The Estimation of Breakdown Voltage of Vegetable Oil using Support Vector Machine

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ABSTRACT

Oil as an insulating medium is widely used in power apparatus and it is important to have knowledge about its breakdown characteristics. Support Vector Machine (SVM) can be a fruitful tool for estimation of breakdown voltage (BDV). In this work, the objective is to explore the application of SVM to estimate breakdown voltage of vegetable oil. Experiments are carried out on vegetable oil to obtain its characteristic breakdown voltage using Weibull distribution. Experiments are carried out using different electrode geometry and electrode gap. At the breakdown condition, the electric field distribution is simulated using FLUX software and various electric field features such as electric field intensity, energy density, etc. are extracted. These electric field features are preprocessed and used to train SVM. The optimum value of SVM parameters are obtained using grid search and K − fold cross validation technique. The trained SVM model is used to estimate the breakdown voltage of the oil medium under different electrode gap and shape. It is seen that the estimated BDV fairly matches with the experimental results.

Keywords: Breakdown Voltage, Weibull Distribution, Support Vector Machine, Principal Component Analysis, K − Fold Cross Validation, Grid Search, Mean Square Error

1. INTRODUCTION

The insulating medium plays vital role for the systematic and reliable operation of power equipments. Oil insulating medium is widely used in oil filled cables, oil circuit breaker, power transformers etc., and breakdown voltage is one of the dominant characteristics. Many research is being carried out to understand the breakdown characteristics of oil insulating medium in various equipments [1-3]. Therefore, estimation of breakdown voltage is important.

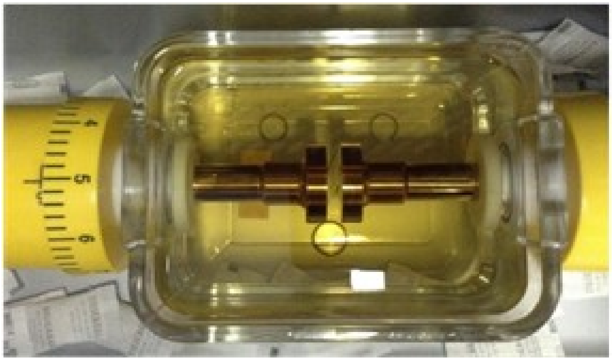

Fig. 1: Experimental set up for breakdown test.

Quantitative assessment of breakdown voltage using statistical tool is essential [4]. Weibull distribution is used to quantify breakdown voltage behaviour and is preferred to normal distribution owing to its asymmetric nature [5]. On the other hand, statistical machine learning tools i.e. Support Vector Machine (SVM) is a state of art technique, and is widely used in non-electrical domain [6, 7]. In electrical domain, SVM has been use in the field of high voltage such as impulse fault identification in transformers, optimization of electric field in insulators and classification of partial discharge in XLPE cable joints, prediction of air breakdown voltage, etc. [8 - 13].

In this work, SVM is used to estimate breakdown voltage of vegetable oil. Experimental data are analysed using Weibull distribution. Using FLUX software, electric field distribution at breakdown condition is simulated. Various electric field features are extracted from the simulated field distribution and pre-processed to train SVM. The trained SVM model is used to estimate breakdown voltage of vegetable oil under different electrode gap and electrode shape. An error analysis is done, to compare the experimental and the SVM estimated breakdown voltage

2. METHODOLOGY

In this work, breakdown tests are carried out on vegetable oil as a dielectric medium under different experimental conditions. The experimental results are statistically analysed to obtain breakdown voltage characteristics of the oil medium. The breakdown test data are used to train and test SVM for prediction of breakdown voltage. The estimation of breakdown voltage using SVM comprises of (1) Binary labelling of breakdown

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voltage, (2) Extraction of electric field features, (3) feature dimension reduction and (??) SVM training and estimation of BDV.

2.1 Experimental Procedure & Statistical Analysis

The breakdown test experiments are carried out on BAUR DPA 75 C, a oil breakdown voltage tester. The equipment have applied voltage range from 0 to 75 kV$_{rms}$ with varying voltage slew rate from 0.5 kV/sec to 10 kV/sec. In this experiment, using plate – plate electrode configuration, electrode gap distance is varied from 1.5 mm to 5.5 mm in a step of 0.5 mm. The applied voltage slew rate or ramp rate is kept constant at 5 kV/sec. For each electrode gap, ten breakdown tests are conducted with a time gap of 15 minutes between consecutive breakdown tests. Also the same breakdown test is carried out with sphere – sphere electrodes. The experimental set–up is shown in Fig. 1.

Two parameter Weibull distribution function given by equation (1) is used to obtain characteristic breakdown voltage of oil medium. Scale parameter (α) provides information about breakdown voltage whose probability of occurrence is 63.2 %, whereas shape parameter (β) gives information about the nature of breakdown.

$$F(V) = 1 - exp\left[-\left(\frac{V}{\alpha}\right)^{\beta}\right] \quad (1)$$

Based on the characteristic breakdown voltage or scale parameter, upper and lower range of breakdown voltage is selected. If the characteristic breakdown occurs at V$_o$, then the voltage range V$_o$ to V$_o$ + 10 kV is assigned as +1, and V$_o$ to V$_o$ − 10 kV is assigned as -1. The voltage range V$_o$ to V$_o$ + 10 kV pertains to the decision that breakdown may occur in oil insulation whereas V$_o$ to V$_o$ − 10 kV relates to the decision that oil insulation may withstand breakdown. The electric field features for the entire voltage range is extracted from the simulated electric field distribution.

