Transformer Oil Degradation Prediction Using Machine Learning

Vidya Moni
Department of Electrical Engineering
National Institute of Technology, Warangal

S. S. Gouri M
Department of Electrical Engineering
National Institute of Technology, Warangal

Abstract—**Transformer oil is a special type of insulating oil used to maintain and increase the life time of electrical transformers. It gets degraded over the years due to several reasons. Typically, testing of transformer oils happens physically in specialized labs, which can be expensive and time consuming. The aim of our work is to predict the degradation of transformer oil using mathematical approaches, to expedite the process and save the expenses of physical testing. In this research, we analyze the various parameters of transformer oil and correlate them to the extent of degradation using Machine Learning and Deep Learning algorithms.**

I. INTRODUCTION

Transformer oil is a special kind of oil used for the protection of electrical transformers. Transformers are typically submerged in transformer oil to prevent damage to the windings and cores of the transformer [1]. It is used as an insulator, to suppress corona discharge and prevent arcing, and as a coolant. Transformer oil is essential to preserve the condition of electric transformers, enhancing their quality and effectiveness, and increasing the number of years of their life. Thus, transformer oil degradation is very detrimental to the performance of transformers [2].

Fortunately, several tests can be conducted on transformer oil samples to assess the extent of their degradation [3]. However, each of these tests is expensive and can only be performed in specialized laboratories. They take varying amounts of time to produce results. However, these issues can be circumvented by using modern technology, specifically using electronic sensors to measure these values so the tests can be conducted in real-time. In this research, we propose a method of using Machine Learning techniques to predict the degradation [4].

II. COMMON TRANSFORMER OIL TESTS

The twelve common tests performed on transformer oils to test their quality are as follows:

1. Colour and Appearance
2. Inter facial tension
3. Viscosity
4. Flash point
5. Pour point
6. Water content
7. Acidity
8. Breakdown Voltage test
9. Specific resistance
10. Dielectric Dissipation Factor
11. Dissolved gas analysis
12. Furan analysis

<u>Colour and Appearance</u>

Darken coloration is typically a sign of degradation of transformer oil [5]. Dark colored oils need to be filtered or changed. Generally, oil that is yellow, orange, or even somewhat red in color is fresher and will work as intended. As oil ages, it transforms to a brown or black color and its efficacy diminishes. Most transformer oils need to be filtered or tested at least once every six months; this prevents corrosion of the transformer. The appearance of the transformer oil can be visually inspected, thereby making it a very popular test to determine the state of the oil.

<u>Interfacial Tension</u>

Inter facial tension (IFT) between liquids is the property by virtue of which molecular cohesive and adhesive forces cause a thin film to form between the surfaces of the liquids, which has an associated tension force. Inter facial tension is very sensitive to impurities in either liquid. As the transformer oils get degraded with time, the percentage of impurities increases in the oil, causing the IFT between that particular sample of oil and distilled water to drop with time [6].

<u>Viscosity</u>

Viscosity is the measurement of a fluid’s resistance to flow. High quality transformer oils are formulated to have relatively lower values of viscosity compared to degraded oils. Standards for insulating oils (IEC 60296, ASTM 3487 and others) there is an upper limit for viscosity which is 12 mm2/sec at 40°C [7]. High quality transformer oils are normally in the range of 7- 8 mm2/sec at 40°C and even with such low viscosity, they still meet the requirement for flash point (<135°C) from the same standard.

<u>Flash point and Pour point</u>

The flash point of a substance is the temperature at which it gives off sufficient vapour, so it is possible for it to ignite in air. The pour point of a substance is defined as the temperature at which it loses its ability to remain pourable, meaning it stops behaving like a Newtonian fluid. The typical specifications of the flash point and pour point for non-degraded transformer oils are that the flash point must be over 140 degrees Celsius and that the pour point must be below -40 degrees Celsius [8].

<u>Water Content</u>

The water content that seeps into transformer oils with continuous use is one of the most important factors in

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determining the extent of the degradation of that particular sample, especially in humid areas and coastal areas. It causes damage to both the transformer oil and the paper insulation. If the paper insulation loses its mechanical strength due to unwanted moisture, it cannot be restored to its original condition, and will cause severe repercussions to the state of the transformer. The general permissible limits for water content in transformer oil is 30-35 ppm [9].

Acidity/Neutralization Value

Acidity in the context of transformer oil degradation refers to the formation of carboxylic acids within the oil. Oil gets oxidized at high temperatures with oxygen, and small metal particles present in the oil are usually the catalyst that triggers this process [10]. The acidity can be measured as the required amount of KOH needed to neutralize the acidic material present in one gram of oil. This is termed as the neutralization value. The effects of high acidity in transformer oils include the following; sludge and varnish deposits, oil breakdown, damaging effects on the paper insulator, decrease in dielectric strength, and increased moisture content.

