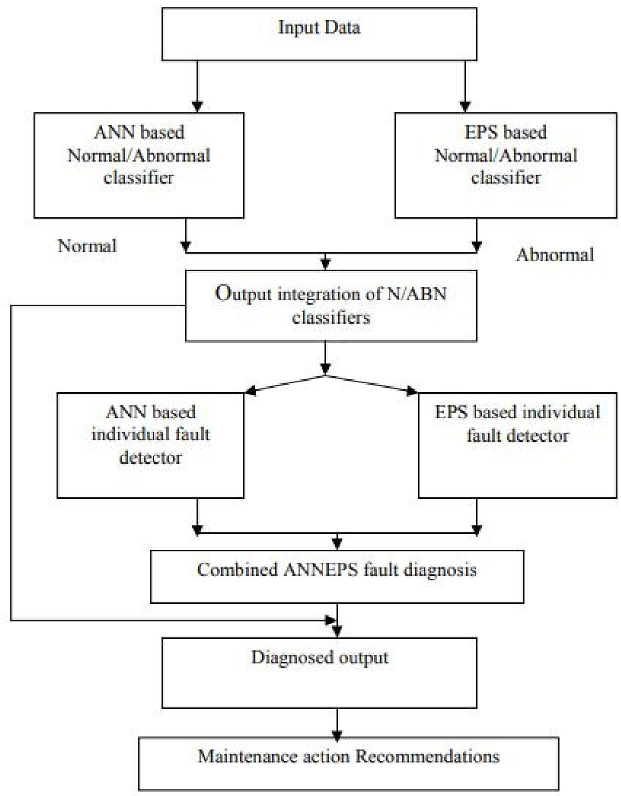

Figure 3: Power transformer protection by ANNEPS model

3.2 Input data

All data pertaining to petroleum samples and transformers must be included. Input factors like error identification and the rate of increase in concentration of H 2, CH4, C2H2, C2H6, CO, and CO2 are crucial when analyzing a petroleum sample for gas-in-oil gas. Important characteristics to think about when purchasing a transformer include the manufacturer, type, centre type, number of stages, number of windings, rated voltage, size (capacity), with/without LTC, age, petroleum volume, water information, and so on. All data pertaining to a petroleum sample, such as data on extracted gases, should be entered into the proposed module.

The second ANN classifier uses a single input layer of 5 nerves, a single hidden layer of 1-5 neurons, and a single output layer of 1 output neuron. All inputs are of the same concentration. In ANN classifier, H2, CH4, C2H2, C2H4, C2H6, and absolute combustible gasoline concentrations have been used as two of the inputs. Inch inputs to ANN classifier were H2, CH4, C2H2, C2H4, and C2H6 concentrations. The architecture consists of a single input layer with five nerves, a hidden layer with one to five neurons, and a single output layer with a single output neuron. The inputs to the first ANN classifier were the percentages of several flammable gas components, including H2, CH4, C2H2, C2H4, C2H6, and the whole mixture.

3.3 EPS based Normal/Abnormal detector

Comparisons are made between the gas concentrations (ppm) of H 2, CH4, C2H2, C2H4, C2H6, CO, and CO2 in oil, as well as TDCG (complete dissolved (gas) utilizing all the pre-established limiting criteria (l 1). If any of them is abnormally high relative to their norms, the sensor will signal an "unnatural" indication. Table 2 summarizes the various norms used by various services. Conventional IEEE (c5-7.104) values, with the exception of the C2H2 value, were chosen to be more cautious such that no defendant could possibly pass the screening. This table compares the overall gassing rate (in parts per million per day) of H 2, CH4, C2H2, C2H4, C2H6, CO, and TDCG with the global cap of 10 ppm/day.