2.2 Electric Field Feature Extraction and Processing

The electric field distribution with plate – plate and sphere – sphere electrode geometry is created in FLUX software. The electric field distribution space is divided into three areas i.e. (i) Whole Region (WR) – entire oil filled medium, (ii) Central Region (CR) – oil filled region between the two electrodes and (iii) Electrode Region (ER) – solely the surface area of the electrodes. These areas are selected based on the possibility of occurrence of breakdown channels. The characteristic breakdown voltage obtained from weibull distribution for the oil insulation is used as a boundary condition to simulate the electric field distribution.

Based on the experimental conditions, eleven electric field features are extracted from the simulated electric field distribution space. The electric field features considered are (i) Maximum electric filed strength: E_{Max}, (ii) Average electric field strength: E_{Avg}, (iii) Distortion factor of the electric field: E_{DF}, (iv) Total Electric Field energy: U, (v) Energy density: U_{Den}, (vi) Total Area: A, *(vii)* Area ratio of the region which exceeds x % of the maximum electric field strength: A_{rx}, (viii) Energy ratio of the region which exceeds x % of the maximum electric field strength: U_{rx}, (ix) The area of the high voltage electrode surface: S, *(x)* The area of the region on the surface of the high voltage electrode which exceeds x % of the maximum electric field strength: S_x, (xi) Area ratio of the region on the surface of the high voltage electrode which exceeds x % of the maximum electric field strength: S_{rx}. Considering these eleven electric field features, region-wise i.e. Whole Region, Central Region and Electrode Region thirty-three field components are extracted. In WR, CR and ER, thirteen, eleven and nine field components are extracted respectively [11].

2.3 Electric Field Feature Dimension Reduction

In machine learning, Feature Dimension Reduction is a pre-processing step. This is to select few dimensional features from a large set of dimensional features. This reduces the feature space optimally depending on certain evaluation criterion. This helps to increase computational efficiency and can eliminate redundancy. The electric field features considered i.e. field strength, energy density, area, etc., have different magnitude and units. To eliminate the influence of different order of magnitudes and units, the electric field features are normalized. Also, normalization will accelerate the training and convergence speed of the prediction model [14,15]. The features are normalized between the interval 1 and 2. The normalization method is given by equation (2).

$$x_i' = \frac{x_i - x_{min}}{x_{max} - x_{min}} + 1 \quad (2)$$

where x_i' is the normalized value of a certain feature x_i, x_{min} and x_{max} are the minimum and maximum values of x_i.

All the normalised electric field features may or may not be a significant parameter for oil breakdown. To identify the significant parameters causing oil breakdown, PCA is carried out. PCA extracts relevant information and eliminates redundant or insignificant information. PCA solves the eigenvalue problem of covariance matrix of the normalised electric field features. The cumulative variance of the eigen vectors is represented by the index value (P) of PCA and is given by equation (3) [16].

$$\boldsymbol{P} = \frac{\sum_{i=1}^{k} \boldsymbol{D}_i}{\sum_{i=1}^{d} \boldsymbol{D}_i} \quad (3)$$

where D_i is the i th eigen value, d is the number of original electric field features and k is the number of principal components.

From equation (3), the range of P is chosen in such way that the dominant electric field features lie within

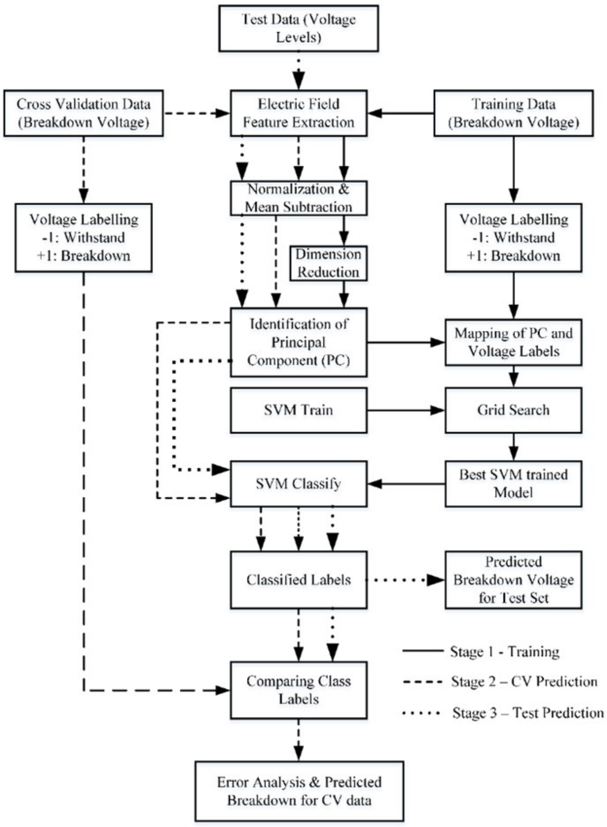

***Fig. 2**: Flowchart of breakdown voltage prediction model.*

***Table 1**: Weibull parameters for different electrode gap.*

Electrode Gap (mm)	Scale Parameter (kV)	Shape Parameter
1.5	18.19	7.37
2	27.46	4.38
2.5	32.32	5.77
3	38.05	5.19
3.5	48.92	5.58
4	50.40	8.15
4.5	58.70	7.01
5	67.71	5.34
5.5	71.20	14.17

