Health Estimation of Electrical Transformer

Project report submitted to

Visvesvaraya National Institute of Technology, Nagpur in partial fulfillment of the requirements for the award of the degree

Bachelor of Technology
In
Electrical and Electronics Engineering

by

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Declaration

We, Ganesh Rohit, Nishit Khandelwal, Vinit Kavalekar, Aadhithya Iyer, Arihant Gaur, Vyankatesh Muley, hereby declare that this project work titled "Health Estimation of Electrical Engineering" is carried out by us in the Department of Electrical Engineering of Visvesvaraya National Institute of Technology, Nagpur. The work is original and has not been submitted earlier whole or in part for the award of any degree/diploma at this or any other Institution / University.

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Certificate

This is to certify that the project titled "Health Estimation of Electrical Transformer", submitted by **Ganesh Rohit, Nishit Khandelwal, Vinit Kavalekar, Aadhithya Iyer, Arihant Gaur, Vyankatesh Muley** in partial fulfillment of the requirements for the award of the degree of **Bachelor of Technology in Electrical and Electronics Engineering**, VNIT Nagpur. The work is comprehensive, complete and fit for final evaluation.

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ABSTRACT

Transformer is one of the main components in distribution system of electrical power system towards the consumers, thereby any damage to the transformers will hinder the distribution of electricity towards the consumers. High temperature in transformers can cause degradation in the insulation of transformers which in turn will cause failure in transformers. Damage in transformers will cause disturbance in electrical power system and result in a major economic loss. Before damages occur, transformers need to be changed up until it is deemed to be no longer efficient, this can be done by replacing the transformer that is about to be damaged. To evaluate the transformer health, many assessment techniques have been studied and developed. These tools will support the transformer operators in predicting the status of the distribution transformer and responding effectively.

This report reviews advances in estimating the health of a three phase distribution transformer. We generate the transformer data synthetically, for the ambient temperature conditions of Nagpur, Maharashtra, India. We also present a scheme to obtain the ground truth health index for our setting.

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Chapter 1

Introduction

Energy has became a basic necessity today, We can't imagine a day without electricity. Be it a person working in an IT company or a farmer, everyone requires electricity. It is a vital commodity for the survival of modern economies. Therefore a healthy power system is very essential to guarantee a continuous electricity supply.

Transformer plays an important role in transmission of electricity. It links the energy transmission from generation station to all the way to end users like us. But during the event, transformers may fail due to various reasons which results in utilities experiencing major loss such as loss of revenue and market backlash. These problems aren't limited to utilities only, it affects consumer as well. The consumer could face an electrical shortage or fluctuations in supply can damage the equipments installed. This could lead to shutdown of industries, hampering production and leading to unemployment. As a result Transformer Asset Management is of prime importance to prevent suddenly occurring failures of transformers.

A proper asset management will allow quality assessment of conditions and to develop future management strategies of transformers. But for that we first need to understand and identify the root cause of failures in transformers. Authors in [1] presented the statistical data of component failures from 350 transformers to establish a three-level model of failure mechanism, failure linkages, and failure modes. It was found out that the most critical to power transformer health is insulation with an incident rate of about 41%; then, components showing high failure rates are windings, 14%, bushings, 13%, and on-load tap changers at about 10%. Other components such as the cooling system, core, and operational errors do not have a significant impact. This is shown in Figure 1.1.

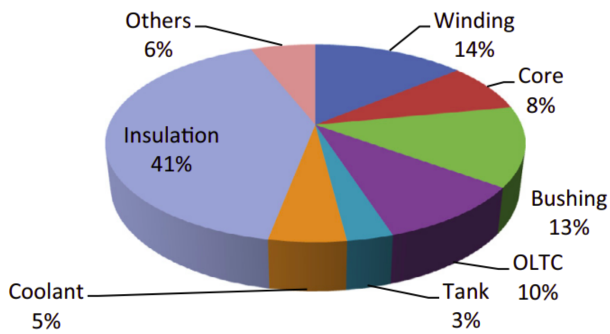

Figure 1.1: Failure statistics of power transformer component based failures [1]

Investigating data from transformers supervisors in utilities, component failures of transformers, failure rate and operation impact level is shown in Table 1.1

1.1 Health Index

There are many approaches in transformer asset management to tackle such issues and plan and prioritize the predictive maintenance of transformers. One of the approaches is a useful calculation technique

Table 1.1: Number of power transformer failure per voltage population during 2009–2013

Years	400–230kV	230–110kV	110–66kV	110–33kV	110–22kV	110–11kV	66–11kV	33–11kV	Total Failures
2009	0	0	0	0	3	7	0	11	21
2010	0	1	1	9	9	6	0	15	41
2011	0	1	0	10	8	11	0	14	44
2012	0	0	0	10	7	8	0	16	41
2013	0	2	1	13	8	9	1	15	49
Total	0	4	2	42	35	41	1	71	196

known as Health Index (HI) calculation. This method not only allow us to plan maintenance strategies for transformers but also help us to identify risk and opportunities. Generally there are three parts of HI formulation which are Input, Computational Algorithm and Output or the interpretation of the calculation part. This has been summarized in Figure 1.2 [2].

