Assessment of Partial Discharge Signatures in Transformer Oil Insulation using Hidden Markov Model

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Abstract: Condition based monitoring and assessment of insulating oil has become a vital constituent for ascertaining the reliability of oil-filled transformers. Partial Discharge (PD) measurement is one of the proven techniques to analyze the variations in discharge activity in insulating oil degradation under normal and abnormal operating conditions. PD activity is connected with the physical characteristics of oil and other external influencing factors like applied voltage, temperature, etc. Since PD pulse signature patterns are complex non-markovian process, capturing the time dependent variation of discharges during degradation of oil is important in understanding the dynamics of degradation. PD data is measured under the influence of both accelerated electrical stress conditions. Hidden Markov Model (HMM) is applied to characterize the stochastic behavior of the PD pulse transition in the insulation system. Continuous Density Hidden Markov Model (CDHMM) has been implemented to analyze the changes associated with PD phenomenon stress conditions. The PD signal has been preprocessed to compute the optimal state transition matrix using the Viterbi algorithm. The results show that the transition of PD pulses can be identified using the state transition matrix which display unique and significant changes in the discharge activity in insulating oil under different accelerated electrical stress conditions.

Keywords: Oil insulation, Accelerated Aging, Partial Discharges, Degradation Dynamics, Hidden Markov Model.

1. Introduction

A. Transformer Insulation System and Degradation

Mineral oil, Kraft paper and Pressboard form the major components of the complex insulation system in transformers. Suddenly varying system operating voltage due to transient phenomenon may lead to PD in oil insulation, which in turn leads to degradation of insulation. In addition, several losses which occur in transformers may increase the temperature of the liquid insulation and cumulatively lead to enhanced PD activity in the oil even under nominal operating voltage [2]. The influence of temperature in dielectric strength of oil insulation is also very much obvious as the results reported in [3]-[4] shows that the breakdown voltage decreases with increase in temperature initially and recover back at higher temperatures. In addition, different types of oil insulations exhibit unique variations in their physical and chemical characteristics during its normal real-time operation which may also lead to degradation. Catastrophic insulation failures due to the cumulative effect of degradation of major and minor insulation system in transformers continue to present impediments in ensuring improved reliability. The condition assessment techniques serve as a vital methodology to characterize the dynamics of key parameters related to the functioning of the equipment like transformers [1].

B. Stochastic Nature of Partial Discharge Phenomena

According to International Electrotechnical Commission (IEC 60270), Partial Discharge

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(PD) is a localized electrical discharge that only partially bridges the insulation between the conductors which may or may not occur adjacent to a conductor [5]. The locally enhanced electric field leads to the manifestation of a series of high frequency pulses [6]. Several detailed studies carried out by researchers to analyze the behavior of PD broadly categorize PD phenomenon either as a deterministic process or as a stochastic process [7]. Though classical approaches deal with measurement of mean value of PD (in pico-Coulomb) since computational difficulties are minimal, PD activity has an innate stochastic behavior due to a variety of aspects such as time of appearance of first initiatory electron for discharge, temperature and pressure at the site of discharge, space charge effect etc. According to [7]-[8], there are several factors which govern the stochastic behavior of PD in oil such as the growth rate of cavities in liquids, presence of ionizing radiation, probability of electron injection, electrical field strength, memory propagation effect, transition from positive to negative PD etc. Moreover, it is evident and appropriate that the process of assessing PD is carried out based on stochastic analysis due to the inherent statistical nature of electron avalanche. Major parameters which characterize PD signature sequence, namely the number of PD pulses (n), magnitude of discharge (q) and the phase instant of occurrence (Φ), describes the inter-relationship between these statistically varying parameters with respect to time, with constant applied voltage between electrodes.

It is more appropriate to correlate this unique feature of PD signature patterns with probabilistic model that utilizes a sequence similarity based strategy for analyzing the dynamics of oil degradation during PD monitoring and diagnosis. Hidden Markov Model (HMM), a statistical sequential clustering paradigm [9]-[10], augurs well in characterizing the stochastic nature of PD pulse transitions. HMM facilitates considerably better understanding of the variation of PD pulses and its transitions with respect to time through a sequence of observations in terms of the probability density estimates during every hidden state transition [11].