the limits. Within this limit, the eigen vectors of the covariance matrix of normalised electric field features are used to identify the Principal Component (PC) responsible for occurrence of breakdown or not. It is seen that, in case of varying electrode gap with constant ramp rate, the dominant electric field features lies within 0.78 and 0.99 of index value of P i.e. $0.78 < P < 0.99$.

2.4 SVM Training and Estimation of BDV

The estimation of breakdown voltage using SVM comprises of three steps i.e. Training, Cross Validation (CV) and Test. The training data is utilised to train SVM model, while CV data validates the prediction model and confirms whether SVM will be able to perform on new test data or not. Fig. 2 shows the flowchart of breakdown voltage estimation model comprising of SVM training, classification, Cross Validation and estimation or test. Initially the SVM is trained and then using K – Fold cross validation and grid search technique SVM parameters i.e. C and γ are optimised. With the optimised SVM parameters breakdown voltage is estimated.

The SVM classifier is constructed based on dimensionally reduced electric field features under different electrode gap and applied voltage ramp rate. The training and classification of data set using Support Vector Machine uses Radial Basis Function as Kernel function. The K – Fold cross validation in association with grid search optimisation technique is used to estimate the optimal value of penalty coefficient (C) and kernel parameter (γ). The penalty coefficient (C) and the kernel parameter (γ) are the tuning parameters of SVM model. The estimation of these parameters is important for optimum performance of SVM model. In grid search method, the range of γ is taken from 2^{-4} to 2^{4} and range of C is taken from 2^{2} to 2^{10} with step size of $2^{0.1}$. The range of C and γ is so selected that less points cover a large range of search space. The finer the search space, the better will be the solution obtained however at the cost of computational burden [14 - 19].

The optimised SVM model is then used to estimate breakdown voltage. Initially the estimated breakdown voltage is assumed to be V_{br} and its dimensionally reduced electric field features are fed to SVM model. If the output of SVM is − 1, the assumed breakdown voltage magnitude is increased by dV i.e., V_o + dV. This updated breakdown voltage is again fed to SVM model and its output is recorded. This process continues until at a critical voltage magnitude such that the SVM output changes from − 1 to + 1. This critical voltage magnitude defines the estimated breakdown voltage. Thus, a regression problem is converted to a binary classification problem [11].

3. RESULTS AND DISCUSSION

This section presents the experimental results and the estimated breakdown voltage using SVM. The breakdown test and estimation of breakdown voltage using SVM are carried out for two different electrode configurations i.e. plate – plate and sphere – sphere. The electrode gap distance is varied and the ramp rate of applied voltage is maintained constant.

3.1 Plate – Plate Electrodes

The breakdown test of oil insulating medium is carried out using oil insulation breakdown voltage tester. The electrode gap is varied from 1.5 mm to 5.5 mm. The applied voltage ramp rate is kept constant at 5 kV/sec. At each electrode gap, ten breakdown tests are carried out. Weibull analysis is carried out using these ten breakdown test data. The table 1 shows the Weibull parameters i.e. scale parameter and shape parameter of the oil breakdown test. It is observed that with increase

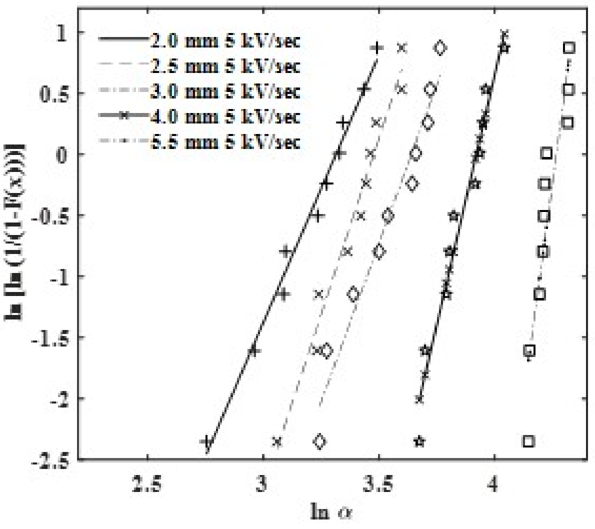

Fig. 3: Weibull plot for different electrode gap.

