Selection Criteria for Oil Transformer Measurements to Calculate the Health Index

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ABSTRACT

In this paper, a study of the effect of a group of transformer measurements on Health Index (HI) calculation is presented. Different methodologies for selecting the most efficient group of diagnostic measurements used in classifying transformer HI are investigated. A Binary Cat Swarm Optimization (BCSO) technique is undertaken based on Support Vector Machines (SVM). The technique depends on selecting the optimal parameters for SVM. The effect of selecting HI classes as well as class's boundaries is also studied. The measurements of fourteen diagnostic transformer tests, including the furan analysis, dissolved gas analysis, and further oil analysis for 724 distribution transformers are studied, and the corresponding HI is calculated according to industrial standards. The model renders the best-selected group of measurements that assist in the formulation of the health index with minimum error and high confidence.

Index Terms - **Asset management, condition monitoring, oil insulation, insulation testing, support vector machines, optimization.**

1 INTRODUCTION

TRANSFORMERS are one of the most important asset in the power utility because of their relatively higher initial price and their proximity to customers. Failure of these assets can often be disastrous and results in direct and/or indirect financial and technical burden on the industrial, commercial, and residential sectors.

Transformer condition monitoring improves the system reliability; knowledge about the general condition of the system transformers helps in calculating transformer risk of failure. HI is generally used to summarize in numerical form the transformers' reliability for the purpose of evaluating, ranking and comparing different transformers. Long-term degradation of a transformer cannot be easily determined by routine inspection. HI is a good tool to monitor transformer degradation. HI assessment relies on collecting different measurement parameters about the transformer, including the dielectric and thermal conditions, the mechanical condition as well as the electrical condition [1-2].

Traditionally HI is determined through a combination of the utmost count of available measurement parameters. These measurements give a detailed information about each part of the transformer and therefore it depicts the current status of the transformer conditions.

In general, HI is calculated using traditional schemes such as Ranking Method (weighting factors) [2-3]. The uncertainty for determining the weight for each test is considered as the main drawback of this method.

The use of intelligent computational methods overcomes the problem of weights. Such methods include the Fuzzy Logic [1, 4], Neural Networks [5], Multivariate Analysis [6-7], Entropy Weight Health Index Method [8-9], Equipment Health Rating Program (EHR) [10] or DiagConsole software [11] methods. To date, the problem of unavailable transformer measurements is not resolved by utilizing intelligent methods.

HI calculation is based on on-line as well as off-line transformer's measurement date. The accuracy of the HI calculation depends on the availability of the updated measurement data. Since some of the transformers' measurements are very expensive they are not done frequently, which affect the accuracy of the HI using the

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above methods. Selecting the most effective transformers' measurements amongst the online and offline measurements that lead to an acceptable HI result is a challenge. Some attempts were reported in the literature for determining the most significant subsets of oil measurements. In [12] Common factor analysis and Minimum-Redundancy-Maximum-Relevance (mRMR) feature selection techniques are adopted to select the subset of the most significant oil measurements; thus assisting the SVM algorithm in the HI classification process. Results show an improvement in HI classification accuracy, by the reduction of SVM input features count from twelve to seven. Yet, the process was based on the specific contributions of each measurement based on mutual information. The mutual information values and the effect of the selection of the HI group boundaries on the chosen measurements were not addressed in the paper.

In this research, a new approach for the selection criteria of the best measurements is presented with the utilization of a readily automobile method. The new approach is based on the selection of the best group of measurements that calculate the most informative HI. A specific measurement is chosen amongst the group based on the mutual information between various measurements and not solely based on the mutual information between the HI and this specific measurement. In addition; the change of transformer's HI group boundaries that form a foundation for the selection criteria of HI parameters is investigated.

The aim of this research is to automate the transformer condition assessment process; thus making it an easily implementable method. The capability of each individual measurement to classify HI is examined. An efficient supervised classification model is developed using Binary Cat Swarm Optimization technique (BCSO) in combination with Support Vector Machine learning (SVM). The automobile technique should be capable of filtering the different transformer field diagnosis measurements and selecting the optimal least count of available online measurements. The selected measurements represent an efficient description of the transformer condition; therefore, are capable of classifying successfully HI into three or five specified groups with high confidence. The effect of the change in the boundaries of the HI groups is investigated and presented.