2. Test Setup for Experimentation–PD Detection, Measurement and Data Acquisition Process

The experimentation process involves testing and measurement of PD in the different oil insulation system at different voltages and aging time. This experimentation process provides a framework to ascertain various characteristics related to measurement of PD. IEC 60270 provides guidelines for carrying out PD measurement and analysis, which comprises three methods, namely Straight (Direct) detection method (consisting of two variant circuits), Pulse Discrimination Method and Balanced Bridge Detection method. The direct detection method is utilized for the experimentation in this research study since the work has been carried out in a controlled laboratory setup with suitable electromagnetic shielding, in addition to utilizing software filters using noise thresholding and removal as a part of the PD acquisition system software.

PD test setup comprises a High Voltage test transformer (MWB Make) of rating 10 kVA, 100 kV_{rms}, 50Hz along with a 1000 pF coupling capacitor and a measuring impedance (coupling quadrapole). Digital PD measurement and acquisition system with a built-in Tektronix digital storage oscilloscope (TDS2002 B) which displays pulse measurement in the range of 2 to 5000 pC is used. This oscilloscope also comprises a tunable filter-insert with a variable center select frequency (600 kHz – 2400 kHz) at a bandwidth of 9 kHz. [12].

A Perspex container of capacity 500 ml with an arrangement comprising a needle-plane electrode conFigureuration is fabricated to carry out experimental investigations pertaining to electrical stress in transformer oil at different voltage levels. The gap between the electrodes is maintained constant at 10 mm throughout the experimental studies. The needle tip radius is of the order of 200 µm. The various categories of oil samples and methodology for the preparation are mentioned in Table 1.

Table 1. Description of oil samples and its preparation process

Sample Description		Sample Preparation Process	Accelerated Electrical ageing tests
Sample 1	New untreated oil sample	New Iso-Paraffin Base ELECTROL® Oil as per IS 335	5 different voltage levels ranging from 13 kV - 21 kV
Sample 2	Oil aged during real-time operation	One naphthenic based oil sample is taken from an in-service transformer working since 2004.	
Sample 3	Oil with a mixture of solid dielectric material	New oil is mixed with Pressboard, Kraft paper, cotton tape, mica sheet, copper conductor wrapped with Paper and tape. The sample is heated in an oven to facilitate the disintegration of solid compounds into oil.	
Sample 4	Oil degraded with transient high voltage stress	Oil sample is subjected to 500 lightning impulse voltage shots generated from a Marx Impulse Voltage Generator.	
Sample 5	Thermally degraded oil	Oil under test is subjected to accelerated thermal ageing process in an air circulated thermal oven capable of heating up to 250ºC within ± 2ºC tolerance. The heated oil sample is cooled down to room temperature before subjecting them for PD measurement	

