Prognostication Of Health Index For Oil-Immersed Transformers Using Random Forest

M. S. Qureshi, P.S. Swami, Dr. A. G. Thosar

Abstract: Energy is a basic demand around the Globe. With that demand, a healthy and functional power system is therefore, requires to guarantee uninterrupted electric power supply to their end users. Therefore, health index has become a handy and an essential parameter which, for sure will help guide us to know how are transformer`s condition, with that well planned steps might be taken at appropriate period. An effort is put into this paper, so as to explore a new way to prognosticate transformers health with their condition by utilizing diagnostic oil tests. And these diagnostic oil tests on which this method relies are, Furan, Dissolved Gas Analysis, and other oil tests results are the medium to predict Health index. Few models based on A.I and statistic method like fuzzy logic, Fuzzy Inference Systems, adaptive neuro fuzzy logic inference system, binary logistic regression and General Regression Neural Network have been published in recently. Thus, a method is proposed employing Random Forest one of the robust model in Machine Learning. The results were then cross referred with the results of other published methods too.

Index Terms: Bootstrapping, Condition, Decision Tree, Failures, Health Index, Random Forest, RMSE.

1 INTRODUCTION

TPower transformers in the electrical power system, are often acknowledged as the very expensive equipment and which comprises of large portion of investment about 60% in the network [1]. For complete utilization of assets, and also to evade reinvestments, owners of utility continuously find methods to prolong the operating life of transformers. These transformers are crucial link between stages of generation, transmission and distribution in the electrical power systems. A survey carried out by the IEEE a standard organization, points out that during the operating period of 16-year, a fleet of 10% power transformers are expect to evince a catastrophic failure [2,39]. But a major issue here is, sudden failure which can pose danger to the environment from oil leakages and a hazard to utility personale through explosions and flames. Thus, transformer requires assessment and thorough supervision by Asset owners to ensure operations are uninterrupted. For proper assessment, there is need to develop a robust and effective methods, techniques and mechanisms for monitoring health of power transformer[38,4]. With various studies it was accepted that life of transformer is on an average 30 to 40 years[1]. Insulation degradation and moisture are main influencer in the ageing of power transformer. Insulation condition monitoring and online health monitoring done with routine test reflect importance of appropriate operation of transformer.Health Indices evaluation during these decade have been acknowledged to be a robust tool in assessing transformer condition.

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For this evaluation, transformer's present condition obtain from various test such as Furan , Dissolved Gas Analysis, and other oil tests results, with that and an expert data from field inspection diagnostics with observations are merged into a one quantitative indices, which may indicate an overall condition. There are many cases like [1],[5]; Where it is done by amounting the each of their score and weightage which are defined for each very particular parameters converted to a quantified values to guide utility handlers on the condition of transformer insulation. Insulation condition a factor on which Transformer life dependents upon [2]. Objectively, the health indices which are acquired does not provide the condition of any specific part of a transformer concerning repair, it does showcases levels for long-term degradation, a routine inspection may not determine condition that easily [1],[3]. Industrial standards guides such as IEEE, IEC and CIGRE , provides standards for individual scores and weightage factor which are well established practices at utility companies. The linear approach for health index can be formulated into mathematical expression by the following equation. $h(x) = \frac{w_1x_1+w_2x_2+w_3x_3 \ldots\ldots\ldots+w_nx_n}{w_1+w_2\ldots\ldots\ldots+w_n}$ (1)where, h – Health Index Metric. w – Weight of each Test. x – Individual scores of each Test. n – Number of Test done for HI calculation. Health Index with an ease can be a main determiner of degradation for power transformer.

2 TRANSFORMER DIFFICULTIES & FAILURES

Different conditions and criticalities give occurrences to Transformer failure. These setbacks can generally be defined as follows [6 , 7]: Service transformer suffering from damage such as winding damage or tap-changer failure, which may lead to forced outage. Problem such as excessive gas production or high moisture levels might facilitate requirement such as extensive field repair or removing of the transformer and sending it to a repair facility.