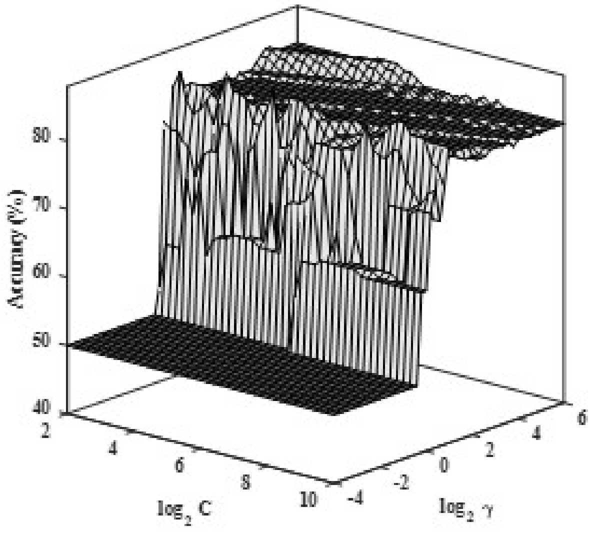

Fig. 5: Accuracy vs. log_2C vs $log_2\gamma$ for Whole Region.

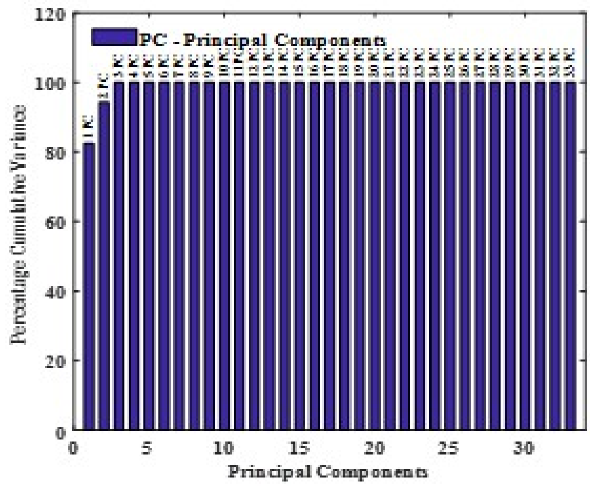

Fig. 4: Percentage cumulative variance of the principal components for Whole Region.

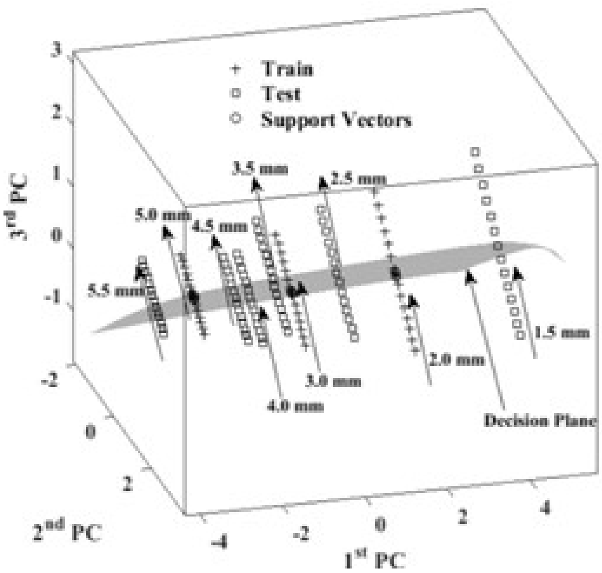

Fig. 6: Trained SVM model for Whole Region.

in electrode gap the breakdown voltage magnitude increases. It is obvious that with increase in electrode gap, higher voltage is required to create electric field strength more than the breakdown strength of oil to cause breakdown. The shape parameter lies between 4 to 15 which indicates intrinsic breakdown of oil [5]. Fig. 3 shows the Weibull plot of oil medium for different electrode gap.

The electric field features for three areas of possible breakdown channels were extracted namely: (i) Whole Region, (ii) Central Region and (iii) Electrode Region. The details of eleven electric field features are discussed in section 2.2. The breakdown voltage prediction using SVM is discussed region wise.

Whole Region: Electric field features corresponding to entire region of oil medium are extracted. Features are post processed by normalization and dimension reduction is carried out using PCA. Fig. 4 shows the percentage cumulative variance vs the number of principal components arranged in ascending order of Eigen values. It is observed that the first 3 components show significant cumulative variance. These 3 components are considered to be dominant electric field feature for breakdown of oil medium. The Eigen values of these dominant principal components accounts to an index value P i.e. $0.78 \leq P \leq 0.99$. These components hold major information of the original features while reducing the number of features. The tuning of SVM model depends on C and γ parameters.

The range of C and γ considered to estimate optimum value is mentioned in section 2.4. In Grid Search method, for different combination of C and γ, the prediction accuracy will be different. Fig. 5 shows the effect of change of C and γ on the accuracy of the prediction model. With best values of C = 6.69 and γ = 1.23, a