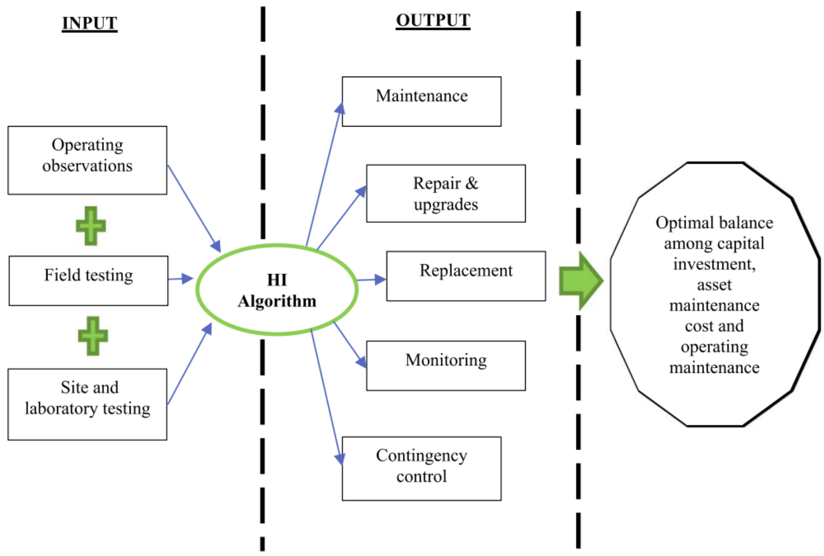

Figure 1.2: Number of power transformer failure per voltage population during 2009–2013

Different test have been conducted on transformers and on basis of that, inputs are being taken. The input for HI is usually obtained from the operating observations, field, site and laboratory testing. Some common diagnostic tests that are usually used for calculation of HI are dissolved gas analysis (DGA), oil quality [breakdown voltage (BDV)], interfacial tension (IFT), acidity, water content (WC), color), furan analysis (FA), and degree of polymerization (DP). Some advanced diagnostic tests such as frequency response analysis (FRA) and recovery voltage measurement (RVM) have also being used by several studies. Other parameters include tap changer and bushing, load history, maintenance data and age.

A lot of fomulations have been defined for Health Index. Ballal et. al. [3] represented health index as,

$$\text{HI} = \frac{\sum_{c_i=1}^{n} S_{P_i} W_{P_i}}{S_{max} \sum_{c_i=1}^{n} W_{P_i}} \tag{1.1.1}$$

Where HI is the health index metric, S_{P_i} is the score of each assessment condition that is defined based on measured data, S_{max} is the maximum score of assessment condition, W_{P_i} is its corresponding weight and n are the number of such conditions.

Different parameters have different weightage according to the degree of importance given to any particular parameter that affects the condition of transformer [4, 5, 6, 7, 8]. Parameters like Load History and Power Factors have higher weightage as compared to weightage given to Age or Location. Different

Table 1.2: Weighing Factor of Various Transformer Parameters

Parameters	Weighting Factor
Dissolved Gas Analysis	10, 3
Load History	10
Power Factor	10
Global loss factor	10
Thermo Scan	10
Infrared Thermography	10, 8
Conductivity factor	10
Polarisation Index	10
Furanic Compound content	9, 6, 5
Oil Quality	8, 6
Overall transformer condition	8, 6
Leakage reactance	8
Winding resistance	8, 6, 2
Bushing Condition	7,5
Frequency Response Analysis	6
DGA of tap changer oil	6
Turns ratio	5,2
Tap changer contact condition	5
Overall LTC condition	5, 2
Age	4
Paper Insulation factor	4
Internal faults history	4
Dielectric Breakdown test	4
Water content test	3
Surge arrester	3
Cooling equipment condition	3
Tap changer oil quality	3, 2
Location	3
Main tank corrosion	2
Insulation Resistance test	2, 1
Core to ground connection	2
Oil leaks	2

researchers have considered different weightage for same factor. The number of parameters used in the calculation of HI is also different among researchers. This has been shown in Table 1.2

Prior works have developed several mathematical equations or algorithms for the formulation of HI. Even though they are using the same basic equation, some improvements have been made from time to time to make the equations more reliable and scientifically proven.