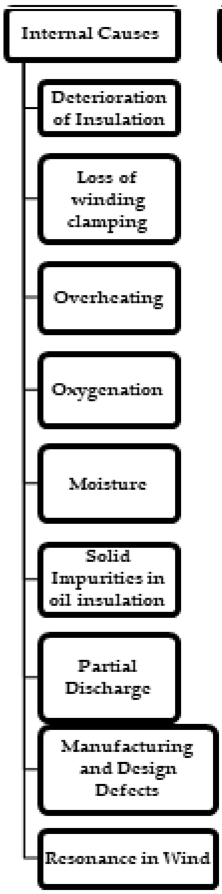


Fig. 1 Prototypical of Transformer Failures

Predominantly transformer failure can be categorize into electrical, mechanical, or thermal. These failure can be internal or external[36], which is shown in fig. 1. Over loading, lightning impulses or Switching surges, such factors in domain of Electrical stresses directly affect insulation`s dielectric strength and perhaps decline in it, might eventually lead toward transformer failure. The decaying rate of insulation and acceleration in electrical failure take place with combination of contamination and moisture, mechanical deformity and stresses like thermal stress. Analysis about the factors common to transformer failure illustrated in Fig. 2 [8]. Regarding the location of transformer failure such as tap changer, windings, bushings, leads, insulation and core take place. Out of which windings are the place in transformer where majority of failure take place about 45%, tap changer with 26 % and 17% with bushings according [9].

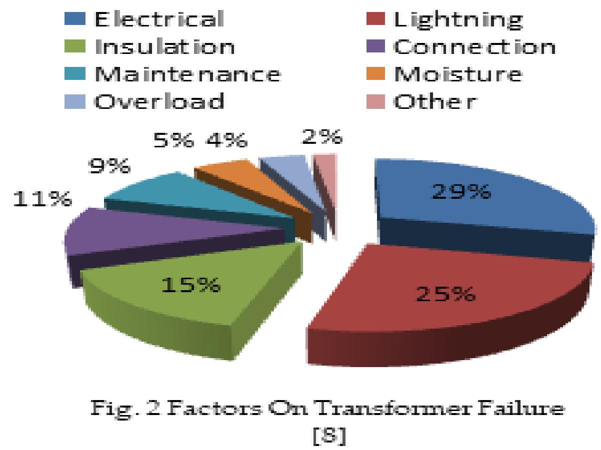


Fig. 2 Factors On Transformer Failure [8]

These nuances in difficulties, failure and criticalities of transformers, are taken into account which are then indentified and constituted into evaluation for the purpose of monitoring of power transformer`s health[2]. Past studies and research have provided different notions have been introduced concerning with transformer life management such as [31], end of life [1,10, 14]; effective age vs. actual age [1,14,13]; remaining life and life consumption [1,10,13]; probability and risk of failure, and reliability [1,10,11]. *Hence, HI !* A combined Health Index which is a useful parameter to illustrate the overall health of a complicate equipment. HI gives quantifiable details on conditions of equipment depending upon various condition and criterions that are concerning the long duration factors associated with degradation, which on successive addition might lead end-of-life of asset. Looking for defects and anomalies through scheduled maintenance or condition-based monitoring, that might help maintenance or repair, to maintain the equipment operation during some time period, whose results might differ from HI.

3 PARAMETERS AND TESTS

Transformer insulation comprise mainly of mineral oil and paper. Thus with that acknowledgement, method like monitoring and diagnostic for transformers are prominently used by methods like DGA, dielectric characteristic test, furan analysis, oil quality test , equipment inspection, visual inspection, power factor test and history on loading.

3.1 Dissolved Gas Analysis (DGA)

DGA technique used in evaluating various gas concentrations that are bring about by decomposition of the oil insulations under odd electrical or break down under thermal stresses, liberating few quantity of gases (H_2, CH_4, C_2H_6, C_2H_4) [15] and (CO, CO_2) [16] which have dissolved in oil. Partial Discharge, arcing, severe overheating and overloading in the insulation system which in and itself all internal faults and can be evaluated with help of DGA by IEC 60599 [17] standard. IEEE C57.104 [18] provide a range of classification for transformers to continue its operation at various combustible gas levels[10]. Here TDCG is used with conditions shown Table 1 as per IEEE C57.104 [18]