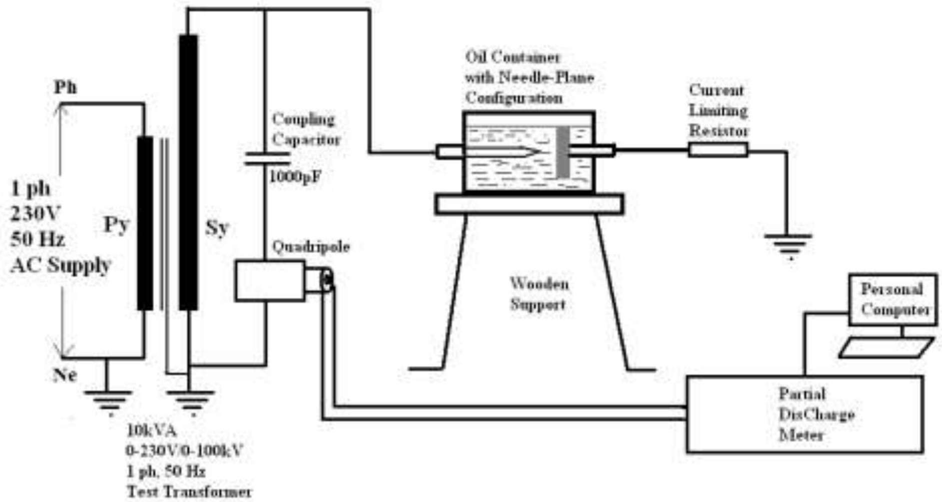

Figure 1. Test circuit for PD testing and measurement

During the experiment, the measurement of Discharge Inception Voltage (DIV) is also noted for all the samples and the subsequent acquisition of PD data is measured at the voltage levels ranging from 13 kV to 21 kV [13]. The test voltage has been chosen distinctly above the magnitude of DIV between 50% and 80 % of the breakdown voltage of the oil. In order to ensure meaningful, consistent and comparable physical conditions during testing and measurement of PD, the voltage across the electrodes has been maintained identical for all the benchmark sample studies. A current limiting resistor has also been connected in series with the sample under test to limit the current through the oil at the instant of breakdown. In addition to different accelerated voltage levels, the oil insulation has been stressed for longer time duration at a constant voltage to assess the influence of aging time on PD activity of oil samples. One new oil sample and an aged oil samples have been subjected to a fixed electrical stress for a time duration of 4 hour duration continuously and PD activity has been recorded every 20 minutes time interval. The data has been preprocessed and the optimal state transition matrix has been computed for each test case. Figureure 1 shows the test circuit for PD testing and measurement and Figureure 2 shows the snapshot of the test setup for PD testing. Figureure 3 shows the Partial Discharge measurement and data acquisition system. Figure 4 shows the typical PD pulse signature under a specific test condition.

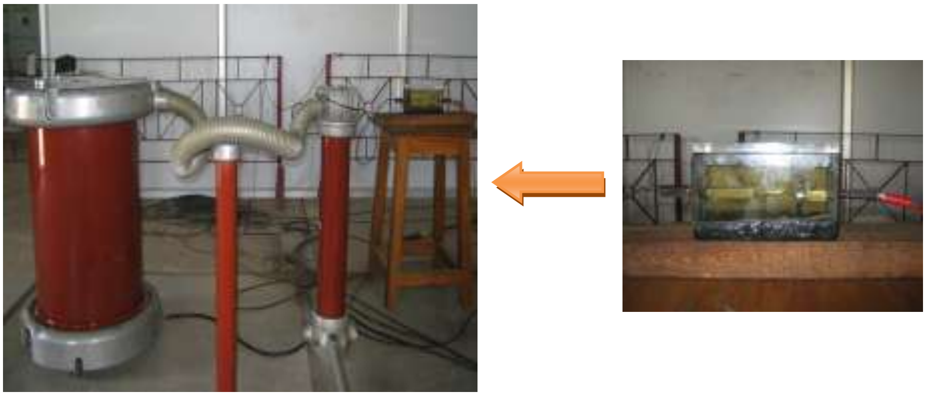

Figure. 2. Test Setup for PD Testing with oil test container.

Figure 3. PD Measurement and Acquisition System

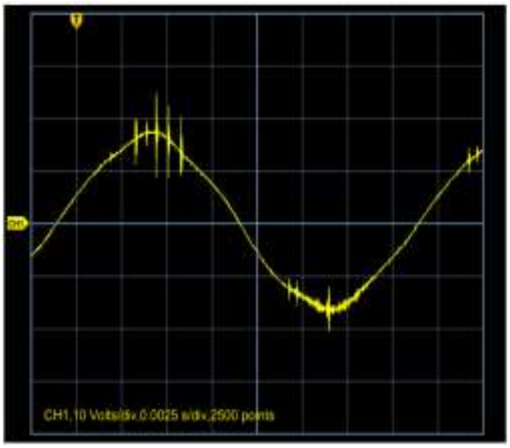

Figure 4.Typical PD pulse signature sequence

3. HMM – Continuous Density State Estimates for PD Dynamics in Insulating Oil

HMM is a doubly stochastic process which comprises an underlying stochastic process that is not directly observable but can only be visualized through another set of stochastic processes that produce a sequence of observations [14]. HMM is a compilation of states connected by transitions and emits an output during each transition. HMM falls under a subclass of Bayesian networks known as dynamic Bayesian networks, which are used to model time series data [15]. Two types of HMM are used by the researchers to analyze the dynamism in PD pattern recognition, namely (i) Ergodic HMM where in every state can be reached from every other state of the model in a finite time step and (ii) Non-ergodic HMM or left-right HMM wherein the state index increases with the increase in time. Figureure 4 shows the ergodic model of HMM.