The output of the final HI will be subjected to a certain range where the preventive action will be taken accordingly. There are various ranges presented by researchers and there is no standard in determining the range and the preventive action taken. Two specific examples [8, 9] have been shown in Table 1.4 and 1.3.

The HI method have some limitations as well:

1. The accuracy depends heavily on weighted parameters
2. The condition monitoring may costly and the results only reflect the preferences of the human-expert
3. Low accuracy for the systems and devices are controlled linguistically, or have a contradictory condition

Table 1.3: Output of Health Index as shown in [8]

HI	Condition	Action
85-100	Very good	Normal maintenance.
70-85	Good	Normal maintenance.
50-70	Fair	Increase the number of diagnostic tests, corrective maintenance or need of replacement, depending on the criticity.
30-50	Poor	Start planning the replacement process or repair, taking in account the risk.
0-30	Very Poor	Immediate risk assessment, replacement or repair, depending on the case.

Table 1.4: Expected Lifetime based on Health Index as shown in [9]

Health Index	Condition	Description	Approximate Expected Lifetime
85-100	Very good	Some aging or minor deterioration of a limited number of components.	More than 15 years
70-85	Good	Significant deterioration of some components.	More than 10 years
50-70	Fair	Widespread significant deterioration or serious deterioration of specific components.	Up to 10 years
30-50	Poor	Widespread serious deterioration.	Less than 3 years
0-30	Very poor	Extensive serious deterioration.	At end of life

To alleviate some of the issues, we attempt a thorough literature review of recent advances in health index estimation of transformer.

Chapter 2

Related Work

In order to provide information about the transformer's state of health and detect incipient faults, the monitoring system must perform physical measurements and analyze the results in the context of given environmental conditions. They are important for asset management because they help to identify, prioritize, and schedule required investments into capital and maintenance programs. Effective methods of monitoring the condition and health of distribution transformers could help utilities to proactively mitigate failures and degradation. Ultimately, this will improve reliability and reduce the cost of electric service. It is particularly important with the advent of higher penetrations of distributed PV, electric vehicles, and other energy resources that are rapidly changing the operation of the grid and have the potential to introduce added stress to service transformers. Since then, many methods have been used to estimate the health of the distribution transformer. We list the methods prevalent in literature to estimate the health of the transformer.

2.1 Health Index Calculation

Health index (HI) calculation is a useful technique, it is the most basic method that was used to create maintenance strategies for transformers [10]. This method uses the representative indexes of the transformer's operation and statement to convert them into a quantitative index and evaluate the general condition of the transformer. In a health index calculation method is applied to assess the distribution transformer conditions comprehensively. The statement of the transformer is classified in a range from "perfect health" to "very poor condition". A general formulation of HI has been presented in Section 1.1.

2.2 HI Estimation using Thermal Model and Loss Life Calculation

Aging or deterioration of insulation is closely related to temperature, humidity level and the amount of oxygen in the air. The factor which greatly affects the life of the transformer is temperature. The temperature of the transformer surface is not uniform, so to find out the most influential temperature which reduces the life of the transformer, a hotspot or the hottest point on a transformer is used. The aging of the transformer can be evaluated using HST (Hot spot temperature). The value of HST depends on ambient temperature (AT), increase in TOT (Top oil temperature) against AT, and increase in HST against TOT. The increase in the TOT value, which is also an increase in HST, has an effect that can reduce the insulation life of the transformer. Abnormal conditions, such as overloading, supplying non-sinusoidal loads, and the influence of high ambient temperatures, can accelerate the aging of the transformer, which will eventually speed up the use of transformers. So it can be concluded that the increase in TOT and HST can shorten the life of the transformer. When the transformer is energized and loaded with ambient temperature (AT), the dissipation caused by core loss, winding loss, and stray losses in the tank, harmonics present as well as metal support structure, as sources of heat, will cause oil temperature and winding temperature to increase. Total loss = ohmic + Iron + Stray To take the harmonic distortion into account, the power loss is modified with the current factor. The core density, core dimensions, frequency and voltage is taken into account to calculate the flux density. Top oil temperature is calculated by the method mentioned before and according to these two factors, Top oil temperature and thereby the Hot spot temperature is obtained. Based on the

TOT, the aging factor FAA is calculated as,

$$FAA = \exp^{\frac{15000}{383} - \frac{15000}{\theta_h + 273}} \tag{2.2.1}$$

To estimate insulation heating effect, the loss of life factor is integrated over a given period of time. Where FAA has a value greater than 1 for winding hottest-spot temperatures greater than the reference temperature 110°C and less than 1 for temperatures below 110°C. Since insulation aging is a cumulative effect ,the percent loss of life per day is the summation of the percent loss of life [11].