Breakdown Voltage

The breakdown voltage (BDV) is measured using the BDV test; this is a simple method to test the degradation extent of transformer oil. In order to perform this test, a mobile BDV computing kit is usually placed near the equipment, within which oil is retained in a small pot and a set of electrodes are placed in it. Voltage is applied between the teo electrodes and gradually increased. The oil is continuously observed to find the value of the voltage at which flashing initiates fire between the pair of electrodes. The value of the voltage at which the dielectric ability of the transformer oil holding the electrodes gets defected is known as the breakdown voltage. As per IEC, the minimum BDV of transformer oil should be 30 KV as per transformer oil BDV test standard [11].

Specific resistance

The resistivity or specific resistance of a material is the measure of the resistance offered by it, when electric current is made to flow through it. It can be determined by finding the direct resistance across the two opposite sides of a one cm^3 slab of oil. The resistivity of the transformer oil considerably increases when the temperature of the oil reduces. The ideal values of restitivity for transformer oils are 35×10^{12} ohm-cm at 90ºC and 1500×10^{12} ohm-cm at 27ºC [12].

Dielectric Dissipation Factor

When transformer oils age, it leads to dielectric losses within it. The dielectric dissipation factor (loss factor), tan δ measured allows us to gauge the extent of dielectric losses that have occurred in the transformer oils during operation [13]. It is the ratio between the active and reactive currents flowing in a measurement circuit, and it is significantly affected by impurities that may be found in the oil sample such as water, size of molecules, temperature-dependent viscosity, etc., in addition to the aging of the oil. It has been found that the tan δ value of the transformer oil is inversely proportional to the resistivity of the oil, and vice versa; this eliminates the need for separate tests.

Dissolved gas analysis

The idea with dissolved gas analysis is based on the fact that during its lifetime the transformer generates decomposition gases, essentially from the organic insulation (breakdown of paper or oil), under the influence of various stresses, both normal and abnormal.

The motivation behind the Dissolved Gas Analysis (DGA) test is that during the lifetime of transformer oil, it generates decomposition gases, which are brought about by organic insulation, i.e., the breakdown of insulating paper or transformer oils, under the influence of various physical stresses [14]. With regular DGA test, several problems such as overheating, loose connections, breakdown in cellulose, corona and arcing, and partial discharge can be detected several months in advance, thereby greatly improving the life of the transformer. The most important gases detected during DGA test are hydrogen, methane, ethane and ethylene.

Furan analysis

Furan analysis gives us an idea of the condition of the paper insulation by testing an oil sample. As time goes by, cellulose insulating material experiences degradation. In this process, an aromatic chemical compound is produced, which is known as furan [15]. Testing is typically performed for the five main furans, as follows:

• 2FOL (2-furfurol), to test for high moisture
• 5H2F (5-hydroxymethl – 2-furaldehyde), to test for oxidation;
• 2FAL (2-furaldehyde), to test for overheating and faults
• 5M2F (5-methyl – 2-furaldehyde), to test for local, severe overheat
• 2ACF (2-acetylfuran), to test for lightning (it is rarely used)

The results of the Furan test are used to determine an average expected degree of polymerization for the insulating paper, which is in turn used to estimate the percentage of solid life insulation remaining inside the transformer.

III. INFORMATION ABOUT THE DATASET

The dataset obtained for this research was provided to us by the Central Power Research Institute, Bangalore. It consisted of thirty two samples of non-degraded transformer oils from various locations all across India, and the various parameters of each of the oils divided into three categories; DGA analysis parameters, electrical parameters and physio-chemical parameters. In [16], we obtained one sample of a non-degraded transformer oil from Central Power Research Institute, Kolkata. After an exploratory data analysis, we included the most relevant parameters to predict the condition of the transformer oil sample (degraded or non-degraded). The final common parameters between the two datasets that were included in our research were as follows:

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1. Flash point
2. Acidity/Neutralization value
3. Average Breakdown Voltage Test value
4. Dielectric Dissipation Factor
5. Specific resistivity at 27^{o}C
6. Specific resistivity at 90^{o}C
7. Water content

The final dataset used is given below:

