

Regression Approach to Power Transformer Health Assessment Using Health Index



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Abstract A regression approach is utilized for health assessment based on transformer oil diagnostic test data. A support vector, linear regression and fine tree decision based regression model has been simulated for health prediction. The oil diagnostic test data have sufficient diversity in terms of power rating, voltage level, and installed location. These data sets are like water content, total acidity, oil breakdown voltage (BDV), dissipation factor, 2-Furfuraldehyde content, and combustible dissolved gas analysis (DGA). These dataset of thirty transformers provided by Asset Management and health assessment (AMHA) consulting company and employed to train the proposed regression models in MATLAB environment. The reported results using fuzzy logic, binary logistic regression are compared with the results of proposed regression models. The root mean squared error (RMSE) for linear regression model has attained minimum value and found an effective approach for computing health index of a power transformer. In addition to above proposed models also validated another twenty different transformer oil dataset, which are entirely different from training set of thirty transformers.

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Keywords Health index · Support vector machine · Linear regression · Decision tree · Oil diagnosis-tests

1 Introduction

Distribution system performance is badly hampered by its complexity, poor operation and maintenance. As, power transformer cost comprise of at least 60–70% of total cost of high-voltage substation. Therefore an optimal balance between various investment/cost need to be taken care by power utilities. The power transformer failure rates are resulted in revenue loss, and customer dissatisfaction. This is a serious concern for power utilities and required to assess periodical health of power transformer in decision making for scheduled or forced outage of supply. In this context, health

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Index (HI) is a comprehensive indicator to assess overall condition of transformers. Health Index (HI) is computed using transformer oil diagnosis tests. Various online and offline tests for health index (HI) of transformer are in practice as per standards such as IEC, IEEE and CIGRE. Generally, water content, total acidity, oil breakdown voltage (BDV), dissipation factor, 2-Furfuraldehyde content, and dissolved gas analysis (DCG) are considered as input variables to determine the health index of power transformer. The weighting factor for above parameters is decided by utility expert, which differs from online and offline tests. The selection of these weighting factors is a sole discretion of experts and required to develop an intelligent model for computing the health index, which is independent of the above weighting factors.

A sensibility test is offered to analyze influencing parameters for health index in real time environment [1]. A practical way of computing transformer health index needed to have quantitative information pertains to field inspection, laboratory tests, and live operational observations [2]. There are different twenty one testing methods for predicting overall condition and an effective maintenance plan for a power transformer [3]. A fuzzy based health index is developed with the help of real field data of 90 working transformers. The obtained results compared with results of experienced and health assessment consulting company for same set of transformers [4]. A binary logistic regression method is utilized to predict health index (HI) of power transformer using a sample data of 30 transformers [5]. A multi-criterion based fuzzy system is designed to assess health condition of working transformers. The effectiveness of this fuzzy system validated on 200 working transformers of state utility [6]. A feed forward neural network is employed to predict the health index of transformers. This neural network is trained with 59 real time data of working transformer and tested on 29 working transformers [7]. The degree of polymerization of insulation reflect the incipient faults diagnosis and used to measure deterioration rates and health index of power transformers for an intelligent diagnosis system [8]. The parameters obtained from dissolved gas analysis is utilized to detect different types of faults and to predict reasonable recommendations for future maintenance action [9]. R. D. Medina et al., presented a fuzzy logic based approach to assess the health index of transformers having operational voltage range from zero to 230 kV. The oil test parameters are represented with six different membership functions with the help of expert judgment [10]. H. Zeinoddini-Meymand and B. Vahidi presented two artificial intelligence and adaptive neuro-fuzzy inference models to predict the health condition of working transformers. The input variables for this model obtained from 226 experimental field datasets of transformers. The 80% datasets utilized for training and remaining 20% used for testing purpose [11]. In this paper, six inputs namely “water content, total acidity, oil breakdown voltage (BDV), dissipation factor, 2-Furfuraldehyde content, and dissolved gas analysis (DGA)” were utilized for proposed regression models. The models are trained on 30 experimental field datasets of transformers given by “Asset Management and health assessment (AMHA) consulting company” [5]. The main contributions of the paper is to propose regression models such as support vector, linear regression and fine tree decision to assess of transformer health. The reported results using fuzzy logic, binary logistic regression are compared with the results of proposed regression models. In addition to above proposed models also validated

another twenty different transformer oil dataset, which are entirely different from training set of thirty transformers [12].