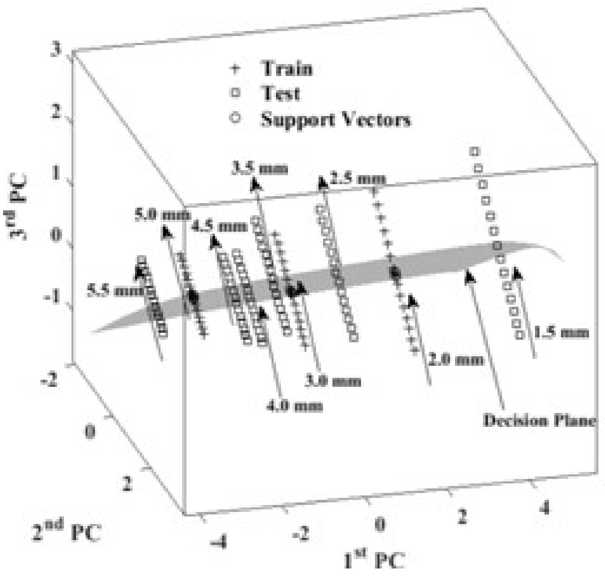

***Fig. 7**: Comparison of experimental and estimated breakdown voltage for Whole Region.*

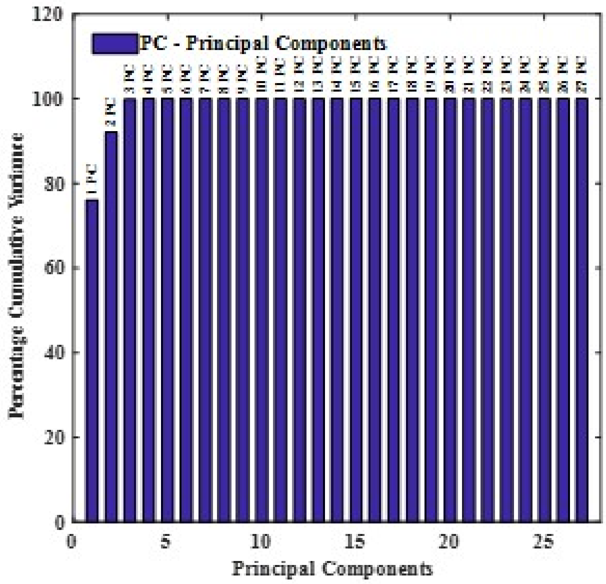

***Fig. 8**: Percentage cumulative variance vs. Principal Components in central region.*

maximum accuracy of 83.55 % is obtained. In the search space due to exponential range of C and γ, x and y axes are plotted with log base 2 i.e. $log_2 C$ and $log_2 \gamma$. This is done to obtain to show uniform scaling.

The SVM plot of the trained model considering 3 principal components i.e., by 1^{st} PC, 2^{nd} PC and 3^{rd} PC respectively is shown in Fig 6. The plot shows electric field features corresponding to the applied voltage for a particular electrode gap have clustered, and when dimensionally reduced electric field features corresponding to the applied voltage will cross the SVM plane, a breakdown is recorded. Also it is seen that the support vectors are placed on the hyperplane and lies along the line of the training data. Also, from the graph it can be clearly seen than that the 1^{st} PC captures the maximum variance of the electric field features followed by 2^{nd} and 3^{rd} PC respectively. Even though the cumulative variance contribution of 2^{nd} and 3^{rd} PC is not much in comparison to the 1^{st} PC, still there must be a non-linear relationship between the features of electric field and breakdown voltage. Fig. 7 shows the comparison of the estimated breakdown voltage and experimental breakdown voltage.

Central Region: Electric field features corresponding to central region are extracted from simulated electric field distribution. It is observed that the last six field components of the central region did not change because of the uniformity of the electric field in this region. Therefore the analysis was further carried out with the rest 27 components of electric field. The field features are post processed by normalization and dimension reduction using PCA. Fig. 8 shows the percentage cumulative variance vs the number of PC's arranged in ascending order of eigen values. It is seen that only 3 components are dominant out of 27 components considered. The PC's corresponding to the eigen values whose cumulative contribution of variance accounted to an index value P ($0.78 \leq P \leq 0.99$) are selected. These components are significant and dominant electric features for breakdown.

Grid search is employed and for different combination of C and γ, the prediction accuracy will be different for the proposed model. Fig. 9 shows the effect of change of C and γ on the accuracy of the prediction model. It is seen that with $C = 4$ and $\gamma = 1.14$, maximum accuracy is 82.89%. The SVM plot of the trained model considering first 3 principal components i.e. 1^{st} PC, 2^{nd} PC and 3^{rd} PC is shown in Fig. 9. In Fig. 10, the support vectors on the hyperplane coincides with the training data. It is observed, similar to Whole Region, that 1^{st} PC is more dominant than 2^{nd} and 3^{rd} components. However all 3 components are the most significant to cause breakdown. Fig. 11 shows the comparison of the estimated breakdown voltage and the experimental value.