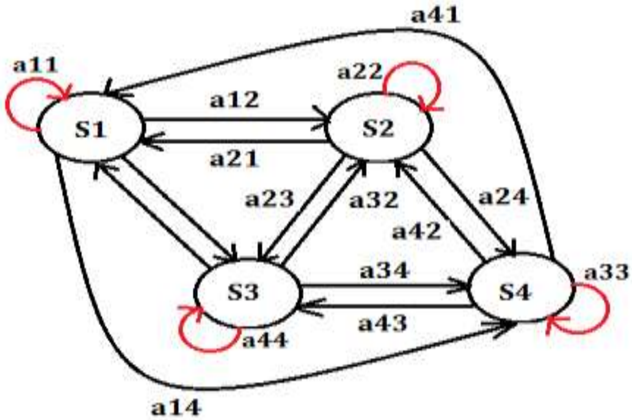

Figure 4. Ergodic Model of HMM

Further, HMMs are classified based on the process of computing probability density estimates as Discrete Density HMM (DDHMM) and Continuous Density HMM (CDHMM).

It is evident from recent research studies that the non-ergodic Continuous Density HMM has been implemented for the dynamic multiple source PD pattern classification task in a standard laboratory model to a considerable degree of success [12]. However, in this research, the ergodic CDHMM is implemented for computing the optimal state transition matrix for different oil samples treated under different applied voltages and aging time. The ergodic CDHMM is found most appropriate for implementation in this research for analyzing the dynamism involved in oil degradation since it has a capability to correlate distinct time dependent PD signature patterns.

Review of several studies carried out by researchers [10] clearly indicates that the discrete density HMM has been utilized for PD pattern recognition. In DDHMM, the observation probability density for a particular hidden state is discrete and is characterized by a unique value while the observation densities at each time step in the case of CDHMM are P-dimensional real valued vectors [16].

Implementation of HMM for the study of dynamic system response includes the following three major steps:

Calculation of probability of the observation sequence Pr $(O|\lambda)$ for $O = \{O_1, O_2, \ldots\ldots O_T\}$ using basic probability principles.

Computation of most optimal state sequence $I = \{i_1, i_2, \ldots .. i_T\}$ for a given observation sequence $O = \{O_1, O_2, \ldots\ldots O_T\}$ and model λ using Viterbi Algorithm. Viterbi algorithm gives the best sequence which maximizes the probability $Pr(O,I|\lambda)$

Adjustment of model parameters $\lambda = \{A, B, \Pi\}$ to maximize $Pr(O|\lambda)$

4. Preprocessing and Feature Extraction of PD Data

In HMM, the one–dimensional data are divided into segments wherein the sequence of features that represent the dynamism of the data are extracted unlike the conventional feature extraction process which extracts a single feature for the entire data set [17]. Conventionally, the preprocessed data of PD contain the phase angle (Φ), apparent charge (q) and number of discharge pulses (n). Though several research studies [18] proved the efficacy of Φ-q-n, the feature extraction methodology implemented in this research focuses on mean-slope-curvature based attributes in order to ascertain the capability of the CDHMM in capturing the dynamics of oil PD data.

It is appropriate that instead of obtaining discrete sets of features from the time varying signal, the features extracted for HMM analysis is based on an approach which captures the essence of time related to the dynamics of PD signature patterns. Hence, in this research, unique crossover points which represent critical changes occurring in the PD pulses is taken into consideration namely mean, slope and curvature features. Figure. 5 shows a typical statistically and stochastically time varying signal. The preprocessing of data is carried out by dividing the signal obtained during measured in a number of segments as phase windows of the same length. Hence, for each segment having a particular length, the slope, curvature and mean data has been computed such that it captures the critical points of the time varying signal. These sets of three tuple feature vectors are applied to obtain the state transition matrix and observation probability density estimates from the CDHMM.