2 Proposed Regression Model Health Index

2.1 Transformer Health Index

Any internal fault in power transformer will be mainly resulted into overheating, arcing, partial discharge and insulation deterioration. The transformer oil temperature raised the concentrations of different combustible dissolved gases in oil, which is measured by dissolved gas analysis (DGA). These gases are separated from transformer oil using vacuum extractor. These gases are mainly as “Carbon monoxide (CO), Carbon dioxide (CO₂), Hydrogen (H₂), Methane (CH₄), Ethylene (C₂H₄), Ethane (C₂H₆), Acetylene (C₂H₂)” etc. The ratio of CO₂ and CO is used to predict the health of transformer [4, 5, 12]. Dissolved gas analysis (DGA) does not give sufficient and accurate overall assessment of transformer. As transformer winding is winding submerged in transformer oil and insulated by paper or cotton insulating material. The oil and insulating material formed solid hydrocarbons and obstructs cooling mechanism, electrochemical deterioration in transformer oil. The water content in transformer oil, acidic level of oil, and oil breakdown voltage (BDV) are severely affects transformer oil health, whereas dissipation factor (DF), and 2-Furfuraldehyde contents have impact on health of solid insulation of transformer. Deterioration in oil breakdown voltage (BDV) indicates the level of moisture, and sludge. Dissipation factor (DF) measures the winding insulation quality. The moisture level in oil adversely affects electrical characteristics of oil and solid insulation. This should within prescribed ppm (parts per million by weight). Suspended organic and inorganic compounds in oil change the PH level of oil, which deteriorate solid insulation of winding and neutralize by potassium hydroxide. As transformer oil decomposed in various gases as mentioned must be remain in specified limits. The level of these dissolved gases predicts internal condition of transformer. Depolymerization of solid dielectric can be detected in furfurals compounds in oil. The rise in these compounds is used predict life cycle of solid dielectric in power transformer [12]. Therefore for overall health assessment of transformer, “water content in transformer oil, acidity of oil, oil breakdown voltage (BDV), dissipation factor (DF), and 2-Furfuraldehyde contents” is to be considering for health assessment of transformer [1].

2.2 Regression Techniques

The strong point of this work is to use diverse dataset of power transformers with different voltage levels, power ratings and location. Proposed regression models

are data centric tools and weight parameters are adjusted by input/output data. In multiple linear regressions, multiple independent variables predict single dependent variable as output. The dependent variable Y must be a continuous type variable while independent variables can take any form of distributions.

$$Y = \beta_0 + \beta_1 * X_1 + \beta_2 * X_2 + \dots + \beta_n * X_n \quad (1)$$

where β_i denotes regression coefficient for X_i and Y , X_i are dependent and independent variables. In support vector regression, the input X is primarily mapped onto an m -dimensional feature space with some fixed mapping techniques, and further a linear model is built d in specified feature space. Accordingly, in this feature space, a linear model is $f(x, \omega)$ represented by

$$f(x, \omega) = \sum_{j=1}^m \omega_j g_j(x) + b \quad (2)$$

where $g_j(x)$ represents nonlinear transformation sets and b as “bias” term. In case of pre-processing of input data, this bias term assumed to be zero. A multivariate linear regression model is used to predict health index (HI) by using least squares method. The training data sets are computed in same statistically manner as adopted in testing data sets. To validate the health index (HI), a cross validation with 10 fold is chosen for coefficients adjustment and error minimization. The accuracy of models depicted by root mean square error (RMSE) and mean square error (MSE) on sample testing and training data. To improve prediction, principal component analysis (PCA) is disabled in designed model. The performance of this model is evaluated in term of response plot, predicated versus actual plot and residuals plot as shown in Figs. 1, 2, 3, 4, 5, 6, 7, 8 and 9.