TABLE 1
BY IEEE C57.104-1991 DGA INTERPRETATION[18]

	H_2	CH_4	C_2H_2	C_2H_4	C_2H_6	CO	CO_2	TDCG
Condition1	100	120	35	50	65	350	2500	720
Condition2	101-700	121-400	36-50	51-100	66-100	351-570	2500-4K	721-1920
Condition3	701-1800	410-1K	51-80	101-200	101-150	571-400	4001-10K	1921-4630
Condition4	>1800	>1000	>80	>200	>150	>1400	>10K	>4630

**K = 1000*

3.1 OIL QUALITY TEST

As the name suggest itself that the result from this test gives physical aspect of oil, in short quality of oil. These physical attributes of the oil in the transformers were measured periodically, Table 2 summarizes these test for evaluating condition and rating of oil under test in accordance to the IEEE recommended standards found on the ASTM standard and CIGRE recommended the IEC standard [10], [17], [18]. In accordance to standards following Table 2 on oil tests.

TABLE 6
OIL QUALITY RATING[1]

Oil Physical Attributes	Good	Fair	Poor	Standards
Acidity	<0.10	0.10-0.20	>0.20	IEC 62021
IFT	>28	22-28	<22	ASTM D971-99a
BDV	>50	40-50	<40	IEC 60156
Water Content	<5	5-15	>15	IEC 60814

3.1 FURAN ANALYSIS

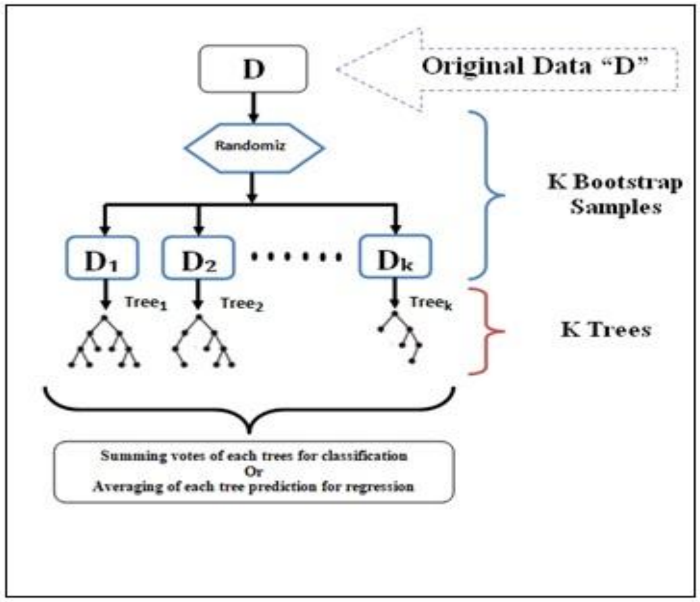
For power transformers, furan test is not done on specific interval of time or routinely. But, it can be assigned to post-diagnostic analysis[1]. Traces of furanic compounds in the oil by the measurement according IEC 61198 [19] explanation. Degree of polymerisation of an insulation paper can also be evaluated while measuring the content of furfural in the oil[37]. Table 3, gives the rating and condition on the analysis of furanic compound obtain from Furan Analysis

TABLE 3
FURAN ANALYSIS RATING [1]

Conditions	Furaldehyde(ppm)	Age(Years)
A	0 – 0.10	< 20
B	0.10 – 0.25	20 to 40
C	0.25 – 0.50	40 to 60
D	0.50 – 1.0	> 60
E	> 1.0	–

4 METHODOLOGY

This section discuss the proposed model; the model deals with prognostication and than assess with other models used in HI calculation, and how does this proposed prognostic model perform in comparison with the other models cited in this paper. As in the era of computer, data is the emergence from the utilization of computers, in spectrum of utility companies



just like that utility companies having asset like Transformer, concerning with their management and condition data are obtain from test like DGA, Furan Analysis, Oil Quality Test, Dielectric Characteristic and etc. With this data obtain from such test are used; thus also making it data driven model. This proposed model is built upon machine learning. Machine Learning is a subset or even an application of Artificial Intelligence. Machine learning assess computer to use data and self learn from it by using various program and algorithm. The proposed model is based on Random Forest which is ensemble method machine learning`s algorithm. Before going into discussion on the proposed model, basic building block have to be understood.

