Fault Diagnosis of a Transformer using Fuzzy Model and Unsupervised Learning

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***Abstract*— In this paper a power transformer fault diagnosis system (PDFDS) based on soft computing and computational intelligence is proposed. Fault diagnosis and analysis is an integral part of operational reliability. Systems like SCADA collect data of various equipment in power system network, however, fails to provide a critique fault diagnosis for the same which further leads to additional cost of replacing the equipment. This paper proposes a supervised-unsupervised predictive model for the data collected from various power transformers across Himachal Pradesh and IEC 10 database. To identify the different fault types in a transformer a fuzzy model is developed using the DGA interpretation techniques. Since, not all data samples in the collected dataset fall under the standards specified in the ratio tables it thus becomes difficult to identify the type of fault for such cases. To overcome this an improved fuzzy model with unsupervised clustering algorithm or Fuzzy Clustering means is used. Employing this improved model optimizes the data before feeding it to the different predictive machine learning models. Further, a particle swarm optimization algorithm with passive congregation is employed to optimize the performance of these machine learning models.**

Index Terms*— *Dissolved Gas Analysis; Fuzzy Model; Fuzzy- C means Clustering; Multiclass Classification; Support Vector Machine, Particle Swarm Optimization

I. INTRODUCTION

Electrical utilities heavily rely on their infrastructure to provide a reliable and continuous power supply to customers. Transformers are a cardinal part of a power system network since their reliability directly affects the safety of power operations. Any fault in transformers leads to the interruption of the power supply, which further leads to the replacement of the respective equipment, thereby increasing the financial losses. Thus, for a stable and reliable operating power system, it is necessary to diagnose faults in a transformer. There are several methods to analyses and diagnose the technical condition of a transformer. Some of these methods include Dissolved Gas Analysis (DGA), furan analysis, frequency response analysis, infrared analysis, partial discharge, and so on. The data for transformer oil alone is collected for the purpose of this paper. As the “health” of the oil reflects health of a transformer, Dissolved Gas Analysis (DGA) is employed to collect data for various transformers.

Now, faults in a transformer occur due to mechanical, thermal, and electrical stresses that subsequently lead to a release of gases in the transformer oil. The gases produced are hydrogen (H_2), methane (CH_4), ethane (C_2H_6), ethylene (C_2H_4), acetylene (C_2H_2), carbon dioxide (CO_2), and carbon monoxide (CO). These gases are also known as fault gases.

Any one of these gases or a combination of the same identifies the type of fault that occurs in a transformer. Using the concentration of these gases dissolved in the transformer oil, the technical condition and primary defects in a transformer can be deduced. Each gas depicts the kind of fault in a transformer. Here, six fault types namely partial discharge (PD), thermal faults < 150°C (T1), thermal faults between 150°C – 300°C (T2), thermal faults 300°C - 700°C (T3), >700°C (T4), electrical discharge of low energy (D1), and electrical discharge of high energy (D2) are diagnosed. The IEC ratio method and the Duval triangle both DGA interpretation techniques are used to develop the fuzzy model. The model investigates the relationships between the dissolved gas ratios, R1= C_2H_2/C_2H_4, R2 =CH_4/H_2, R3 = C_2H_4/C_2H_6, and the type of fault.

Furthermore, artificial intelligence and machine learning is incorporated in several fields including engineering owing to their wide and rapid development. Many foreign and domestic scholars have integrated machine learning methods into transformer fault diagnosis model and have achieved excellent results. Among the various ongoing tools to assess the transformer’s condition, this paper uses soft computing and computational intelligence (CI) techniques to classify the different faults in a transformer. In the past SVM, has proven to provide good classification results. Even though traditional SVM gets good results, its accuracy can further be improved by optimization algorithms. Several optimization algorithms are available out there, including metaheuristics which finds the best hyperparameters for the SVM model. In this paper, a hybrid particle swarm optimization (PSO) algorithm is used to improve accuracy of classification and regression models.