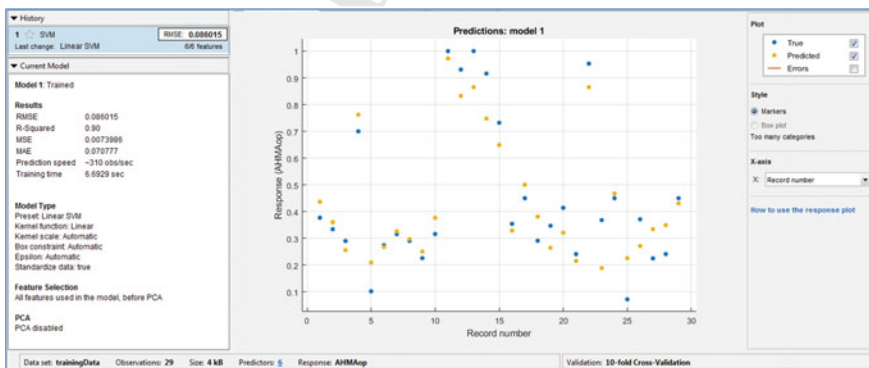


Fig. 1 Predicted outputs and true outputs by linear support vector model

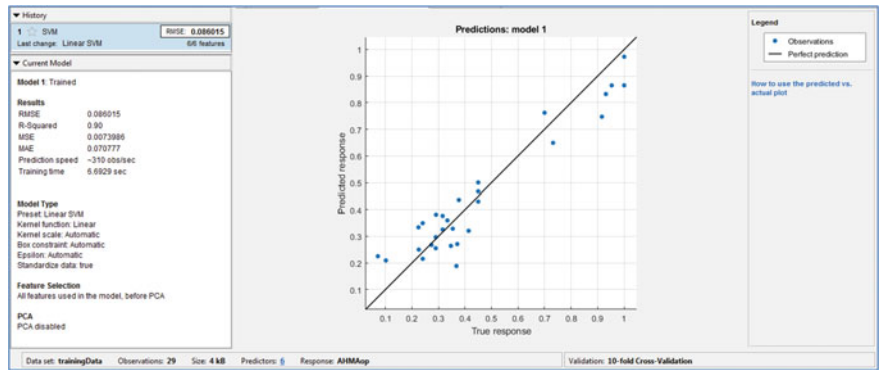


Fig. 2 Predicted outputs and true outputs by linear support vector model

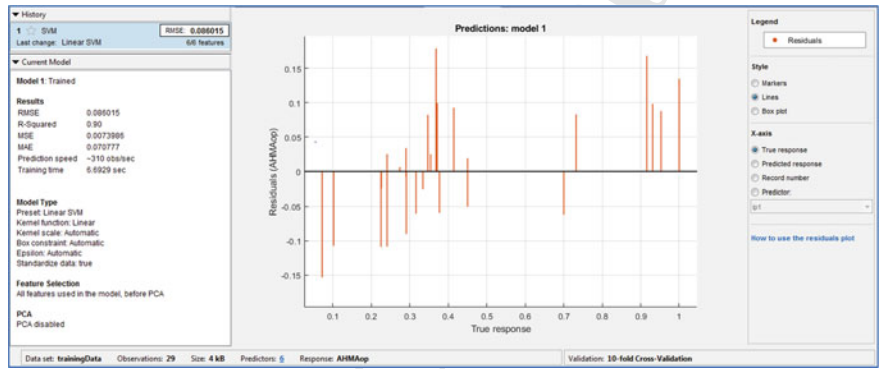


Fig. 3 Residuals by linear support vector model

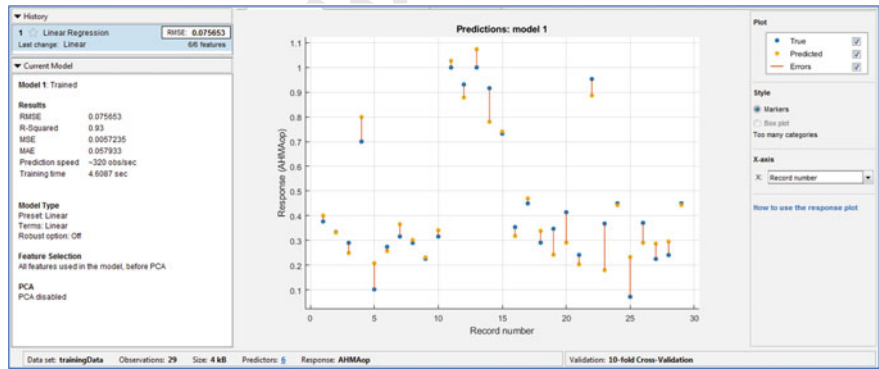


Fig. 4 Predicted outputs and true outputs by linear regression model

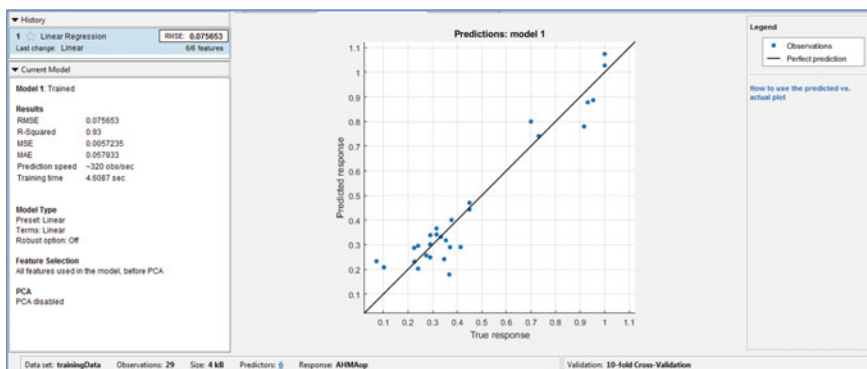


Fig. 5 Relation between predicted outputs and true outputs by linear regression model