2.3 Fuzzy Logic

To overcome the limitations of the health index calculation method, fuzzy logic has been proposed as a suitable approach. Fuzzy logic is supposed to be used for representing vague concepts and uncertain information, especially in cases in which conventional logic techniques couldn't be applied effectively. The structure of a complete fuzzy control system includes three steps: fuzzification,inference and defuzzification. At the first step, fuzzification calculates fuzzy values from exact values at the input. The fuzzy inference applies all applicable fuzzy rules to calculate the fuzzy value for the output. The defuzzification determines the exact output value from the fuzzy result obtained in the fuzzy inference step [12].

2.4 Machine Learning

2.4.1 Neural Networks

An artificial neural network is a collection of neurons, connected to other neurons in a layerwise fashion. Each connection is assigned a weight, which is determined by training the neural network, using training data and a validation set, to check for overfitting (that is, the network should be generalizable to other scenarios, rather than memorizing the training set). In this particular case, the inputs to the neural network can be various transformer parameters. The paper [13] proposes the use of ANNs , with four parameters as input (voltage, load current, oil level and oil temperature). There are two hidden layers (with logsig and purelin as the nonlinearities respectively), with the output layer denoting the health status of transformer. The method provided an accuracy of 97.2% on data provided by MSEDCL on a 15kVA, 400/400V three phase distribution transformer.

Another work estimates the health of transformer using two sets of ANNs [14], with input parameters to the first network being DGA for gases, Furan, insulation power factor, O & M (Oil and Maintenance), and age. The output from first network is fed to the second network, along with a few other parameters like turns ratio test, short circuit impedance, DC winding resistance, FRA and degree of polymerization. Test results showed an accuracy of a max of 92.4 %, on a transformer with primary voltage as 150kV, under MSEDCL Indonesia.

2.4.2 kNN (k-Nearest Neighbour)

The kNN algorithm is a supervised learning technique that has been used in many ML applications. It classifies objects based on the closest training examples in the feature space. The idea behind kNN is to find a predefined number of training samples closest in distance to a given query instance and predict the label of the query instance from them.

2.4.3 Support Vector Machines (SVMs)

The objective of the support vector machine [15] is to find a hyperplane in the N-dimensional(N is the number of features) space that distinctly classifies the data points. It is generally used for binary classification problems. For Multi class classification problems the SVM is used by breaking the multi class problem into individual binary classification problems.

2.4.4 Decision Trees

Decision Tree is a Supervised learning technique that can be used for both classification and Regression .Decision tree is a tree-like structure that includes internal nodes, branches, and leaf nodes. where internal nodes represent the features of a dataset, branches represent the decision rules and each leaf node represents the outcome. Each internal node denotes a test on an attribute, each branch denotes the outcome of a test, and each leaf node holds a class label. The topmost node in the tree is the root node. A decision tree is a class discriminator that recursively partitions the training set until each partition consists entirely or dominantly of examples from one class. Each non-leaf node of the tree contains a split point that is a test on one or more attributes and determines how the data is partitioned uses decision trees to estimate the health of the transformer. Several papers [16, 17] presented this technique for health estimation of transformers and compared it with techniques like random forest, support vector machines and kNN.

2.4.5 Random Forest

Random forest [18] is an ensemble learning method for classification and regression, which is a process of combining multiple classifiers to solve a complex problem and to improve the performance of the model. Random Forest is a classifier that contains a number of decision trees on various subsets of the given dataset and takes the average to improve the predictive accuracy of that dataset. Instead of relying on one decision tree, the random forest takes the prediction from each tree and based on the majority votes of predictions, and it predicts the final output. The greater number of trees in the forest leads to higher accuracy and prevents the problem of overfitting. This method has been used to estimate the health of transformer in [16]

2.5 Hidden Markov Model

Hidden Markov Models (HMM) can be used to transform various data collected from substation equipment into failure probabilities. Based on these failure probabilities a mathematical decision tool can be created, which could be used in system-level simulation and experimentation. The Markov Model (MM) is one of the prediction methods that can be used to determine the future states of transformers based on HI. Markov decision process is normally characterized as a memoryless process where it predicts the future condition of equipment as a probabilistic estimate. This paper [19] discusses the use of hidden markov model for prediction of health of transformer.