Electrode Region: Similar to whole Region and Central Region, electric field features corresponding to Electrode Region are extracted and processed. All 33 components of electric field features are considered. Fig. 12 shows the percentage cumulative variance vs the number of PC's arranged in ascending order of Eigen values. Similar to the previous regions, 1^{st} PC, 2^{nd} PC and 3^{rd} PC are dominant. The index value (P) of Principal Components corresponding to the Eigen values are seen to lie within $0.78 \leq P \leq 0.99$. Using Grid search technique, the optimum value of C and γ i.e. the tuning parameters of SVM is found to be 12.99 and 1.14 respectively and with highest accuracy of 84.87 %. Fig. 13 shows the variation of C and γ with

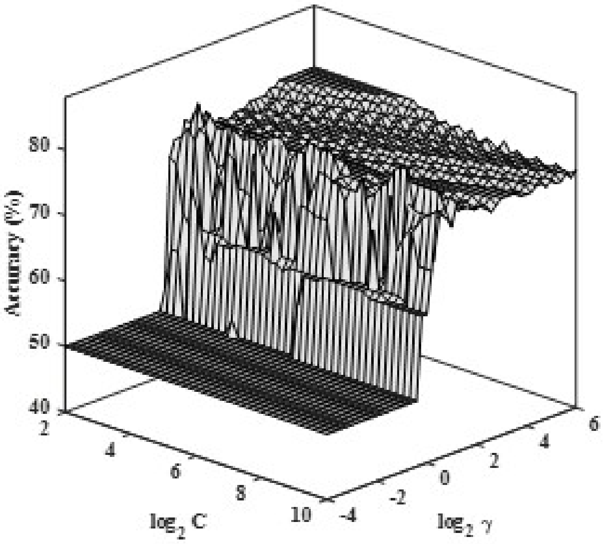

***Fig. 9**: Accuracy vs log_2C and $log_2\gamma$ for grid search for Central Region.*

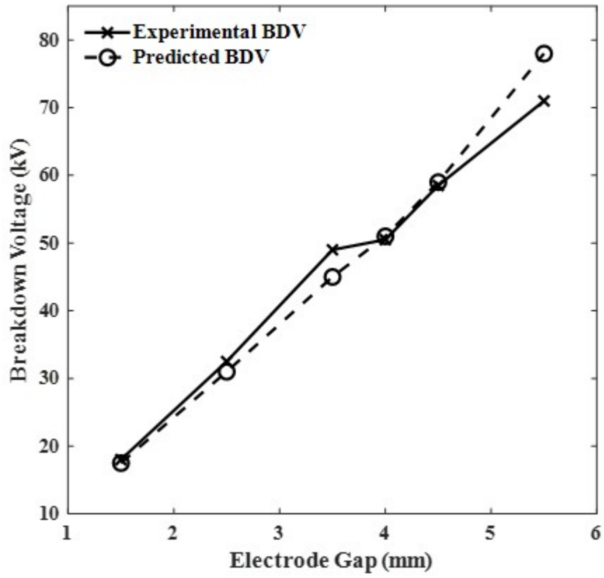

***Fig. 11**: Comparison of experimental and estimated breakdown voltage for Central Region.*

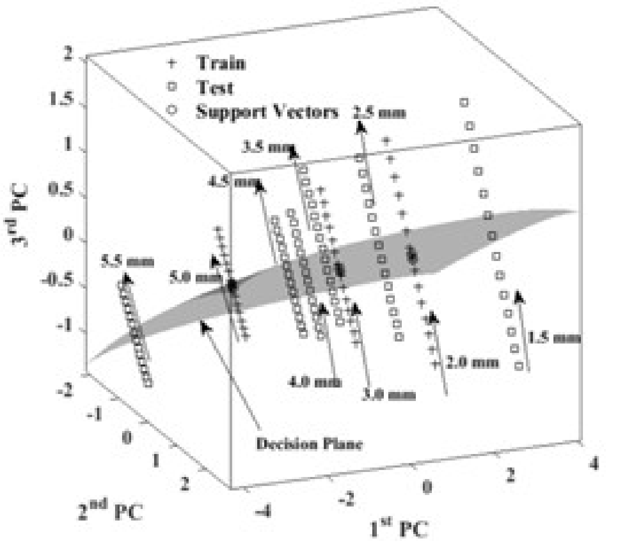

***Fig. 10**: Trained SVM model for Central Region.*

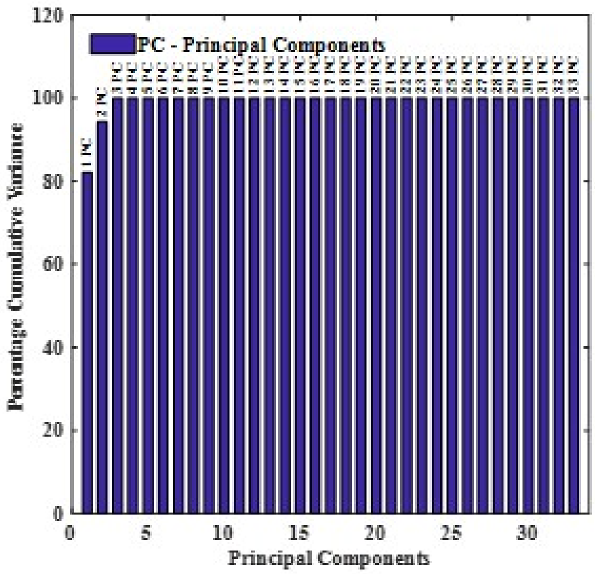

***Fig. 12**: Percentage cumulative variance vs. PCs for Electrode Region.*

the accuracy of the prediction model. The plot of the trained SVM model considering 1^{st} PC, 2^{nd} PC and 3^{rd} PC is shown in Fig. 14. Comparing to other regions, similar observation is recorded. The electric field features corresponding to the applied voltage have clustered for a particular electrode. Also, the 1^{st} PC captures the maximum variance of the electric field features followed by 2^{nd} and 3^{rd} PC respectively. However, all the 3 components are significant. The support vectors lie on the hyperplane and superimposed with the training data. Fig. 15 shows the comparison of the experimental and estimated breakdown voltage.