4.1 BOOTSTRAPPING AND BAGGING

Bootstrap was introduced by Efron[22]. Iteratively obtaining different samples from the same dataset, this technique of resampling is Bootstrapping. From the dataset, samples are drawn in a way that it increases the size of test data and with replacement of resample from the training data that produces a plethora of bootstrap samples[21].Bagging is used typically in simple term reduction of the variance by keeping the bias, which is to pile up the fitted values in various ways[21]. The abbreviation of bootstrap aggregating is bagging.

4.2 Decision Tree

Decision tree is and had been the building block for the prominent and important tasks of supervised learning classification/regression algorithms[33]. Thus, Forest the name has been labeled to set of trees for that classification/regression problem[33]. Decision trees makes model for classification and/or regression by forming a tree from the root node to a particular leaf node. Entire data set of observations is iteratively split into subsets along different branches so that similar observations are grouped together at the end leaves. Which makes decision(having more than one branches) and leaf nodes. The best predictor in the tree is root node which is the topmost decision node. The leaf nodes of the tree contain an output variable representing as prediction or classification.

4.3 Random Forest

Leo Breiman in 2001[23], devised a random forest which is a simple and robust algorithm comprised of an collection of independently trained decision trees. Random Forest in way is a powerful collection of classifier methods, that enhances CART (Classification and Regression Tree) by providing lots of trees and than averaging these classifiers. Random Forests are also a type of machine learning algorithms making predictions with low errors. Following figure 3 illustrate Random Forest methodology. As for decision trees are more likely to be unstable. Different trees might emerge due to small changes in training data. Robust prognostic model like "random forest" can be obtain from training a group of trees and "ensembling" to create such robust model. The proposed prognostic model in this paper is random forest (RF). Following steps are RF algorithm: For a given training dataset, using bootstrap method a new sample dataset is retrieve by repeatedly k times the random sampling with the size of each training dataset the same as that of the original training dataset. One third of the samples which are not been taken constitutes Out-Of Bag data (OOB). Trees like a regression or a decision tree are constructed as per the sample dataset which are the outcome from step 1; Repeating step 1 and step 2 until all the data are being used. Leading to the formation of lots of trees making a forest. Let every tree in the forest vote (for classification) or average(for regression). The end prediction is evaluated by averaging the predictions or summing of votes for final classification from all decision trees.

4.4 RMSE

Residuals (prediction errors) are values showing how far away is it from the regression line. And for the residuals, the standard deviation here is utilized as RMSE (Root Mean Square Error). RMSE is a metric value tell us how a model performance is, and it is the most vital criteria in the proposed model is prediction in this paper. Root mean square error is mostly utilized in climate studies, meteorology, forecasting, and regression analysis for validating experimental response[34]. General expression is as follows: $RMSE = \sqrt{\overline{(f-o)^2}}$ (2)Where, f = forecasts (predicted results), o = observed (actual results). The bar denotes the mean above the squared differences RMSE can be rewritten as follows: $RMSE = \sqrt{\frac{\sum_{i=1}^{n}(\hat{y}_i - y_i)^2}{n}}$ (3) Where, $\hat{y}_i$= predicted value, y_i= observed value

5 Proposed model

Proposed model here utilizes 30 transformers samples from [25] as input data and prognostication of health index carried out using Random Forest in R. In these transformer sample data, Water Content, Dielectric Dissipation Factor, TDCG (Total Dissolve Combustion Gases), Breakdown Voltage, 2-FAL and acidity are taken as important variable/parameter in Health Index calculation. Figure 4. shows %IncMSE which give the most robust and informative measure. The higher number, the more important. From [25] sample transformer data 2-FAL most important variable in prognostication of HI followed by Acidity, BDV, Dissipation Factor, Water Content and very least of them all TDCG. After training the proposed model, and an error vs. trees plot was obtain to analyze at which tree does we get less error in prognostication following figure 6 shows plot in which error gets least value with the trees in training. With these analysis, tuning of parameter of the proposed model is done, and from the figure 7 it is seen that RF model have less RMSE at 140 maxnodes and 70 trees.