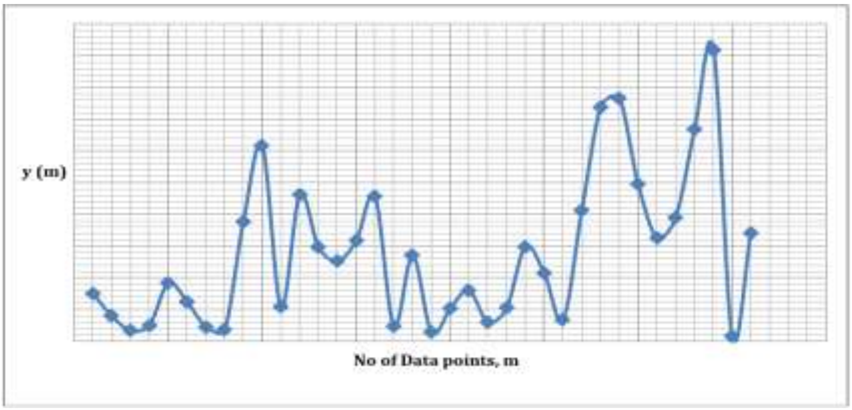

Figure. 5. Sample Time Varying Signal

In this research, PD signature data from different oil insulation samples have been preprocessed with the three features that describe the dynamics in the PD signature sequence, i.e. slope, curvature and mean at every 10° phase window of sinusoidal signal. Thus, the preprocessed data comprises 36 phase windows of 3 features each. This model utilizes 4 state transition labels for characterizing the dynamical behavior of oil insulation interms PD magnitude. Table 2 shows the PD data description for preprocessing.

Table 2. PD Data Description for preprocessing

Raw PD Data Dimension	PD data dimension after Preprocessing	Dimension of State Transition Matrix	Dimension of probability density estimate
100 x 199	100 x 108 (each bin contains mean – slope – curvature feature every 10° of PD data)	100 x 36	100 x 36

PD signal is usually observed to be distributed about the peak of both the positive and negative sinusoidal cycle while at the remaining points the data is very sparse. The state transition labels are chosen in such a way it represents the appropriate features of the entire PD data set. Figure. 6 depicts the choice of a number of state transition labels.

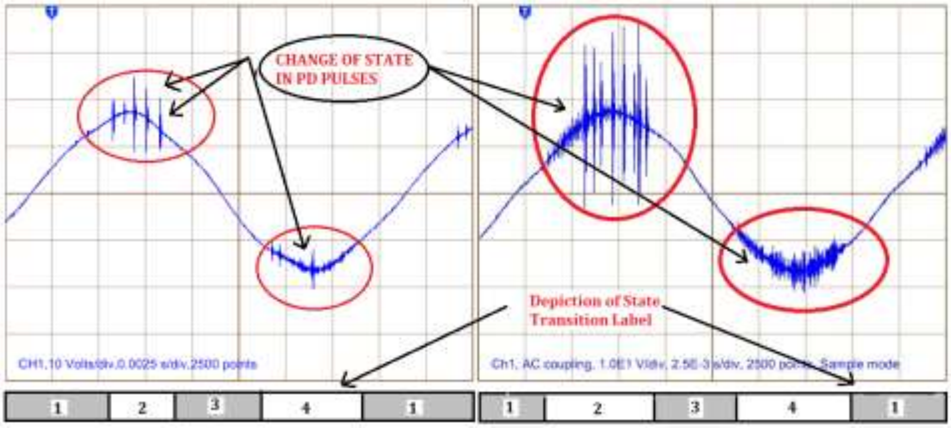

Figure. 6. Typical Pulse Signature with State Transition Labels

Figure 7 shows the implementation methodology for CDHMM taken up for the experimentation and detailed analysis of dynamical PD signature.