Breakdown voltage of vegetable oil medium is estimated considering three different regions of the electric field distribution space. Comparing all 3 regions, it is seen that experimental breakdown voltage fairly matches with the estimated values. However, it is not clear which region corresponds to better prediction. The error analysis is carried out to identify the region that provides nearly accurate estimated breakdown voltage. The experimental breakdown data is compared with the estimated values of each region and the Mean Square Error (MSE) is calculated. MSE ensures that the trained model has no outlier predictions with huge errors.

Table 2 shows the experimental and estimated breakdown voltage values. It is observed that mean square error is least for Electrode Region compared to other

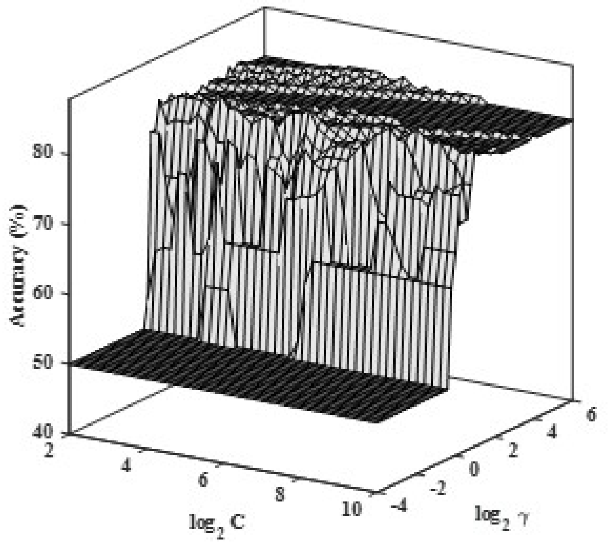

Fig. 13: *Accuracylog$_2C$ vs log$_2\gamma$ and for grid search for Electrode Region.*

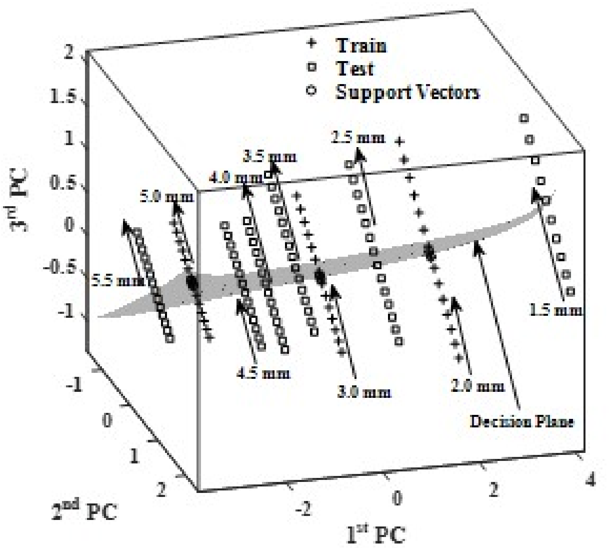

Fig. 14: *Trained SVM model for Electrode Region.*

Table 2: *Prediction and error calculation for three cases of discharge channel.*

Electrode Gap (mm)	Expt. (kV)	SVM Estimated (kV)		
		WR	CR	ER
1.5	18.0	18.0	16.0	16.0
2.5	32.5	31.0	30.5	30.5
3.5	49.0	45.5	46.0	46.0
4.0	50.5	51.5	52.0	52.0
4.5	58.5	59.5	61.0	60.5
5.5	71.0	77.0	69.5	70.0
MSE		1.2076	0.8779	0.8207

regions. Therefore, it can be expected that the breakdown occurred near the electrode region and of an intrinsic

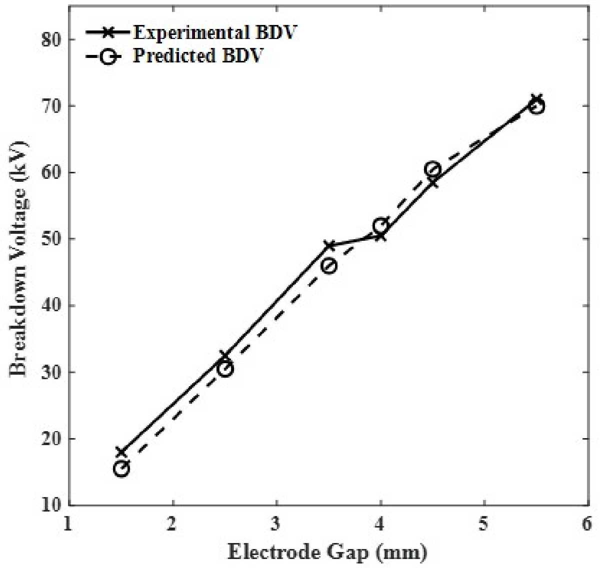

Fig. 15: *Comparison of experimental and estimated breakdown voltage for Electrode Region.*