TABLE 4
RMSE TUNING BEFORE AND AFTER

Transformer Samples from [25]	RMSE value	
	Before Tuning	After Tuning
	0.05043763	0.04455745

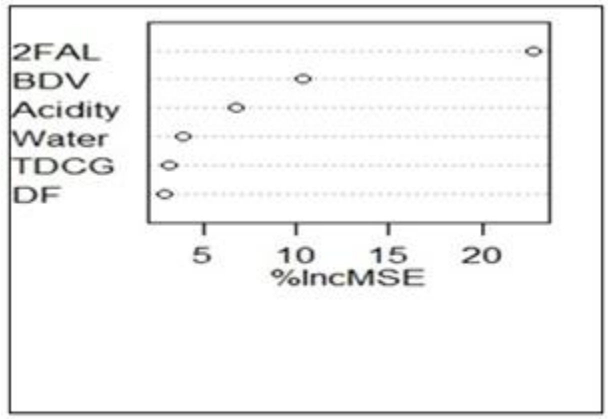


Fig. 3 Simple flow diagram of random forest algorithm

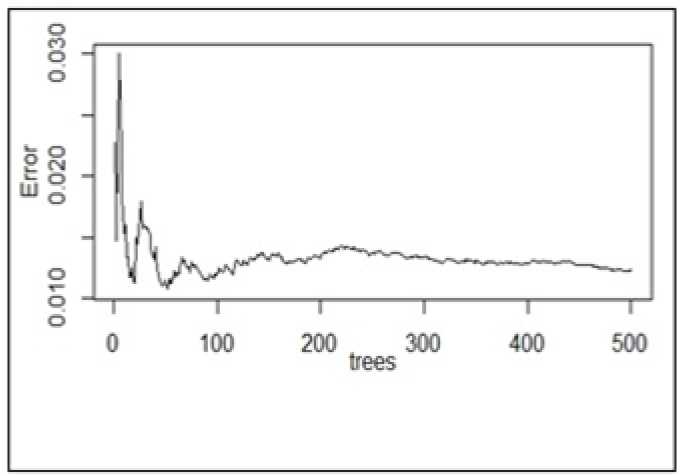


Fig. 4 Important Variable in Health Index Prognostication

Table 4 Shows RMSE values before tuning and after tuning and improvement, the model gain in prognostication after tuning it. The values shows how efficient the proposed model gets at learning.

6 Validation with other proposed models

In this section the proposed model comparison in summarized way is done in Table 6, with other published methods for the Health Indices. Like, AMHA classificarions[25], Fuzzy Logic[25], General Regression Neural Network[28] and Binary Logistic Regression[27]. The proposed model used condition such as Very Good (VG) at 0 – 0.20, Good (G) at 0.20 – 0.40, Moderate (M) at 0.40 – 0.60, Bad (B) for 0.60 – 0.80 and Very Bad (VB) between 0.80 – 1, in its prognostication of HI values for transformer health. The proposed model took AMHA classification method values as a reference value. And AMHA classification is used as a target value by published methods like GRNN[28] model, Fuzzy Logic[25], Binary Logistic Regression[27] too. The proposed model is also tested with the 16 PT from [29] which also calculated the health indices and conditions using Fuzzy Inference Systems. Table 8 gives 30 data samples of transformer used by [25] for it`s method. The [29] samples are used as a test data for the proposed RF model in this paper and 30 transformer sample taken from [25] and samples for 69kV to 230kV PT from [26] as training data.In published method [29] used Degree Polymerisation(DP) for making it`s method robust, thus using Myers et al. I [30] for DP in training data