In this paper, we utilize actual field measurements for 724 working distribution transformers within the distribution network of an industrial facility. The undertaken diagnostic measurements are hydrogen content (H_2), carbon monoxide (CO), carbon dioxide (CO_2), methane (CH_4), acetylene (C_2H_2), ethane (C_2H_6), ethylene (C_2H_4), color, the water content (H_2O), oil breakdown voltage (BDV), acidity, interfacial tension (IFT) dissipation factor (DF) and furans content (FFA); where the health index (HI) is graded from zero for a brand new transformer to unity for a transformer at the end of its lifetime and should be replaced immediately. The technique is tested on a different group of data provided for measurements from a different set of transformers [13].

The paper is divided into six sections. In section II, the undertaken binary CSO technique is presented. Section III demonstrates the data pre-processing procedure. In section IV, the application of BCSO based SVM and the undertaken case studies are explained. Section V provides the discussion and Section VI concludes the paper.

2 BINARY CAT SWARM OPTIMIZATION (BCSO)

Cat Swarm Optimization technique (CSO) is utilized to select the best group of transformer measurements. CSO was utilized to enhance the reliability of distribution system. The performance of the CSO was compared before with those obtained by genetic algorithm (GA) and particle swarm optimization (PSO). Results indicate that CSO is a better candidate for finding the global best solutions in comparison to GA and PSO, but it takes more time to complete the same number of iterations than GA and PSO algorithms [14].

Figure 1 shows the flow chart of CSO process [15-16]. CSO algorithm models the major two behaviors of cats into two sub models nominated by seeking mode and tracing mode. Similar to population based optimization techniques, the search space will be presented by the user as a pre-defined number of cats. Each cat has its own position depending on the search space dimensions. Velocities for each dimension, a fitness value, and a flag to identify whether the cat is in the seeking mode or the tracing mode are specified. CSO algorithm keeps the best solution of all cats until it reaches the end of iterations or the fitness limit; hence, the final solution would be the best

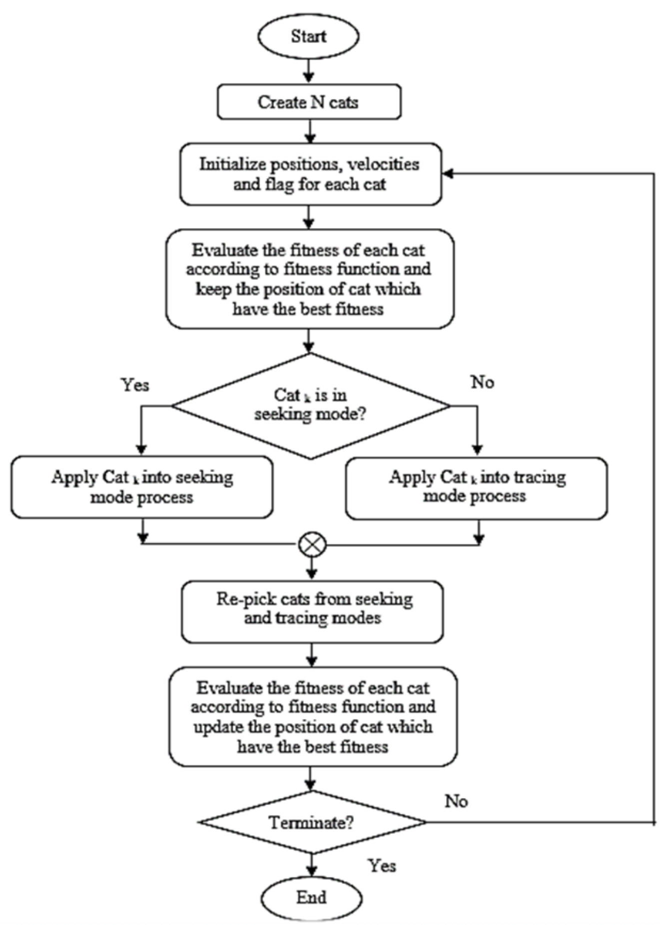


Figure 1. Flow chart of BCSO process.

position of one of the cats. A detailed information about discrete seeking and tracing modes can be found in [13, 17]. In this work, we utilize the Binary Cat Swarm as an optimizer due to the robustness and the reliable results obtained in [18]. BCSO is automated to select the best group of transformer measurements as well as optimizing the SVM parameters. Section IV explains in detail the adopted technique.