3.4 ANN based individual fault detector

If anything seems out of place, the data is sent to the relevant fault sensor. Figure 2 shows the four separate ANN sensors used by the ANN-based human defect sensor. In each case, it is the responsibility of these to identify a single flaw. The configuration outperforms a single ANN structure with 4 magnets in terms of identification accuracy and training rate. Therefore, 4 human ANN sensors were used for this task's mistake detection. Many distinct ANN designs, all of which are ultimately responsible for human defect diagnosis, were first developed. Each design uses 6 nerves at 1 input to detect H2, CH4, C2H2, C2H4, C2H6, and total combustible gas speed, and a single output to signal the presence or absence of an aberrant condition. The experiments have been completed; however the results show that the number of neurons in a single hidden layer may range from 18 nerves to 32 neurons depending on the task at hand. The construction of an individual fault sensor, as determined via experiments, is shown in figure 3. When it comes to identifying human mistake, every person's structure is the same. A single input layer of 6 nerves, a single hidden layer of 18 neurons, and a single output layer of a single neuron make up the network. Each neuron has been given a log sigmoid activation function, and a back propagation technique may be used to train the network. Only if most of the parts are in good shape can we say that the end result is average.

3.5 Knowledge (EPS) based individual fault detector

Using if-then rules, we may create error detectors that are specific to EPS. Because of their convenience, modules are generally accepted, and excellent results are produced when used for crucial error categorization. As a result of following the recommended technique, the knowledge-based (EPS) human defect sensor has been reduced to only three modules. Based on the above, the Knowledge (EPS) created individual error sensor was developed (see figure 3 for its three parts). The "ordinary," "over-heating (OH)," and "low energy release (LED)," and "high energy release or arcing (HEDA)" sensors make up the bulk of these three modules; their regulations are derived from IEC standard 599 with some minor revisions made to the code mix ratio and the additional time boundaries. There are several examples of industrial applications of the ideas for "overheating of petroleum" and Cellulose Degradation.

3.6 Combined ANNEPS fault diagnosis

If sufficient and consistent data is supplied for training, the ANN's output signal will outweigh the joint output signal. When the signal from an ANN's output is unclear, a middle ground is discovered between the two possible results in order to consult the knowledge base (EPS). In addition, TCG-recommended courses of action for care delivery are provided (in PPM) using criteria derived from IEEE C57.104-1991. Combining ANN with principle-based sensors for an output depends on rivalry and undermining. The EPSi component of the understanding-based person fault sensor and the ANNi component of the ANN-based person fault sensor both exist in the context of an outcome guarantee. The OH,OHO, LED, and CD joint output assurance COCi is granted in accordance with the following guideline to acquire a particular fault type "I".

Ten and a half different power transformer data samples gathered from practical D-GA evaluation reports of various utilities, including the Tamil Nadu Electricity Board (TNEB) system, are used to evaluate the proposed ANNEPS; among these samples, 28 represent typical situations, 2-9 represent overheating of petroleum, 16 represent cellulose degradation, 1-3 represent arcing, and 17 represent corona. As a whole, there will be 70 data samples used for training and 33 for testing. The results of a MATLAB 6.5 simulation of this proposed plot using artificial neural networks (ANN), empirical probability sampling (EPS), and a combined (ANNEPS) are shown in table (3) .

Table 4: table for finding Accuracy (%) of training and testing data set

Device	ANN based Accuracy			EPS based Test Accuracy			ANNEPS based test Accuracy		
Data Set	Training (%)	Testing (%)	Overall (%)	Training (%)	Testing (%)	Overall (%)	Training (%)	Testing (%)	Overall (%)
OHO	100	95	98.6	99.3	90	96.6	100	95	98.6
LED	100	95	98.6	95.3	90	93.8	100	95	98.6
HEDA	98	88.3	95.2	96.7	85	93.4	99.3	96.7	98.6
CD	98.7	91.7	96.7	90.7	91.7	91	99.3	93.3	97.6