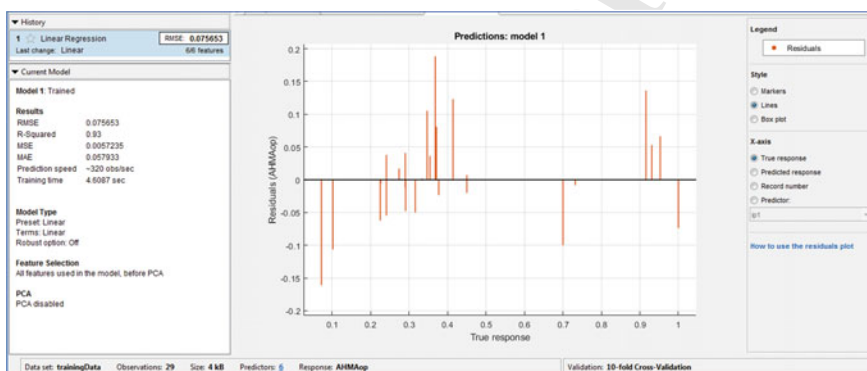


Fig. 6 Residuals by linear regression model

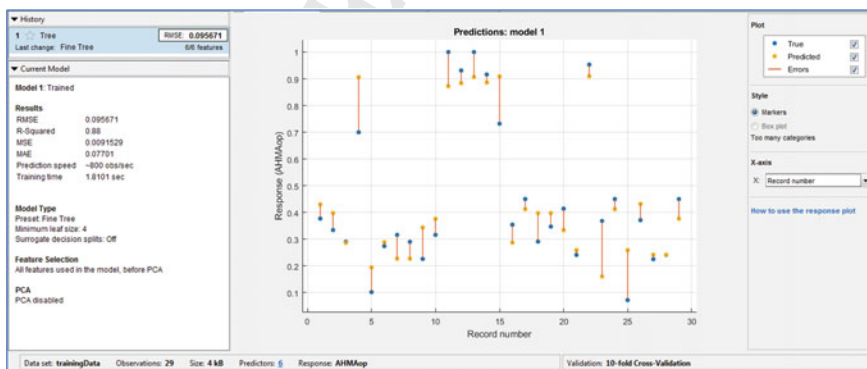


Fig. 7 Predicted outputs and true outputs by fine tree model

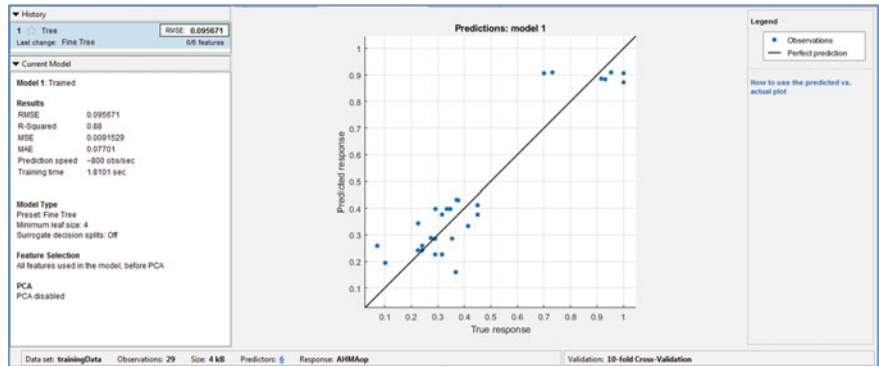


Fig. 8 Relation between predicted responses and true response by fine tree model

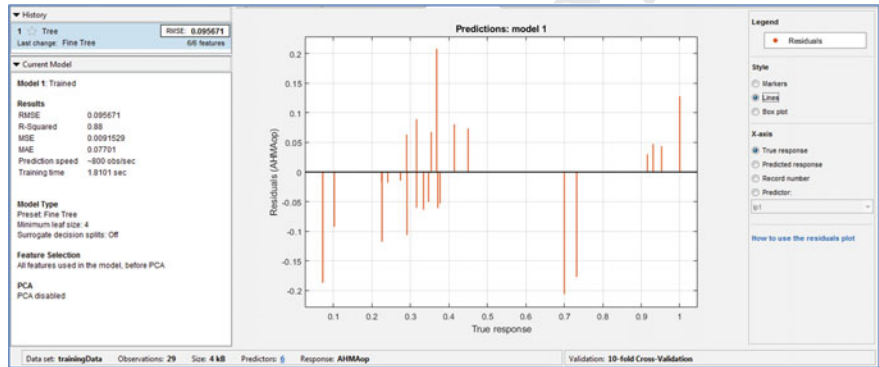


Fig. 9 Residuals by fine tree model

3 Results and Discussion

Presence of dissolved gases, sludge, and acidic environment of oil has serious impact on performance and life of transformer. The regression models are proposed using support vector, linear regression and fine tree decision approach. In this paper two sample having 30 and 20 data set are used for training and validation purpose respectively. The details about these data sets are mentioned in Tables 5 and 6. It is observed from Table 6 that dissipation factor for 19 transformers is 67; while for rest of transformer same is less than 01. Therefore data set for 19 transformers is not considered for train the regression models. The proposed regression models are trained with remaining 29 data set of transformers [5]. The health index of proposed regression models are compared with the results obtained using AMHA, fuzzy logic, binary logistic regression methods [4, 5]. In the AMHA method, the health index categories are good, moderate, and bad. But as per EA Technology, health index are classified

Table 1 Comparison of health conditions categories for test sample-1

HI category	AHMA [5]	HI [4]	HI [5]	Proposed SVM	Proposed linear regression	Proposed fine tree
Good ($0 < HI \leq 0.2$)	2	4	20	1	1	4
Moderate ($0.2 < HI \leq 0.45$)	20	15	1	19	20	18
Bad ($0.45 < HI \leq 0.8$)	2	5	2	5	3	0
Very bad ($0.8 < HI \leq 1$)	5	5	6	4	5	7

in four different categories, which are good, moderate, and bad, and very bad. In this paper EA technology based health indices considered.