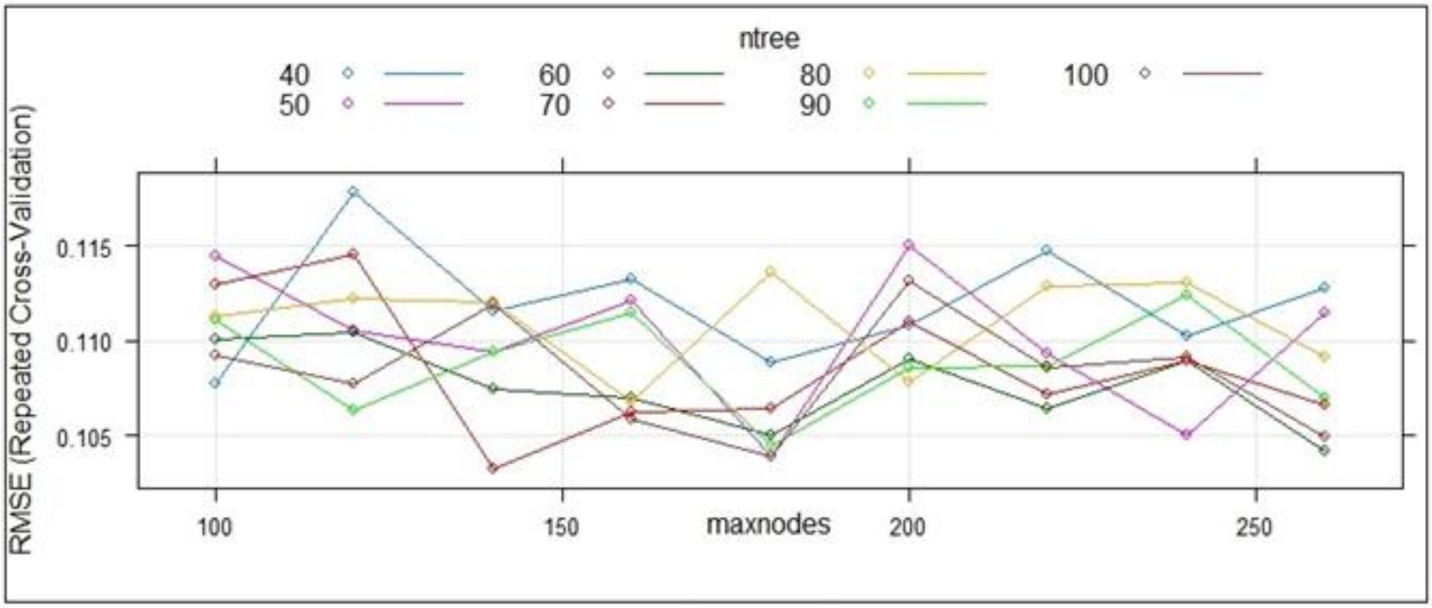


Fig. 6 RMSE Cross Validation with trees and nodes

TABLE 6
PUBLISHED AND PROPOSED MODEL RMSE

Models	RMSE Value
Random Forest	0.04455745
General Regression Neural Network	0.1801082
Binary Logistic Regression	0.2231467
Fuzzy Logic	0.07304816

7 RESULT DISCUSSION

From the Table 6, as AMHA values are being used as target value it can be observe that the proposed model does perform well. While validating with AMHA, this classification method used three conditions, Good(**G**), Bad (**B**), Moderate(**M**). Thus, conditions like Very Good and Good falls under AMHA method`s Good, like wise Very Bad and Bad, under Bad condition of AMHA classification method. In case of other published method like in [25, 27, 28] whose HI and Conditions, took AMHA as its reference values. So the accuracy in condition classification is 96.67% and percentage of error(RMSE in %) in prognostication is 4.46%. Table 6 shows RMSE values of models from which Random Forest(RF) shows promising performance in comparison with the other published cases RMSE. The RF model is applied to the [29] samples and it is clear from the Table 7 that proposed model and [29] published method has digression. In [29] furfural (2-FAL) is not included in samples, the training data sample for the proposed model is taken from [25, 26] and with the 2-FAL variable sample missing, still the proposed method gives a decent result. In case 16, RF model classified condition as Bad(B) which properly classify the condition of sample as the Water Content and BDV crossed its limits. There are 8 transformer which are in Good Conditions. Case 14 and 15 have Water Content above prescribe limits but is given moderate(M) and good(G) respectively, as TDCG value is in within the “Condition 1” prescribe by IEEE C57.104 2008.