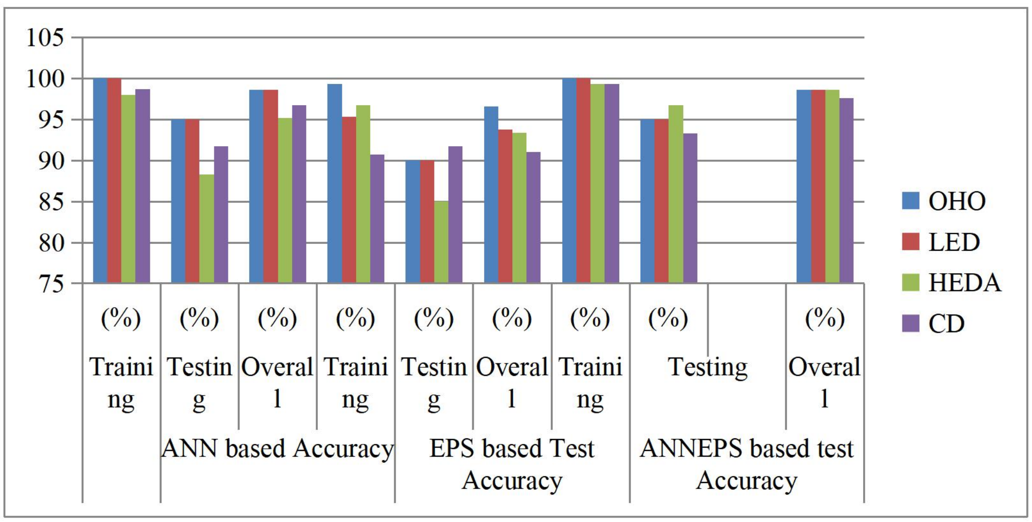

Figure 4: Accuracy (%) of training and testing data set

4.Reslts

In table 4 displays the ANNEPS's training and testing accuracy. The combined accuracy of (ANNEPS) is assumed to be much higher than that of either (ANN) or (EPS) working alone. For (HEDA) fault, for instance, even though ANN alone may be utilized, accuracy is 95.2 percent, whereas accuracy using EPS alone is 93.4 percent. However, if ANNEPS is utilized, accuracy is improved to 98.6 percent using the same sample. In the case of c/d faults, the accuracy is 91% if EPS is used alone but only 96.7% if (ANN) is used alone. However, if (ANNEPS) is employed, accuracy for the same sample increases to 97.6 percent. (ANNEPS) email address information are identical to those obtained from ANN alone instance (i.e., 98.6 percent) for OHO and LED faults.

However, the (ANNEPS) system has a detection rate of above 98.6 percent for combined OHO and LED problems. This training data's accuracy shows that there is inconsistency in the samples used for training, whose total number should be close to one hundred percent for perfect training data selection. A review of this training set's ANN accuracy reveals a recognition capacity that is immediately remarkable, but which proved to be rather complex from the ANNEPS's perspective.

5.Conclusions

The results obtained demonstrate that the proposed technique can accurately distinguish (with respect to squared error) between different operating situations for all types of electrical transformers. However, to acquire yet better results (with regard to number of iterations) by improving this method a combined ANN and Expert program instrument (ANNEPS) is produced for electrical transformer incipient failure diagnosis. Both the ANN and EPS algorithms process the input data simultaneously. Finally, we compared the results of both algorithms. Every one of the machine Artificial neural networks is just Tolstoy three-layer systems that incorporate the ideal limited capability to think for human blunder recognition. The neural networks have learned from selected data so they could gain "encounters" unknown to human specialists. Therefore, they provide more data for a diagnosis, have good repeatability of analysis, and may have excellent identification accuracy. By combining the results of ANN and expert systems, ANNEPS clearly takes use of both artificial intelligence and human expertise. Because of its ability to extrapolate and interpolate from the events, ANN is able to provide the best possible suspect in each given situation and so avoid the "no choice" problem that might arise from time to time when using more conventional methods. Absolute Combustible Gas (TCG) degree and its daily production rate are also advised, along with the oil-sampling interval and necessary maintenance operations. The results showed that the ANNEPS technique was the superior choice for covering transformer incipient errors.

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