The category wise comparison of health index is very much closer to experimental values provided by AMHA. The results provided by linear regression found most suitable model for health index prediction as shown in Table 1. From Table 2, it is observed that health index for 26 transformers is 0.007 and proposed models predict its value as 0.2336, 0.2244 and 0.16 respectively (Table 3).

As regression models tested on other sample 2 and health index by SVM and linear regression found abnormal assessment for 19 transformers as shown in Table 5. From Table 6, it is clear that computed health index is very much closer to experimental values provided by AMHA (Table 4).

4 Conclusion

Health Index (HI) is a powerful tool to monitor transformer condition and risk of failure. This paper proposed three regression models based on support vector, linear regression and fine tree decision to determine a HI for transformers. The input technical parameters of the models are includes water content, total acidity, oil breakdown voltage (BDV), dissipation factor, 2-Furfuraldehyde content, and dissolved gas analysis (DGA). The effectiveness of proposed models are demonstrated by comparing results reported by fuzzy logic, binary logistic regression for sample data set 1. Apart from above proposed models also validated for another twenty different transformer oil dataset, which are different from training set. Next, further study to propose models will be trained and tested with more field data. It is envisioned that the proposed models are very promising and helps for utilities to take investment decisions into an asset's replacement or maintenance intervention.

Table 2 Comparison health index for test sample-1

S. No.	AHMA [5]		HI [4]		HI [5]		Proposed SVM		Proposed linear regression		Proposed fine tree	
1	0.377	M	0.36	M	0.434	M	0.4205	M	0.413	M	0.3476	M
2	0.334	M	0.3	M	0.17	G	0.3514	M	0.3386	M	0.3476	M
3	0.29	M	0.3	M	0.007	G	0.2724	M	0.2543	M	0.2864	M
4	0.7	B	0.78	B	0.826	VB	0.7174	B	0.779	B	0.8903	VB
5	0.102	G	0.2	G	0.002	G	0.1904	G	0.1897	G	0.16	G
6	0.274	M	0.3	M	0.004	G	0.2577	M	0.2625	M	0.2864	M
7	0.316	M	0.3	M	0.023	G	0.3323	M	0.3531	M	0.2864	M
8	0.29	M	0.3	M	0.006	G	0.287	M	0.2881	M	0.2864	M
9	0.226	M	0.22	M	0.003	G	0.2445	M	0.2316	M	0.2864	M
10	0.316	M	0.3	M	0.12	G	0.3595	M	0.3448	M	0.3476	M
11	1	VB	0.94	VB	0.973	VB	0.9803	VB	1.0288	VB	0.8903	VB
12	0.931	VB	0.93	VB	0.841	VB	0.8347	VB	0.8801	VB	0.8903	VB
13	1	VB	0.94	VB	0.973	VB	0.9897	VB	1.0488	VB	0.8903	VB
14	0.916	VB	0.83	VB	0.589	B	0.753	B	0.822	VB	0.8903	VB
15	0.732	B	0.78	B	0.885	VB	0.6937	B	0.7372	B	0.8903	VB
16	0.354	M	0.3	M	0.03	G	0.3437	M	0.3214	M	0.3476	M
17	0.45	M	0.53	B	0.594	B	0.4669	B	0.4711	B	0.4302	M
18	0.291	M	0.3	M	0.037	G	0.3621	M	0.331	M	0.3476	M
19	0.347	M	0.3	M	0.005	G	0.2452	M	0.2405	M	0.3476	M
20	0.414	M	0.15	G	0.077	G	0.3681	M	0.3199	M	0.3476	M
21	0.241	M	0.11	G	0.002	G	0.2266	M	0.2086	M	0.16	G
22	0.953	VB	0.94	VB	0.895	VB	0.8599	VB	0.9226	VB	0.8903	VB
23	0.368	M	0.3	M	0.018	G	0.2467	M	0.2512	M	0.2864	M
24	0.45	M	0.51	B	0.181	G	0.4669	B	0.4415	M	0.4302	M
25	0.072	G	0.11	G	0.004	G	0.2336	M	0.2244	M	0.16	G
26	0.371	M	0.42	M	0.045	G	0.318	M	0.3259	M	0.4302	M
27	0.225	M	0.3	M	0.006	G	0.2832	M	0.2691	M	0.16	G
28	0.241	M	0.3	M	0.015	G	0.3236	M	0.2909	M	0.2864	M
29	0.45	M	0.48	B	0.2	G	0.4398	M	0.4412	M	0.4302	M