3 DATA PRE-PROCESSING

SVM input data is presented by the fourteen transformer measurements mentioned above, while output data is presented by the transformer HI. HI is calculated using industrial standards as in [1, 4, 19]. The calculation dissolved gas factor (DGAF), oil quality factor (OQF) will be according to equations (1-2):

$$\mathrm{DGAF} = \sum_{i=1}^{7} \mathrm{S_i} * \mathrm{W_i} \Big/ \sum_{i=1}^{7} \mathrm{W_i} \tag{1}$$

$$\mathrm{OQF} = \sum_{j=1}^{6} \mathrm{S_j} * \mathrm{W_j} \Big/ \sum_{j=1}^{6} \mathrm{W_j} \tag{2}$$

where; S_i and S_j are the scores decided by test results. W_i and W_j represent the weighting factor of each test measurement.

The paper insulation factor (PIF) is calculated based on the amount of FFA in oil [1]. HI is calculated by combining DGAF, OQF and PIF according to equation (3):

$$\mathrm{HI} = \sum_{i=1}^{3} \mathrm{F_i} * \mathrm{K_i} \Big/ \sum_{i=1}^{3} \mathrm{F_i} \tag{3}$$

where; F_i represents DGAF, OQF and PIF quality factors and K_i represents weighting for each quality factors.

The undertaken data base includes 724 transformer samples, those are divided into 3 unique databases by ratios of 60%, 20% and 20% respectively. Those are used for training, validation and testing of the SVM model respectively. Data normalization is applied by dividing all samples by their corresponding service limit identified by IEEE, IEC and ASTM [20-23].

Categorizing transformers according to the available HI values is the following essential step. In earlier research efforts [3, 10, 19, 24-27], transformer HI divides the transformer condition to 3, 4 or 5 classes. Table 1 shows the classes and its corresponding boundaries as has been widely used.

Table 1. Transformer HI Categorization - Case (I)

Class	Boundaries	HI state	Samples count
A	$0.00 \le HI < 0.15$	Very Good	409
B	$0.15 \le HI < 0.30$	Good	140
C	$0.30 \le HI < 0.50$	Satisfactory	102
D	$0.50 \le HI < 0.70$	Bad	56
E	$0.70 \le HI \le 1.00$	Very Bad	17

It is preferable to combine two or more classes together to obtain a generalized model. It is noted that class E boundaries should not be changed because in practice transformer requires immediate action if its HI reaches class E.

Table 2. Transformer HI Categorization - Case (II)

Class	Boundaries	HI state	Samples count
A	$0.00 \le HI < 0.30$	Good	549
B	$0.30 \le HI < 0.70$	Moderate	158
C	$0.70 \le HI \le 1.00$	Bad	17

Table 3. Transformer HI Categorization - Case (III)

Class	Boundaries	HI state	Samples count
A	$0.00 \le HI < 0.35$	Good	569
B	$0.35 \le HI < 0.70$	Moderate	138
C	$0.70 \le HI \le 1.00$	Bad	17

Table 4. Transformer HI Categorization - Case (IV)

Class	Boundaries	HI state	Samples count
A	$0.00 \le HI < 0.40$	Good	605
B	$0.40 \le HI < 0.70$	Moderate	102
C	$0.70 \le HI \le 1.00$	Bad	17

Thus, a combination of class A with B and class C with D is suggested; thus ending with 3 main classes with the specified boundaries shown in Table 2. An investigation of the effect of changing the boundaries of HI classes A and B on the model performance was of interest. Tables 3 and 4 show the modified boundaries for the HI categorization. This has been utilized and compared to the former boundaries of HI in the following sections of the paper.