TABLE 6
COMPARISON TABLE OF HEALTH INDICES AND THEIR CONDITIONS FOR DIFFERENT MODELS

Fuzzy logic[25]		AMHA		Binary logistic[27]		GRNN[28]		Proposed RF model	
0.360	G	0.377	G	0.434	M	0.370	G	0.398	G
0.300	G	0.334	G	0.170	G	0.560	M	0.35	G
0.300	G	0.290	G	0.007	G	0.047	V G	0.317	G
0.780	B	0.700	B	0.826	V B	0.780	B	0.742	B
0.200	V G	0.102	G	0.002	G	0.030	V G	0.157	V G
0.300	G	0.274	G	0.004	G	0.085	V G	0.313	G
0.300	G	0.316	G	0.023	G	0.316	G	0.356	G
0.300	G	0.290	G	0.006	G	0.133	V G	0.316	G
0.220	V G	0.226	G	0.003	G	0.040	V G	0.265	G
0.300	G	0.316	G	0.120	G	0.586	M	0.357	G
0.940	V B	1.000	B	0.973	V B	0.930	V B	0.958	V B
0.930	V B	0.931	B	0.841	V B	0.690	B	0.909	V B
0.940	V B	1.000	B	0.973	V B	0.830	V B	0.951	V B
0.830	B	0.916	B	0.589	B	0.590	B	0.89	V B
0.780	B	0.732	B	0.885	V B	0.700	B	0.693	B
0.300	G	0.354	G	0.030	G	0.399	G	0.369	G
0.530	M	0.450	M	0.594	B	0.450	M	0.443	M
0.300	G	0.291	G	0.370	G	0.406	G	0.329	G
0.940	V B	1.000	B	0.997	V B	0.790	B	0.885	V B
0.300	G	0.347	G	0.005	G	0.119	V G	0.338	G
0.150	V G	0.414	M	0.077	G	0.360	G	0.424	M
0.110	V G	0.241	G	0.002	G	0.040	V G	0.21	G
0.940	V B	0.953	B	0.895	V B	0.850	V B	0.88	V B
0.300	G	0.368	G	0.018	G	0.015	V G	0.291	G
0.510	M	0.450	M	0.181	G	0.550	M	0.467	M
0.110	V G	0.072	G	0.004	G	0.010	V G	0.149	V G
0.420	M	0.371	G	0.045	G	0.610	M	0.374	G
0.300	G	0.225	G	0.006	G	0.314	G	0.266	G
0.300	G	0.241	G	0.015	G	0.238	G	0.302	G
0.480	M	0.450	M	0.200	M	0.790	B	0.473	M

TABLE 7
PROPOSED METHOD APPLIED TO TRANSFORMER SAMPLES [29]

Health Index [29]		*Health Index (Proposed)*	
0.484	M	0.401	M
0.263	G	0.45	M
0.11	VG	0.234	G
0.3	G	0.358	G
0.439	M	0.489	M
0.300	G	0.358	G
0.378	M	0.474	M
0.515	M	0.469	M
0.166	VG	0.331	G
0.110	VG	0.226	G
0.210	VG	0.346	G
0.150	VG	0.346	G
0.300	G	0.407	M
0.300	G	0.413	M
0.110	VG	0.248	G
0.775	B	0.649	B

8 CONCLUSION

A Machine Learning model approach based on Random Forest has been put forward to prognosticate the health indices of power transformers. Furan analysis, total dissolve combustion gases, break down voltage, acidity, water, and dissipation factor, have been utilize as training data set for the proposed machine learning RF model and on this six important tests four condition classification were based. The conditional classification was derived using If-Then condition based on Health Index values. The RF model results were then validated with the results of AMHA. The validation shows that the results are quite similar, of course after tuning the model parameters. This method to identify transformer health will surely improve efficiency and significantly crunch the overhaul cost for transformers. With availability of more Bigger Data samples having wide variety of values in tests in future might prove this proposed model a robust tool to evaluate power transformer heath and conditions. Near future, further work will be conducted on the model to experiment on field data.

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