Table 3: *Weibull parameters for different Sphere – Sphere electrode gap.*

Electrode Gap (mm)	Scale Parameter (kV)	Shape Parameter
1.5	29.8515	2.6878
2	32.7908	4.2880
2.5	38.1990	8.1537
3	49.8777	6.2251
3.5	56.9057	4.4135
4	61.7906	4.5838
4.5	64.8723	3.0360
5	67.4841	4.2815
5.5	76.4111	4.3095

Table 4: *Prediction and error calculation for electrode region with Sphere – Sphere electrode.*

Electrode Gap (mm)	Experimental (kV)	SVM estimated (kV)
1.5	30.0	27.0
2.5	38.0	40.5
3.5	57.0	57.0
4.0	61.5	62.0
4.5	65.0	68.0
5.5	76.0	72.0
	MSE	1.06

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3.2 Sphere – Sphere Electrodes

The breakdown voltage test is carried out using sphere – sphere electrode configuration. The sphere electrodes

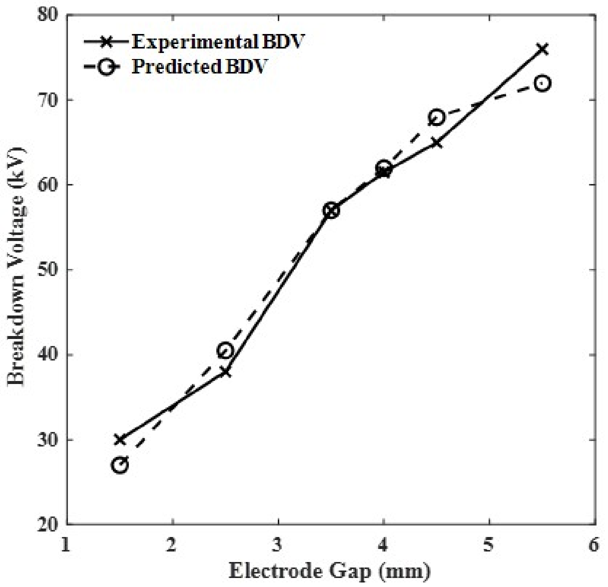

***Fig. 16**: Comparison of experimental and estimated breakdown voltage for Electrode Region.*

or ball type electrodes are as per IEC 60156. The electrode gap is varied from 1.5 mm to 5.5 mm and the ramp rate of applied voltage is kept constant at 5 kV/sec. Ten breakdown tests are carried out for each electrode gap. The table 3 shows the Weibull parameters of the breakdown test. The electric field distribution is simulated in FLUX software with sphere – sphere electrode shape. All the 11 electric field features and its 33 components are extracted for varying electrode gap. Similar to the plate – plate electrodes, these extracted features are post processed by normalization and dimension reduction was carried out using PCA. The electric field features are extracted for all 3 regions i.e., WR, CR and ER. In case of plate – plate electrodes, it is seen that electrode region gives better prediction accuracy compared to other regions. Therefore, in sphere – sphere electrodes the results of Electrode Region is reported. According to PCA, 3 components of electric field features are dominant. The PCA index corresponding to the Eigen values whose cumulative contribution of variance is significant ranges from $0.9003 \leq P \leq 0.9988$. According to grid search technique, prediction model highest accuracy of 89.02 % is obtained for $C = 12.99$ and $\gamma = 1.07$. Similar to plate – plate electrodes, 1^{st} PC is more significant and dominant compared to 2^{nd} PC and 3^{rd} PC. Fig. 16 shows the comparison of experimental and estimated breakdown voltage from the optimized SVM model for Electrode Region. The experimental and estimated values fairly match. Table 4 shows the SVM estimated breakdown voltage values and calculated error. The calculated Mean Square Error between the experimental and estimated value is found to be 1.06. Comparing Table 2 and Table 4, it is observed that estimated breakdown voltage based on ER is higher with Sphere – Sphere electrodes compared to plate – plate electrode. Given the size of the sphere or ball electrodes, this may be attributed to non – uniformity of electric field near the electrode region. Therefore, the accuracy may be less.

4. CONCLUSIONS

The breakdown test of vegetable oil, as an oil insulation medium, is carried out. The tests are done under varying electrode gap and electrode shape. The breakdown test results are analysed using Weibull distribution parameters. The characteristics breakdown voltage value used as a boundary condition to simulate the electric field distribution at breakdown condition. The electric field features are extracted from the simulated field distribution and processed to train SVM model. The trained SVM model is used to predict breakdown voltage.

With plate – plate electrodes, the breakdown voltage estimated using trained SVM model fairly matched with the experimental results. However, estimated breakdown value obtained considering electrode region has the least mean square error. It is seen that among all the 33 components, only 3 components are dominant and plays vital role in prediction of breakdown voltage. Similarly for sphere – sphere electrodes, the 3 components of electric field features are significant to estimate the breakdown voltage using SVM. It is understood that the mean square error is large and can be reduced using large set of experimental data for SVM training. Also it is possible other optimization technique might give better accuracy for estimation of SVM parameters.

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