4 MODEL SIMULATION & RESULTS

Support Vector Machines (SVMs) are a set of related supervised learning methods that analyze data and recognize patterns [28]. SVM parameters as cost (c) and Gaussian (γ) coefficients must be selected appropriately. In this study grid search is utilized to select cost and gamma values.

4.1. HI CLASSIFICATION USING INDIVIDUAL FEATURES

In this section, we examine the classification capability of each separate transformer measurement, each measurement will be fed to the SVM solely to classify the HI for each categorization cases I, II, III and IV. The utilized fitness function will be:

$$\text{FS 1} = (\text{Training error \%} + \text{Validation error \%}) / 100 \tag{4}$$

where;

$$\text{Training error \%} = \frac{\text{Total no. of missclassified training samples} * 100}{\text{Total no. of training samples database}} \tag{5}$$

$$\text{Validation error \%} = \frac{\text{Total no. of missclassified validation samples} * 100}{\text{Total no. of validation samples database}} \tag{6}$$

Table 5 shows the best classification results for the utilization of each measurement in classifying HI for cases I, II, III and IV.

Table 5. Correct Classified Samples Count for Individual Measurements

No.	Measurement	Case I	Case II	Case III	Case IV
1	H_2	414	553	572	607
2	CO	437	552	573	606
3	CO_2	515	600	607	629
4	CH_4	451	552	572	607
5	C_2H_2	462	588	605	639
6	C_2H_4	473	573	590	624
7	C_2H_6	465	553	571	607
8	Color	508	675	661	637
9	H_2O	435	576	590	615
10	BDV	420	562	577	611
11	Acidity	521	668	661	649
12	D.F	473	640	640	623
13	IFT	507	665	664	643
14	FFA	559	703	689	673

As seen in Table 5, SVM classifier cannot obtain reliable results for the HI classification while utilizing each measurement solely, except for FFA measurement. The impact of change in class's boundaries for cases I, II, III and IV is clear; hence, the classification capability for all measurements varies in each case. Case I results in the lowest count of correct classified samples, while Cases II results in the highest count for color, acidity, DF, IFT and FFA measurements. Case IV results in the highest count for the remaining measurements. FFA measurement results in the highest classification count using case II categorized boundaries; hence, 21 out of 724 samples are misclassified. Confusion matrix is presented to compare the actual and predicted classification results calculated by the SVM technique; Table 6 shows the confusion matrix for FFA results using case II boundaries.

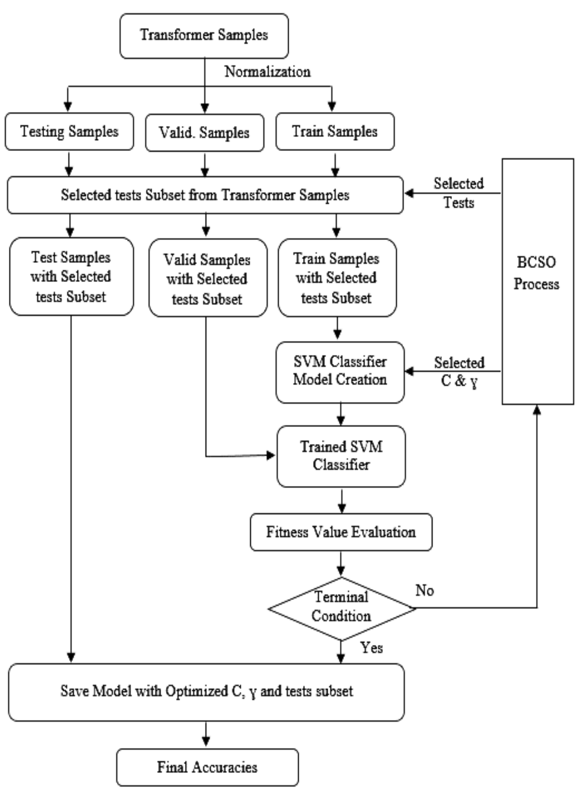


Figure 2. Flow chart of BCSO based SVM method.