II. FUZZY MODEL

Fuzzy model imitates human reasoning and learning and when describing vagueness in data binary logic fails which thereby leads to using fuzzy logic. When dealing with transformer data sometimes the DGA interpretation techniques are not efficient and have a few drawbacks. The ratios R1, R2 and R3 may not fall under the standards specified in TABLE 2. Secondly, it is difficult to identify the faults in borderline cases. To overcome this, we employ fuzzy model to identify the fault properly. Fuzzification, fuzzy inference, and defuzzification are the three sequential processes to develop a fuzzy model. Fuzzification is the process that converts gas ratios and gas concentration percentages into fuzzy inputs memberships functions. The trapezoidal membership function is used here. The inputs, if-then rules and outputs are developed using TABLE 2 and [10]. In addition, IEC gas ratios and percentage concentration are used as inputs. The gas concentrations in percentage are calculated using the Duval triangle method. The percentage gases are as calculated as per [11] and are as shown below:

$$\%C_2H_2 = \frac{100\times C_2H_2}{C_2H_2 + C_2H_4 + CH_4} \quad (1)$$

$$\%C_2H_4 = \frac{100\times C_2H_4}{C_2H_2 + C_2H_4 + CH_4} \quad (2)$$

$$\%CH_4 = \frac{100\times CH_4}{C_2H_2 + C_2H_4 + CH_4} \quad (3)$$

$$\%H_2 = \frac{100\times H_2}{H_2 + C_2H_6 + CO + CO_2} \quad (4)$$

From defuzzification crisp output values are obtained that point to a particular fault type. The fault type or labels obtained for a particular dataset are then used to build a predictive learning model. There were some dataset values for which the fuzzy model was unable to identify the fault type. To overcome this unsupervised learning technique is employed.

The input, rule inference and output membership functions are shown in “Fig.1”, “Fig.2“and “Fig. 3”.

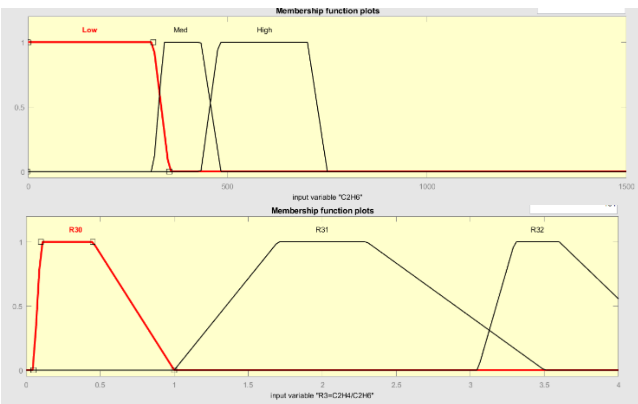

Fig. 1. Input Membership Functions.

Fig. 2. Rule Inference.

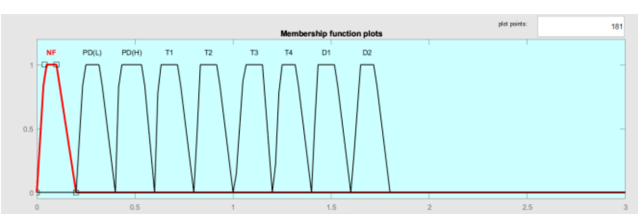

Fig. 3. Output Membership Functions.

A. *Abbreviations and Acronyms*

A detailed list of abbreviations is as listed below:

DGA: Dissolved Gas Analysis

FIS: Fuzzy Inference System

FCM: Fuzzy Clustering Means

PSO: Particle Swarm Optimization

RBF: Radial Bias Function

SCADA: Supervisory Control and Data Acquisition System

SVM: Support Vector Machine

SVC: Support Vector Classification

SVR: Support Vector Regression

III. UNSUPERVISED LEARNING

Machine learning models segregates data using supervised and unsupervised learning techniques. In supervised learning techniques output y is a function of x. Labels are defined for the dataset and the model learns using the features and labels specified. Whereas in unsupervised learning the targets for the dataset are not specified instead the data is clubbed together identifying the patterns and then grouped into specific clusters. The IEC ratio method has a disadvantage that some of the ratio’s i.e., R1, R2 and R3 do not fall under the ratio ranges as specified TABLE 2. In addition, the fuzzy model developed using the IEC ratio table was unable to identify fault type for few data samples. To overcome this disadvantage of IEC ratio table, unsupervised learning model is used to identify the fault type of these data samples.