Table 3 Comparison of health conditions categories for test sample-2 transformer

HI category	HI [12]	Proposed SVM	Proposed linear regression	Proposed fine tree
Good ($0 < HI \leq 0.2$)	2	1	1	1
Moderate ($0.2 < HI \leq 0.45$)	11	12	12	12
Bad ($0.45 < HI \leq 0.8$)	4	2	2	0
Very bad ($0.8 < HI \leq 1$)	3	4	4	7

Table 4 Comparison health index for test sample-2

S. No.	HI [12]		Proposed SVM		Proposed linear regression		Proposed fine tree	
1	0.35	M	0.432	M	0.4237	M	0.3476	M
2	0.413	M	0.2861	M	0.2964	M	0.3476	M
3	0.236	M	0.2929	M	0.2679	M	0.2864	M
4	0.788	B	0.7339	B	0.7823	B	0.8903	VB
5	0.099	G	0.2045	G	0.1961	G	0.16	G
6	0.248	M	0.2478	M	0.2537	M	0.2864	M
7	0.236	M	0.3274	M	0.3474	M	0.2864	M
8	0.248	M	0.2858	M	0.2808	M	0.2864	M
9	0.236	M	0.2368	M	0.2302	M	0.3476	M
10	0.35	M	0.3463	M	0.3353	M	0.3476	M
11	0.776	B	0.998	VB	1.0155	VB	0.8903	VB
12	0.601	B	0.8584	VB	0.8801	VB	0.8903	VB
13	0.622	B	1.0079	VB	1.0362	VB	0.8903	VB
14	0.851	VB	0.8911	VB	0.9577	VB	0.8903	VB
15	0.851	VB	0.7044	B	0.7352	B	0.8903	VB
16	0.256	M	0.3535	M	0.3358	M	0.3476	M
17	0.245	M	0.4458	M	0.4507	M	0.4302	M
18	0.267	M	0.3592	M	0.3349	M	0.3476	M
19	0.843	VB	-2.27		-3.236		0.8903	VB
20	0.11	G	0.2525	M	0.2464	M	0.3476	M

Table 5 Data set to validate models on of test sample 2

WC (ppm)	Acidity (mg KoH/g)	BDV (kV)	DF (%)	DCG (ppm)	2-FAL (mg/L)	HI [12]	
21.3	0.026	29	0.077	489	0.85	0.35	M
26.1	0.092	56	0.892	292	0.61	0.413	M
13.6	0.038	53	0.147	77	0.22	0.236	M
21.8	0.227	47.7	0.431	215	5.54	0.788	B
8	0.016	73	0.118	127	0.01	0.099	G
15.4	0.071	73	0.145	38	0.52	0.248	M
16.1	0.165	70.5	0.261	147	0.74	0.236	M
13	0.083	67.2	0.219	28	0.65	0.248	M
19	0.038	64.5	0.182	8	0.31	0.236	M
27	0.091	39.5	0.357	194	0.21	0.35	M
15.2	0.172	22.7	0.217	38	8.56	0.776	B
14	0.136	36.5	0.192	51	7.45	0.601	B
15.3	0.128	26.6	0.189	76	9.34	0.622	B
17	0.41	55.2	0.267	51	6.62	0.851	VB
25.8	0.069	31.4	0.131	321	5.35	0.851	VB
23.5	0.109	43.8	0.216	33	0.344	0.256	M
27.9	0.021	27.9	0.061	501	1.24	0.245	M
26.3	0.063	37.2	0.213	25	0.57	0.267	M
31	0.069	29.7	66	32	15.543	0.843	VB
19.4	0.064	61.5	0.245	61	0.134	0.11	G