Table 6. FFA Confusion Matrix for Case II

Class	A	B	C
A	540	9	0
B	7	150	1
C	0	4	13

In section 4.1; A study of the classification of transformer's HI using each individual measurement is presented. One measurement can provide a general overview on transformer health, like FFA measurement which results in the highest HI classification count but it fails in assessing 4 bad transformers. In practice we cannot depend on a single measurement for accurate and reliable HI judgment. The calculation of HI should include different measurements to complete the required information about the transformer health state. Therefore, a group of measurements is selected and studied utilizing an optimization technique in the upcoming section of this paper.

4.2. BCSO BASED SVM APPLICATION

BCSO-based feature selection and the parameter optimization for SVM are presented in [29-30]. In this section, an optimization model utilizing BCSO Technique based SVM is applied.

The model will be capable of selecting the optimal SVM parameters instead of using grid search, and this will improve the capability of SVM classification. The technique is also adopted to select the least count of transformer measurements that together form the best group for calculating the HI.

Figure 2 shows the flow chart of the proposed method. BCSO is adopted to select the values of c, γ and selects the indices of the best group of measurements. Training, validation and testing databases is filtered according to the selected measurement indices and then SVM model will be adopted using only the new training and validation databases with the proposed fitness function in equation (4 and 7). The process will be repeated until it reaches the predefined iteration count or fitness limit. Finally, testing database is utilized to assess the accuracy and generalization of the model.

Search space dimensions will be 60 bits, the first 14 bits represent measurements, 1 bit represents selected measurement and zero bit represents unselected measurement. The remaining 50 bits will be split into two halves. Each 25 bits will be converted to a decimal number to represent cost and Gaussian coefficient values. A weighted sum fitness function is utilized and it is represented by the equation:

$$FS\ 2 = (\text{Training error \%} + \text{Validation error \%}) / 100 + \text{Selected measurements count} / 200; \quad (7)$$

The first part of fitness function is used to minimize the training and validation classification error. The second part is used to minimize the count of the selected measurements and is divided by 200 to give larger weight for the best classification accuracy search; thus weights are selected by trial and error method. The proposed model is simulated 25 times for each case study and best results is presented in next tables.

Case I:

Tables 7 and 8 show the best selected groups with the corresponding confusion matrices.

Table 7. Case I: BCSO Based SVM Best Selected Measurement Groups with the Corresponding Correct Classified Samples Count

Group No.	Count of Selected Measurements	Selected Measurements	Correct Classified Samples
1	8	2, 3, 5, 7, 9, 11, 13, 14	695
2	7	2, 3, 5, 7, 9, 13, 14	696

Table 8. Confusion Matrices for Case I Groups

	Class	A	B	C	D	E
Group 1	A	407	2	0	0	0
	B	10	126	4	0	0
	C	1	5	95	1	0
	D	0	0	2	51	3
	E	0	0	0	1	16
	Class	A	B	C	D	E
Group 2	A	406	3	0	0	0
	B	9	127	4	0	0
	C	2	4	95	1	0
	D	0	0	1	52	3
	E	0	0	0	1	16

Case II:

Tables 9 and 10 show the best selected groups with the corresponding confusion matrices.

Table 9. Case II: BCSO Based SVM Best Selected Measurement Groups with the Corresponding Correct Classified Samples Count

Group No.	Count of Selected Measurements	Selected Measurements	Correct Classified Samples
1	4	2, 7, 9, 14	713
2	3	2, 7, 14	713
3	4	2, 7, 12, 14	715

Table 10. Confusion Matrices for Case II Groups

	Group 1				Group 2				Group 3		
Class	A	B	C		A	B	C		A	B	C
A	541	8	0		542	7	0		545	4	0
B	2	156	0		2	155	1		4	154	0
C	0	1	16		0	1	16		0	1	16

Case III:

Tables 11 and 12 show those groups with the corresponding confusion matrices.