Chapter 3

Dataset

3.1 Overview

For the field test of transformer, many organizations such as Maharashtra State Electricity Distribution Company (MSEDCL) [20], National Electrical Manufacturers Association of USA (NEMA) [21], Asset Management and Health Assessment Consulting Company (AMHA) [22], etc., have compiled a lot of data from many transformers (both power and distribution). However, much of their data is restricted to individuals affiliated with the respective organizations. To alleviate the issue of lack of data, we propose a novel dataset for distribution transformer, along with the health index for each instant.

We acquire the electrical specifications from Maharashtra State Electricity Distribution Company Limited (MSEDCL), for various distribution transformers, classified on the basis of their rating. In this report, we present the data for a 3 phase, 25kVA, 11/0.433kV, ONAN cooled distribution transformer. Its nameplate is shown in Figure 3.1. From the nameplate and as per MSEDCL guidelines, the following parameters about the transformer can be inferred.

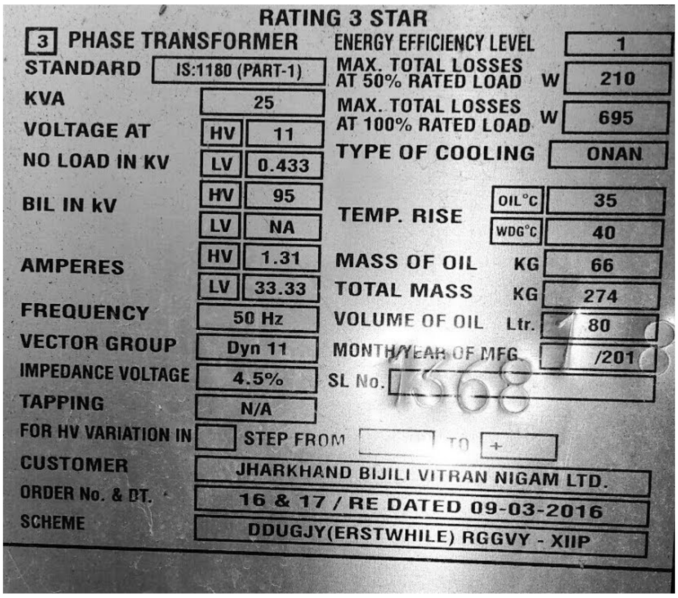

Figure 3.1: Transformer Nameplate

1. **Transformer Rating**: 25kVA
2. **LV Voltage**: 0.433kV
3. **Operating Frequency**: 50Hz
4. **Maximum temperature rise for rated load**: 35°C

5. **BEE Star Rating**: 5
6. **Total loss at** 50% **as per BEE Star rating**: 128W
7. **Total loss at** 100% **as per BEE Star rating**: 448W
8. **Weight of Core**: 208kg
9. **Weight of Tank**: 66kg
10. **Volume of Oil in tank**: 80L

We propose the transformer setting in the city of Nagpur, for the month of April, where readings will be taken every three hours. This means the number of readings for this setting will be 240. In a future work, we will extend the time duration for period of 10 years and use forecasting methods to determine the health index in near future.

3.2 Ambient Temperature

We obtain the ambient temperature, from the data open - sourced by the Indian Meteorological Department (IMD) [23]. The data is presented as a binary file, consisting of grids in the map of India, as shown in Figure 3.2

Figure 3.2: Map of India divided in grids for Temperature Measurement

We convert the gridded binary file to a text file, having maximum and minimum temperatures for each area. We consider the area in and around Nagpur (we take Lat. 21.50°N, Long. 79.50°E) and consider temperatures for the month of April.

The data provided by IMD consists of the maximum and minimum temperature for each day. However, this will only account for 60 readings. Therefore, we linearly interpolate the readings. Given two points (x_1, y_1) and (x_2, y_2), we can obtain the reading for the point between them as,

$$y = y_1 + (x - x_1)\frac{y_2 - y_1}{x_2 - x_1} \tag{3.2.1}$$

Intuitively, this represents traversing a line segment between two points (x_1, y_1) and (x_2, y_2). Therefore for a day, we have two temperature readings, maximum and minimum temperature. Therefore we can interpolate it to having 8 readings per day, and therefore 240 readings for the month.