Table 6 Training data set of sample 1 provided by AMHA

S. No.	Installation year	Voltage ratio (kV), and power rating (kVA)	WC (ppm)	Acidity (mg KOH/g)	BDV (kV)	DF (%)	DCG (ppm)	2-FAL (mg/L)	HI AHMA [5]
1	1980	22/6.9, 5000	21.7	0.024	32.5	0.075	483	0.86	0.377 M
2	1980	22/6.9, 3.15	26.9	0.098	40.5	0.894	254	0.65	0.334 M
3	1980	22/6.6, 8	14.5	0.033	58	0.14	78	0.26	0.29 M
4	1980	22/6.9, 8	21.2	0.226	48.7	0.424	215	5.53	0.7 B
5	2000	22/6.6, 5000	10	0.01	75	0.111	126	0.06	0.102 G
6	1981	22/6.6, 4	15.5	0.075	71	0.143	38	0.53	0.274 M
7	1981	22/6.6, 10	16.8	0.167	70.1	0.255	149	0.78	0.316 M
8	1980	22/7.2, 15	15	0.092	67.8	0.211	28	0.69	0.29 M
9	1981	22/6.9, 8000	17	0.035	62.7	0.113	9	0.21	0.226 M
10	1970	22/3.3, 3.15	30	0.088	37.6	0.353	197	0.31	0.316 M
11	1980	22/6.9, 8000	16.2	0.181	25.5	0.201	35	8.76	1 VB
12	1980	23.5/11, 25,600	15	0.155	37.5	0.182	53	7.29	0.931 VB
13	1980	11/23.5, 25,600	16.8	0.115	25.6	0.174	78	9.6	1 VB
14	1980	11/23.5, 25,601	15	0.21	57.2	0.22	53	6.69	0.916 VB
15	1980	22/6.6, 8	27.6	0.089	30.4	0.128	336	5.12	0.732 B
16	1980	21.45/6.976 5000	23.5	0.106	45.8	0.207	30	0.24	0.354 M
17	1980	21.45/6.9, 8000	24.8	0.012	29.9	0.068	504	1.68	0.45 M
18	1980	21.45/7.2, 15,000	23.6	0.07	39.2	0.203	22	0.5	0.291 M
19	1980	21.45/6.9, 8000	30.5	0.073	28.7	0.67	30	15.7	1 VB
20	1980	21.45/6.9, 8000	18.4	0.063	64.5	0.243	69	0.15	0.347 M
21	1980	22/0.4, 1600	21.1	0.019	28.4	0.025	144	0.02	0.414 M

(continued)

Table 6 (continued)

S. No.	Installation year	Voltage ratio (kV), and power rating (kVA)	WC (ppm)	Acidity (mg KoH/g)	BDV (kV)	DF (%)	DCG (ppm)	2-FAL (mg/L)	HI AHMA [5]
22	1981	22/0.4, 630	8.1	0.01	66.9	0.042	71	0.05	0.241 M
23	1980	23.5/11, 25,600	19.6	0.216	41.1	0.264	48	7.54	0.953 VB
24	2000	22/6.98, 5000	6	0.01	67.6	0.126	427	0.08	0.368 M
25	1981	22/6.6, 10	18.4	0.152	37.2	0.299	81	1.14	0.45 M
26	1997	6.6/0.4, 1600	11.1	0.032	67.2	0.089	119	0.04	0.072 G
27	1980	22/6.6, 3.15	21.5	0.147	60.8	0.938	168	0.92	0.371 M
28	1986	22/6.6, 4	7.5	0.16	70.1	0.448	10	0.06	0.225 M
29	1981	0.38/19.2, 100	35.7	0.229	41.4	0.639	24	1.07	0.45 M
30	1981	0.38/19.2, 100	35.7	0.229	41.4	0.639	24	1.07	0.45 M

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Chapter 54

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