Table 11. Case III: BCSO Based SVM Best Selected Measurement Groups with the Corresponding Correct Classified Samples Count

Group No.	Count of Selected Measurements	Selected Measurements	Correct Classified Samples
1	6	4, 5, 8, 11, 13, 14	713
2	5	4, 5, 8, 13, 14	713

Table 12. Confusion Matrices for Case III Groups

	Group 1				Group 2		
Class	A	B	C		A	B	C
A	569	0	0		569	0	0
B	5	131	2		5	131	2
C	2	2	13		2	2	13

Case IV:

Tables 13 and 14 show the best selected groups with the corresponding confusion matrices.

Table 13. Case IV: BCSO Based SVM Best Selected Measurement Groups with the Corresponding Correct Classified Samples Count

Group No.	Count of Selected Measurements	Selected Measurements	Correct Classified Samples
1	5	2, 5, 6, 13, 14	720
2	5	2, 5, 7, 13, 14	721

Table 14. Confusion Matrices for Case IV Groups

	Group 1				Group 2		
Class	A	B	C		A	B	C
A	604	1	0		605	0	0
B	0	101	1		0	101	1
C	0	2	15		0	2	15

Figure 3 shows the comparison of the count of each measurement during the 25 simulated trials. This is displayed for cases I, II, III and IV.

5 DISCUSSION

In a former section of this paper, the capability of each transformer measurement in classifying transformer HI with different classes' boundary is tested. As seen in Table 5 hydrogen results in the lowest count of correct classified samples followed by BDV, H_2O, CO and CH_4. In the order of increased number of counts, those are followed by IFT, acidity, color and FFA which results in the highest count. FFA prove robustness in classifying the majority of transformers when it has been utilized solely utilizing case II boundaries. Confusion matrix in Table 6 shows that the performance of FFA in the classification of 'good' and 'moderate' transformers is reliable. On the other hand, it fails to identify 4 'bad' transformers out of 17.

SVM performance is enhanced by applying BCSO as a feature selection technique in an optimization model utilized in section 4.2. The model is simulated for each case 25 times and the results show that:

Measurements that solely can result in a high count (Table 5), may not participate in an optimally chosen group of features. For example, Acidity results in 668 counts out of 724 when it used solely, whereas; the applied model considers acidity as a noisy feature that may confuse the classifier so it is filtered in group 2 in Table 7. It is also eliminated in group 2 in Table 11 without affecting the classifier performance.

Measurements inducing low count may participate in optimal groups to improve the model performance as CO and C_2H_2. Table 5 shows that both measurements have low count; it renders 573 and 605 out of 724 respectively while utilizing Case III boundaries. The proposed model selects both CO and C_2H_2 in the optimal groups of Tables 7 and 13 to improve the performance of the classifier. This means that both measurements have complementary information that is useful when combined with other measurements in assessing transformer HI.

Case I represent the biggest challenge for the proposed model; hence we need to classify the transformer HI into five groups. Table 7 shows that the model selected H_2O, IFT and FFA to represent oil characteristics. CO, CO_2, C_2H_2 and C_2H_6 are selected to represent DGA. The model generates considerable results, but actually, it induces the lowest counts in comparison with the other cases; hence 28 out of 724 samples are misclassified. From the confidence point of view, the model has succeeded to classify 'very bad' transformers. Nevertheless, the confusion matrices in Table 8 render high confidence results; only one 'very bad' transformer is misclassified as 'bad' in all selected groups.

Case II boundaries provide high impact on the model performance. It achieves an increase in the number of counts from 696 in case I to 715 samples as shown in Table 9. The count of the selected measurements group is decreased from 7 in case I to only 4 measurements in groups 1 and 3, and to 3 measurements in group 2 as shown in Table 9. Confusion matrices in Table 10 show only high confidence in assessing 'moderate' and 'good' transformers. In this case, the model generates reliable results utilizing a group of the least count of utilized measurements

Case III boundaries do not show improvement in classification results or the count of selected measurements over case II. The count of selected measurements is increased to 5 and 6 as seen in Table 11. Confusion matrices in a Table 12 show that the confidence of results became worse and model misclassified 4 'bad' transformers, 2 as 'moderate' and the other 2 transformers as 'good'. This cannot be practically dependable.