3.3 Oil Temperature Rise Calculation

We assume the transformers has a cold start (the initial temperature rise is zero, that is the temperature of transformer is the same as ambient temperature). As per IEEE Standard C57.91-1995 [24, 25], we can obtain the thermal capacity of transformer as,

$$C_{DT} = 0.0272W_c + 0.0272W_t + 7.305\Theta_{oil} \tag{3.3.1}$$

Where W_c represents weight of core and coil assembly (in kilograms), W_t is the weight of tank and fittings (in kilograms) and Θ_{oil} represents the volume of oil (in litres).

The general expression of top oil time constant is,

$$\tau_{TO} = \tau_{TO,R} \frac{\left(\frac{\Delta\Theta_{TO,U}}{\Delta\Theta_{TO,R}}\right) - \left(\frac{\Delta\Theta_{TO,i}}{\Delta\Theta_{TO,R}}\right)}{\left(\frac{\Delta\Theta_{TO,U}}{\Delta\Theta_{TO,R}}\right)^{\frac{1}{n}} - \left(\frac{\Delta\Theta_{TO,i}}{\Delta\Theta_{TO,R}}\right)^{\frac{1}{n}}}, \tau_{TO,R} = C\frac{\Delta\Theta_{TO,R}}{P_{T,R}} \tag{3.3.2}$$

Where $\tau_{TO,R}$ is the top oil time constant at rated load, $\Delta\Theta_{TO_U}$ represents ultimate top oil rise over ambient temperature for load L, $\Delta\Theta_{TO,i}$ represents initial top oil rise over ambient temperature, $\Delta\Theta_{TO,R}$ is the ultimate top oil rise over ambient temperature at rated load, C is thermal capacity and $P_{T,R}$ is the power loss at rated load. Here, n represents the exponent of heat loss q in the expression $\Delta\Theta_{TO} = kq^n$. If the assumption of direct proportionality holds for heat loss, $n = 1.0$,

$$\tau_{TO} = \tau_{TO,R} \tag{3.3.3}$$

The top-oil temperature rise at a time after a step load change is given by the following exponential expression,

$$\Delta\Theta_{TO} = (\Delta\Theta_{TO,U} - \Delta\Theta_{TO,i})\left(1 - \exp\left(\frac{-t}{\tau_{TO}}\right)\right) + \Delta\Theta_{TO,i} \tag{3.3.4}$$

For each time step, the initial and ultimate temperature rise can be obtained as,

$$\Delta\Theta_{TO,i} = \Delta\Theta_{TO,R}\left[\frac{K_i^2 R + 1}{R + 1}\right]^n, \Delta\Theta_{TO,U} = \Delta\Theta_{TO,R}\left[\frac{K_U^2 R + 1}{R + 1}\right]^n \tag{3.3.5}$$

Where R is the ratio of load loss at rated load to no load loss, K is the ratio of specified load to rated load. From Section 3.1, we have the transformer loss at different loadings (50% and 100%). The ratio R can be determined as,

$$R = \frac{K - 1}{0.25 - K} + 1; K = \frac{P_{T,R/2}}{P_{T,R}} \tag{3.3.6}$$

Where $P_{T,R/2}$ is the loss at half the rated load. Similarly, K can be obtained as,

$$K = \frac{I}{I_r} \tag{3.3.7}$$

Where I_r is the rated current and I is the instantaneous current per phase. For the three phases, the value of K can be averaged across them.

3.4 Per Phase Current and Voltage Calculation

We have the rated voltage per phase as $0.433/\sqrt{3}$kV on the LV side. For the given power rating, the corresponding rated current is 33.33A. To incorporate variation in loading, we add Gaussian Noise to the sequence. The random sequence is generated by sampling from a normal distribution, and added to voltage for each phase. Following [3], we also calculated the unbalanced voltage V_U. As per NEMA, the unbalanced voltage is defined as,

$$V_U = \frac{\sigma_{\max}(V_{ab}, V_{bc}, V_{ca})}{\mu(V_{ab}, V_{bc}, V_{ca})} \tag{3.4.1}$$

Where $\sigma_{\max}$ is the maximum deviation and μ is the mean of line voltages. The unbalance in harmonics and voltages results in the unbalance and harmonics in currents. This can increase the core, copper and eddy current losses.