Interfacial Tension	Flash Point	Neutralisation Value	Average BDV Value	Dielectric Dissipation Factor x100	Dielectric constant	Specific Resistivity at 90 degrees celsius	Specific Resistivity at 27 degrees celsius	Water content in ppm	Outcome (1 for non-degraded, 0 for degraded)
20	168	23	45.8	3.1	2.08	0.61	4.2	30	1
35	152	0.79	43.6	0.31	2.05	26	287	16	1
27	150	1.2	53.9	0.18	2.06	9.3	354	16	1
20	173	7.6	56.1	2.5	2.13	0.84	12	26	1
26	149	2.7	36	1	2.08	2.3	54	13	1
32	149	1.7	69.8	0.98	2.07	4.9	100	12	1
37	149	0.3	66.3	0.002	2.03	140	450	6	1
28	163	4.1	58.7	0.011	2.03	0.96	11	14	1
29	163	4	58.6	8.6	2.03	0.7	7.3	13	1
31	159	1.8	68.6	4.1	2.03	1.9	24	12	1
33	157	0.85	55.8	4.9	2.06	110	1200	11	1
30	157	0.61	50.3	3.7	2.02	80	800	12	1
20	163	28	43	7.1	2.11	0.19	1.9	26	1
36	155	0.58	67.4	0.002	2.01	88	550	8	1
30	167	1.2	54	0.34	2.04	29	430	10	1
32	167	2	60.8	0.75	2.05	9.3	200	10	1
28	161	2.8	60.1	0.63	2.04	9.3	230	9	1
30	161	1.6	65.3	0.83	2.04	7.6	160	10	1
37	161	0.38	69.9	0.03	2.01	190	3100	8	1
32	159	0.39	54.8	0.1	2.01	120	2100	11	1
26	157	1.1	40.1	0.24	2.01	20	320	17	1
26	159	2.9	39.9	0.28	2.02	20	380	14	1
35	159	0	67.1	0.12	2.02	330	3900	7	1
26	157	2.2	54.9	1	2.01	25	500	18	1
25	163	2.5	55.9	1.2	2.02	5.4	120	15	1
28	155	1.4	68.2	0.2	2.01	18	470	15	1
31	153	0.83	66	0.29	2.01	31	680	14	1
22	171	7.8	41.1	0.52	2.02	2.1	33	23	1
26	153	1.5	42.8	0.18	2.01	17	390	16	1
29	155	0.32	82.5	0.03	2.01	40	1100	15	1
31	155	1.4	39.9	0.53	2.01	38	850	16	1
30	159	2.2	65	0.9	2.01	11	210	10	1
42	156	0.029	70	0.18	2.04	60	3300	8	0
39.9	148.2	0.02755	66.5	0.171	2.04	57	3135	8	0
44.1	163.8	0.03045	73.5	0.189	2.04	63	3465	8	0

Table 1: Final Dataset fed into the Machine Learning and Deep Learning Models

IV. METHODOLOGY

In our research, we use Machine Learning algorithms [17-20] to make a binary classification of the transformer oil samples, and we classify them into degraded and non-degraded samples. Based on an exploratory data analysis between each of the parameters provided to us and its correlation to the condition of the oil sample, seven parameters were identified, the combination of which would be the best fit to this classification problem. In this research, we use classification algorithms such as Logistic Regression, ZeroR, K-Nearest Neighbours (KNN), Support Vector Machines (SVM), Decision Trees and Random Forests and Artificial Neural Networks (ANNs) [21].

Since the amount of data available was limited, and the number of positive samples were found to be much higher than the number of negative samples, the dataset was augmented to improve the number of negative samples. The final dataset consisted of thirty five oil samples, with seven parameters. Once the dataset was prepared, it was given as an input to the above mentioned Machine Learning algorithms, and a comparison was made between the machine learning algorithms based on accuracy. The baseline classifier used for this research was ZeroR, and the other algorithms were compared to the results of the baseline classifier [22]. In addition to this, other research based on similar data was studied to understand what Machine Learning model would be the best fit for this particular dataset.

V. RESULTS AND DISCUSSION

We performed an effectiveness comparison between the algorithms considered, while simultaneously minimizing the number of parameters to create the most cost effective algorithm possible. In the table below, the accuracy of each Machine Learning algorithm is given.

Serial Number	Machine Learning Algorithm	Accuracy
1.	ZeroR	91.429%
2.	Naïve Bayes (NB)	100%
3.	Logistic Regression (LR)	100%
4.	Support Vector Machine (SVM)	100%
5.	K-nearest neighbours (KNN)	100%
6.	Decision Trees (DT)	85.714%
7.	Random Forest (RF)	85.714%
8.	Artificial Neural Networks (ANN)	57.142%

Table 2: Results of the accuracy comparison of various Machine and Deep Learning models

The results show that the best algorithms suited for this type of data are Naïve Bayes, Logistic Regression, Support Vector Machines and K-nearest neighbours.

Since the data was so skewed in terms of the number of positive results, the baseline classifier performed comparatively well. With Naïve Bayes, Logistic Regression, Support Vector Machines and K-nearest neighbours, we achieved perfect accuracy, i.e., 100%. With the tree-based algorithms, i.e., Decision trees and Random forests, the performance wasn't as good, giving us an accuracy of only 85.714%. Thus, we can deduce that for data of such nature (small dataset and skewed sampling), tree based algorithms are not suitable.

The most unintuitive result was that of Artificial Neural Networks. Based on common perceptions, Deep learning is generally the best solution to most Machine Learning problems. However, ANNs require a lot of samples of data to perform well, due to the intricacies of the algorithm, and all the independent relationships considered between several combinations of parameters and the outcome.

After analyzing several research studies which use similar data, we came to the conclusion that Support Vector Machines would be the best fit for such data, due to the concept of a hyperplane being compatible with the skewed nature of the data.

VI. CONCLUSIONS AND FUTURE WORK

We can conclude, based on the perfect accuracies achieved by the various Machine Learning algorithms, that this is an efficient technique to classify the given data samples into degraded and non-degraded oils. Support Vector Machines were chosen as the best algorithm for this problem based on the results, as well as a study conducted on various other research problems with similar data.

In the future, we would like to extend the research into Deep Learning when we have sufficient amounts of data. We could even reduce the number of parameters further, with larger amounts of data, thus reducing the cost of the system even further.

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