Case IV boundaries result in the best classification results in comparison with cases I, II and III. It achieves the tradeoff between the best 3lassification results and the least count of selected measurements within the group. Only 3 samples out of 724 are misclassified as in Table 13. Confusion matrices in Table 14 show reliable results, 2 'bad' transformers classified as 'moderate' and one 'moderate' transformer classified as 'bad' using group 2 with only five measurements within the group.

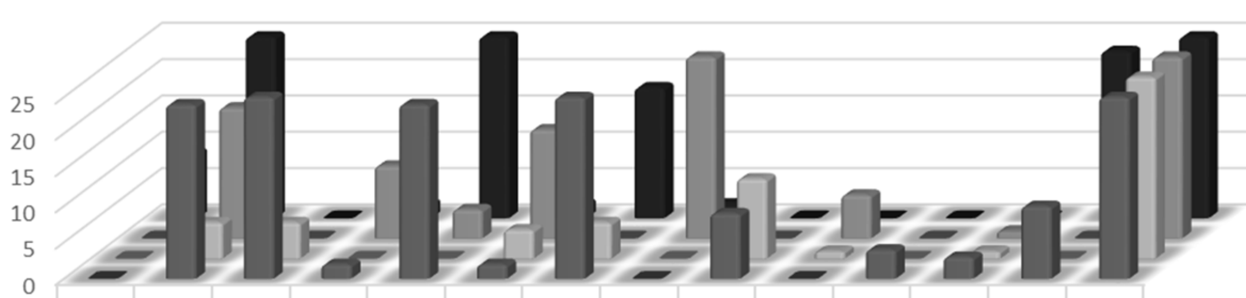
Figure 3. shows the importance of each transformer oil measurement in each case. It is clear that the importance of the selected measurements varies in each case except for FFA measurement which is participating in all of the selected groups. It proves the reliability and importance of this measurement in identifying transformer health state. Case I dominant measurements are CO, CO_2, C_2H_2, C_2H_6, FFA followed by IFT and H_2O. In case II dominant measurements are FFA and H_2O, those changes to color, FFA followed by CO, C_2H_4 and CH_4 in case III. In case IV the group is changed to CO, C_2H_2, FFA followed by IFT, C_2H_6 and H_2.

Measurements of CO, C_2H_2, C_2H_6 and FFA have highest participation counts in the most selected measurement groups in comparison with the remaining measurements. This means that those are the most informative measurements for the calculation of the HI.

Former study in [12] selected 7 transformer measurements namely (CO_2, CH_4, C_2H_2, C_2H_4, C_2H_6, acidity and FFA) out of 12 available measurements. In this study a smaller subset of measurements is selected amongst larger set of database. In the current study the classification accuracy is improved to 99.58% (721/724) as in Table 13. The study also displays a detailed description of how the selection of the HI classes boundaries affect the chosen measurements.

6 CONCLUSIONS

In this paper, we present a new classification model utilizing BCSO based SVM. The aim of this study is to introduce new selection criteria for the most comprehensive group of oil transformer measurements and identifying the transformer condition with high confidence. Fourteen transformer measurements, including oil analysis and DGA are used for the study. Results show that SVM with combined features of CO, C_2H_2, C_2H_6, IFT and FFA measurements are



	H2	CO	CO2	CH4	C2H2	C2H4	C2H6	Color	H2O	BDV	Acid	DF	IFT	FFA
Case I	0	24	25	2	24	2	25	0	9	0	4	3	10	25
Case II	0	5	5	0	0	4	5	0	11	1	0	1	0	25
Case III	0	18	0	10	4	15	0	25	0	6	0	1	0	25
Case IV	9	25	0	2	25	2	18	2	0	0	0	0	23	25

Case I Case II Case III Case IV

Figure 3. Comparison Count Chart of Each Transformer Measurement in Section 4.2.

the best group to identify transformer HI state efficiently within 3 classes 'good', 'moderate' or 'bad'. This work concludes that the chosen group of measurements should not necessarily include the measurements with the highest information content. The group of chosen measurements complements each other to form the best combination for transformer HI assessment. Finally, the tradeoff between classification accuracy, confidence and selected measurements is constrained with the selection of HI classes and their boundaries.

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