We also calculate current and voltage variation for three phase system [10].

$$\Delta I_{DT} = \sqrt{\frac{1}{3}(|I_a - I_r|^2 + |I_b - I_r|^2 + |I_c - I_r|^2)} \tag{3.4.2}$$

$$\Delta V_{DT} = \frac{1}{3}\left(\left|\frac{U_r - U_a}{U_r}\right| + \left|\frac{U_r - U_b}{U_r}\right| + \left|\frac{U_r - U_c}{U_r}\right|\right) \tag{3.4.3}$$

3.5 Data Visualization

All the experiments have been performed using MATLAB, except ambient temperature acquisition, which was done using Python.

3.5.1 Phase Voltages

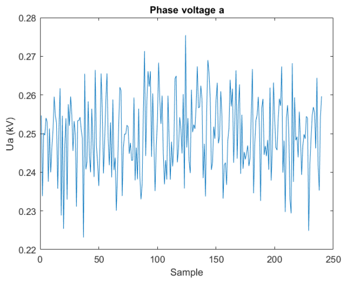

Figure 3.3: Phase Voltage a

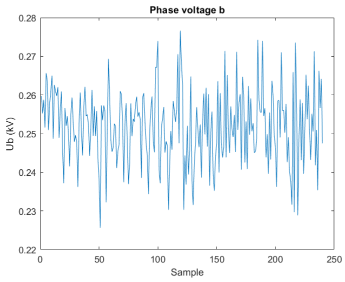

Figure 3.4: Phase Voltage b

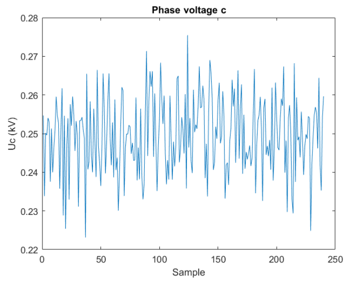

Figure 3.5: Phase Voltage c

3.5.2 Phase Currents

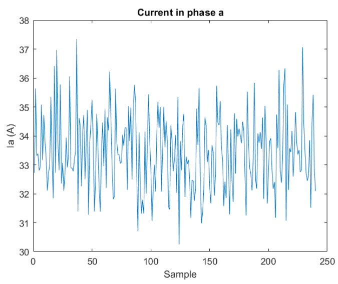

Figure 3.6: Current in Phase a

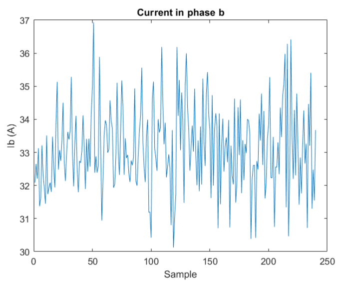

Figure 3.7: Current in Phase b

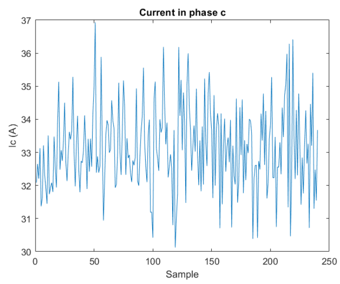

Figure 3.8: Current in Phase c

3.5.3 Current and Voltage Variation

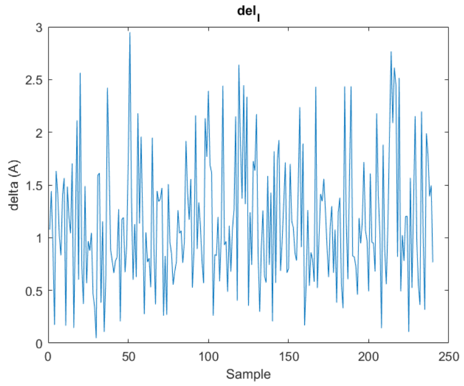

Figure 3.9: 3 Phase Current Deviation

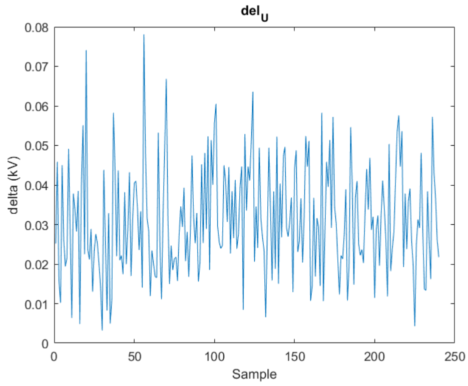

Figure 3.10: 3 Phase Volage Deviation

3.5.4 Transformer Oil Temperature

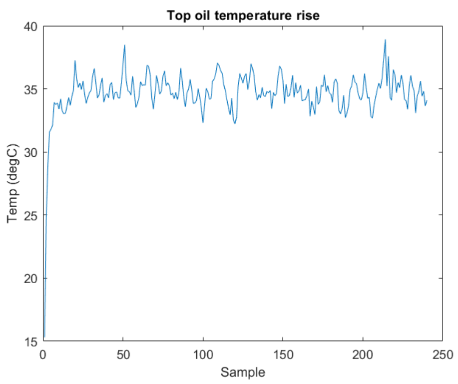

Figure 3.11: Top oil rise Temp.