A. *Fuzzy Clustering Means (FCM)*

Clustering in machine learning is divided into hard and soft clustering. Hard clustering includes classifying the target into distinct clusters whereas soft clustering groups the data into different clusters. This means that a particular dataset can be a part of more than one cluster. In this paper since some of the datasets do not belong the ratio table and the developed fuzzy model also fails to determine the type of fault, we use FCM to identify the fault type. Additionally, the usage of FCM instead of K means clustering is due to the fact a transformer has a mixture of faults instead of only one type of fault. Thus, the data samples can belong to more than one cluster. The cluster that carries the highest weight is assigned the target for the particular dataset.

TABLE I. VIOLATION LIMITS FOR KEY GASES

Key Gas	Maximum Limit
Hydrogen (H2)	100
Acetylene (C2H2)	1
Ethylene (C2H4)	50
Ethane (C2H6)	65
Methane (CH4)	120
Carbon Monoxide (CO)	350

TABLE II. DGA INTERPRETATION TABLE

Code of Ratios	**Gas Ratios**		
	R1	***R2***	***R3***
<0.1	0	1	0
0.1-1	1	0	0
1-3	1	2	1
>3	2	2	2
Characteristic Faults			
No Fault (NF)	0	0	0
Partial Discharge of low energy density PD(L)	0	1	0
Partial Discharge of low energy density PD(H)	1	1	0
Discharges of Low Energy (D1)	1-2	0	1-2
Discharges of High Energy (D2)	1	0	2
Thermal Fault for T < 150 (T1)	0	0	1
Thermal Fault for 150 <T < 300 (T2)	0	2	0
Thermal Fault for 300< T < 700 (T3)	0	2	1
Thermal Fault for T > 700 (T4)	0	2	2

B. Units

The concentration of all six gases is in ppm or µL/L.

IV. SUPPORT VECTOR MACHINE

A. Introduction

SVM is a supervised learning method used for both classification and regression problems. It constructs a higher dimensional hyperplane to perform classification of the dataset into different categories [21]. In this paper, SVM is used as a classifier to predict different faults in a transformer. In the basic classification, SVM performs binary classification. It maximizes the margin to obtain the best classification performance. For a sample dataset (xi, yi) where i = 1,2…...n, and yi ϵ {-1, 1} a linear hyperplane which accurately classifies the sample set xi. Linear hyperplane is denoted as (5), where ω is the hyperplane coefficient, d is the offset vector.

$$y = w^k + d \qquad (5)$$

The above equation (5) is a quadratic programming problem, where its optimization can be defined as (6). Here, Where C is the penalty factor, which specifies the misclassification penalty [22], and ζi is the loss coefficient. Even when the data is linearly separable SVM may overfit the training data, which crucially affects the hyperplane. For this kernel trick is used in SVM. Both linear and RBF kernels are used in this paper to transform the data. RBF kernel maps non-linear data into a higher dimensional space, when the relation between class labels and features is nonlinear. Furthermore, the linear kernel is a special case of RBF. It has the same performance with C as the RBF kernel with some parameters (C, γ) [22]. The parameters gamma and C here are tuned using the PSO algorithm.

$$minJ(\omega,\zeta) = \frac{1}{2}\|\omega\|^2 + C\sum_{i=1}^{N}\zeta_k^2 \qquad (6)$$

$$s.t.\left\{ y_i \begin{pmatrix} \omega^K.x_i + d, \geq 1-\zeta_i, \\ \zeta_i \geq 0, i = 1,2.....n \end{pmatrix} \right\}$$

B. Data Optimization

Classifying a dataset and identifying patterns in the data is a fundamental objective of different classifiers. More than 400 datasets were used in this paper out of which 60% were used as training set, 20% as the validation dataset and the rest as testing dataset. The label/ target for each dataset is pre-processed using the fuzzy model and unsupervised clustering technique as described in the earlier sections. The data optimised is then then fed to different machine learning models which are then compared.