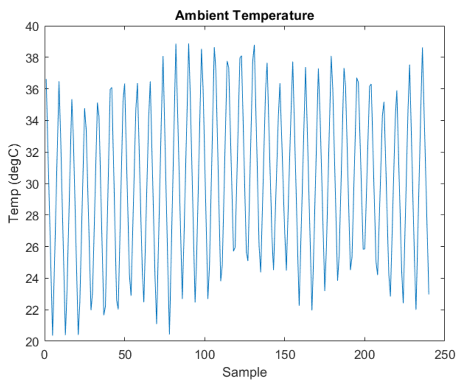

Figure 3.12: Ambient Temperature

3.5.5 Miscellaneous

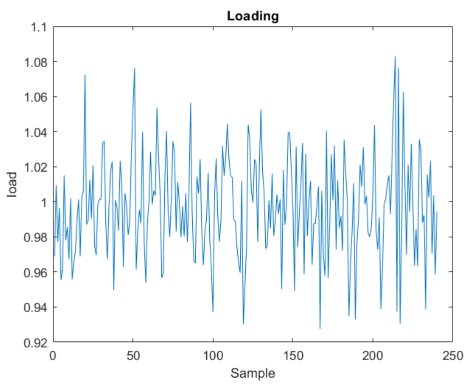

Figure 3.13: Loading

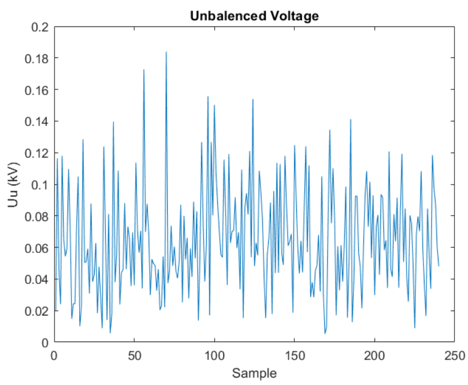

Figure 3.14: Unbalanced Voltage

3.6 Health Index Estimation

Since dataset will require a ground truth, we propose to determine a ground truth health index for each reading. This will help in the supervised training for learning based methods.

For the calculation of health index, the following parameters are utilized: Phase voltages and currents, top oil rise temperature, transformer loading, unbalanced voltage, and 3 phase voltage and current variations. This accounts for 12 different characteristics.

Define the data matrix X of size 240×12, having 240 samples for each of the characteristic. The data is first standardized.

$$Z_i = \frac{X_i - \mu(X)}{\sigma(X)}, i = 1, ..., 240 \tag{3.6.1}$$

Where $\mu(X)_{12\times1}, \sigma(X)_{12\times1}$ represent a mean and standard deviation for each characteristic and i is the sample number. The final health index can then be calculated using the sigmoid of the elementwise inverse for each feature vector,

$$\text{HI}_i = \text{sigmoid}\left(\frac{1}{\sum_{j=1}^{12} Z_{ij}} + \epsilon\right) \tag{3.6.2}$$

$$\text{sigmoid}(x) = \frac{1}{1 + e^{-x}} \tag{3.6.3}$$

Where ϵ is a correction factor. This will be the baseline for the dataset and all the algorithms will be tested as per this scheme.

Chapter 4

Future Work and Conclusion

In this work, we propose a new synthetically created dataset using the transformer parameters, based on standards. We plan to use this dataset for testing the literature and improve upon them, wherever possible. Despite the formation of dataset, there are potential limitations of our method. First is the artificial addition of noise in the data. While this will give a certain randomness to the data, it is certainly not the most accurate representation of the actual working of transformer. Second is the health index calculation scheme, which can certainly have potential areas of improvement, in terms of calculation from the data matrix itself.

We plan to consider this as a time series analysis and anomaly detection problem for our future work, to get a more accurate representation. We also plan to perform an ablation study based on different statistical approaches in literature. Finally, in the phase - II of project, we plan to extend this into forecasting problem, to determine health index of transformer in near future, given its history.

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