The IEC 10 database used has some missing values which are replaced with zero and c/0 is replaced with 20, where c is not equal to zero. Multiclass one versus one SVM is used to classify the different faults in a transformer. The regression model uses These include partial discharge (PD), No Fault (NF), Thermal Faults (T1, T2, T3, T4), low and high discharge faults (D1 and D2).

C. Kernel Trick

SVM is a powerful tool for practical problems. It provides an accurate and unique solution for problems with nonlinear, a small sampling, high dimensions, making it suitable for fault diagnosis of transformers. SVM, is a learning algorithm which heavily depends on the data representation. In case of a non-linear data, we use the kernel trick. Kernels define the similarity between two samples while defining a regularization term for the problem. RBF kernel is employed for this particular dataset and its parameters C and (C, γ, ɛ) are tuned using PSO.

V. NATURE-BASED METAHEURISTIC ALGORITHM

A metaheuristic is an overarching strategy for picking a heuristic (a partial search algorithm) that could solve an optimization problem well enough. As an alternative to exhaustively enumerating all possible solutions, metaheuristics take representative samples from a much larger pool. In general, metaheuristics can be applied to a wide range of issues since they often require few if any assumptions to be made about the underlying optimization problem. Metaheuristics are further classified into evolutionary-based, trajectory based, nature-inspired, and bio-inspired algorithms. Particle swarm optimization (PSO) has been used in this paper. The algorithm is used to tune the parameters of SVM, to improve its accuracy.

A. Particle Swarm Optimization (PSO) with Passive Congregation

Particle swarm optimization, or PSO, is a metaheuristic strategy that takes its inspiration from bird behavior in a flock. PSO, or "particle swarm optimization," is a robust optimization approach that can be applied to challenging optimization tasks.

Imagine a swarm with a population of T. Parameters associated with particles include its velocity, local best position and global best position. $p_{ibest(t)}, p_i(t)$ and $v_i(t)$ represents the optimum location or local best position, current location and velocity of the particle, where "t" is the unit of time.

Additionally, $g_{ibest}(t)$ represents the optimal location w.r.t the rest of the swarm or the global best position. Each particle's velocity and position are updated according to the following equations while the search for the best solution proceeds.

$$v_i(t+1) = w.v_i(t) + c_1 r_1 (p_{ibest}(t) - p_i(t)) + c_2 r_2 (g_{ibest}(t) - p_i(t)) + c_3 r_3 (R_i - p_i(t)) \quad (7)$$

$$p_i(t+1) = p_i(t) + v_i(t+1) \quad (8)$$

In (7), w is calculated using (8). Whereas, r1, r2, r3 are the random factors whereas c1 and c2 are the acceleration coefficients. The optimum value selection for both these factors is still ongoing research. For the purpose for this paper c1, and c2 is taken as 2, whereas, r1, r2 and r3 is varied between [0,1]. In addition, here R_i is a particle randomly selected from the swarm, and c3 is the passive congregation coefficient. As opposed to the traditional PSO algorithm, this PSO algorithm utilizes congregation which is the grouping of organisms by non-social, physical and external forces. Now there are two types of congregations associated one is the active congregation and the other is passive congregation. Passive congregation refers to grouping of organisms by social forces which is primarily the source of attraction in the group itself. To minimize the chance of missed detection and incorrect interpretations passive congregation is utilized. This keeps the model simple and uniform with the standard PSO or SPSO. Thus, the calculation of position and w remain intact except for the velocity term which has a fourth term added to it.

$$w = w_{\max} - (w_{\max} - w_{\min}).\frac{t}{T} \quad (9)$$

B. Fitness Function

To overcome the problem of overfitting and underfitting fitness functions, which are formulated in terms of the optimization problem at hand, are used to evaluate the degree to which parameters have been optimized. A sphere fitness function employed here.

C. Proposed Workflow of PSO.

The proposed workflow of this fault diagnosis system involves optimizing both SVM and regression model to compare the performance. Here we describe how PSO works to optimize the input parameters.

Step 1: A swarm's parameters are set to their initial values, which include swarm size, no. of iterations, weight, and the velocity and position of each particle. With respect to the appropriate experimental data, the velocity is limited to the interval [$-v_{min}$, v_{max}], where v_{max} is a fixed upper constraint.

According to the relevant experimental data, v_{max} serves as a hard upper limit.

Step 2: Determine the optimal placement of the swarm from the particle with the lowest fitness using "(10)".

Step 3: P_{best} is adjusted to the current position if the current value of the particle's position is better than the fitness of P_{best}.

Step 4: Assess the particle's fitness in comparison to G_{best}. G_{best} should be reset to the position of the current particle if its fitness is worse than the current value.

Step 5: Randomly select a particle from the swarm (R_i).

Step 6: Next, we assign each candidate particle to a cross-validated SVM classification model and train it with the appropriate parameters.
Step 7: Each particle's velocity and position is updated using "(7)" and "(8)" followed by the inertial mass w which is calculated as "(9)".
Step 8: Examine the termination criteria in this stage. If one of the termination criteria, i.e., a good fitness value or a fixed number of iterations have been met then stop else go to step 2.

Step 9: Get the best possible SVM settings for both classification and regression models.

VI. RESULTS

The IEC ratio table, which is one of the popular DGA interpretation technique has a disadvantage that not all data values fall under the standards specified in the ratio table. It also sometimes incorrectly interprets the borderline cases. To overcome this disadvantage of IEC ratio tables unsupervised learning or FCM is used to identify the specific cluster of data samples. An improved fuzzy model involving both IEC ratio table standards and Duval triangle is employed as described in section II above. The borderline cases and the fault types that the fuzzy model is unable to identify utilizes the unsupervised learning technique to identify the specific cluster of the data sample. Employing the fuzzy model and then FCM ensures a through optimization of the data collected and correct prediction of the type of fault for a particular data sample. DGA data of over 200 power transformers across Himachal Pradesh along with IEC 10 database is collected and processed it is preprocessed as described in section IV (B). This optimized data is then fed to predictive models including classification and regression models. Since, a major portion of the proposed model focuses on data optimization, the performance of learning models improves tremendously. To optimize their performance more PSO with passive congregation is also employed. The accuracy results are as depicted in TABLE V and VI, whereas TABLE III, and IV are the PSO parameters used and hyperparameters values for tuning the SVM model.

TABLE III. PSO PARAMETERS

C1, C2, C3 and w	**ITERATIONS**	**SWARM SIZE**
2, 2, 2 0.8	200	250
2, 2, 2 0.8	200	250

TABLE IV. HYPERPARAMETER VALUES

ML MODEL	**C**	**γ**	**ε**
SVC	6799.733944551768	0.001	---
SVR	292.9637869191562	0.001	0.024026077435154364

TABLE V. ACCURACY RESULTS OF THE PROPOSED MODEL

ML MODEL	ACCURACY	R^2 SCORE	MSE
PSO Tuned SVC	92%	---	---
Traditional SVC	87%	---	---
PSO Tuned SVR	85%	0.147	0.03
Traditional SVR	82%	0.111	0.04

TABLE VI. ACCURACY RESULTS OF THE PROPOSED MODEL

ML MODEL	PRECISION	RECALL	F1 SCORE
PSO Tuned SVC	0.91	0.92	0.91
Traditional SVC	0.91	0.87	0.85
PSO Tuned SVR	0.87	0.85	0.84
Traditional SVR	0.81	0.82	0.79

VII. CONCLUSION

Data pre-processing and optimization play a major role in machine learning models. In this paper a similar approach is utilised wherein the data is first passed through a fuzzy model and then an unsupervised learning technique. This leads to enhancing the performance of predictive models and correct identification of the different type of faults in a transformer. TABLE V depicts the classification accuracy of different machine learning algorithms, followed with TABLE VI that depict the other performance metrics. TABLE III and IV depict the PSO parameters and the hyperparameters values of γ, ε, and C for different predictive models. The results clearly indicate that using this supervised-unsupervised machine learning model has improved the accuracy of the traditional SVM model. The model can further be tested using other machine learning algorithms. Further, this developed model can also be integrated with SCADA in the future for a thorough analysis and to initiate immediate action to mitigate the effects of incipient faults in various power transformers.

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