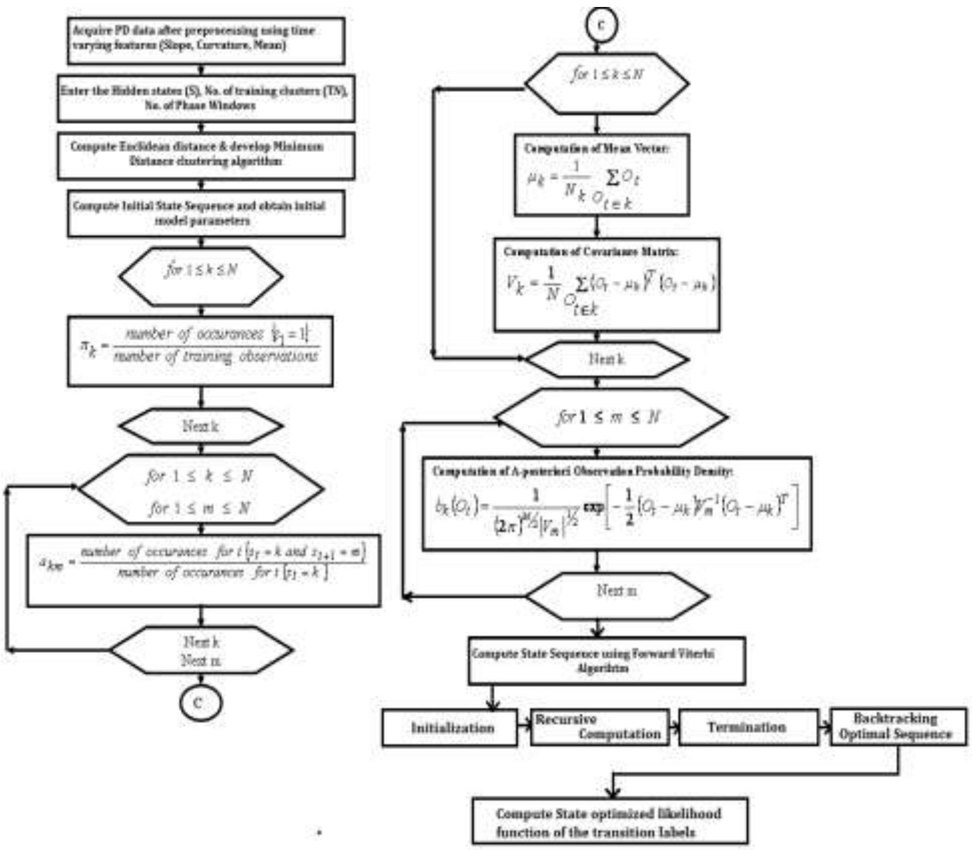

Figure 7. Flow Chart for the Development of CDHMM for PD Analysis

5. Observations and Analysis

The authors of this research had, in their previous work, carried out studies related to comparison of PD activity in different oil samples at different voltages using statistical parameters [15]. The results reported in [15] clearly had indicated the resemblance in the behavior of oil influenced by real-time operation and accelerated ageing mechanism at a particular voltage level.

Investigations carried out in this research are mainly intended to assess the dynamic behavior of PD pulses in oil insulation during degradation using CDHMM. The process of analysis in this research work includes periodic measurement of PD, setting up an appropriately chosen preprocessing strategy for PD data extraction, computation of optimal state transition label. The focus is on providing possible clues in recognizing the transition of PD pulses in oil through the estimation of the optimal state label. In this context, the following case-studies have been taken up for analysis and detailed investigations.

Case Study 1: PD activity and its transition on different oil samples
Case Study 2: Influence of applied electrical stress on insulation on PD activity and its transition
Case Study 3: Influence of aging time on PD activity and its transition

A. Case Study 1: PD activity and its transition on different oil samples

In this study, the PD testing is carried out on all the five samples at a constant voltage of 21 kV for a 10 mm gap spacing. Since the oil samples possess unique physical characteristics, PD activity in the oil exhibit diverse characteristics at different levels of voltages. The variations of PD activity are plotted as shown in Figure. 8 to enable better understanding of the intensity and dispersion of discharge pulses.

The PD behavior in case of the oil sample which has been mixed with solid dielectric materials and the sample which is subjected to thermal degradation are exactly similar when compared with the oil sampled from an in-service transformer. In all the three oil samples, the discharges aggravate intensely with the increase in applied voltage across the electrodes. It is evinced, from Figureure 8, that the role of solid dielectrics and temperature variations conspicuously display enhanced PD activity at higher voltages. Further, it is observed that the discharge pulses tend to concentrate (distribute) more on the positive peak of the voltage wave. Such behavior is not found in new insulating oil. This may be attributed to the theory related to suspended particle mechanisms and the role of breakdown characteristics in liquid dielectrics leading to alignment of particulate impurities. This inturn leads to enhanced PD in degraded oil samples.

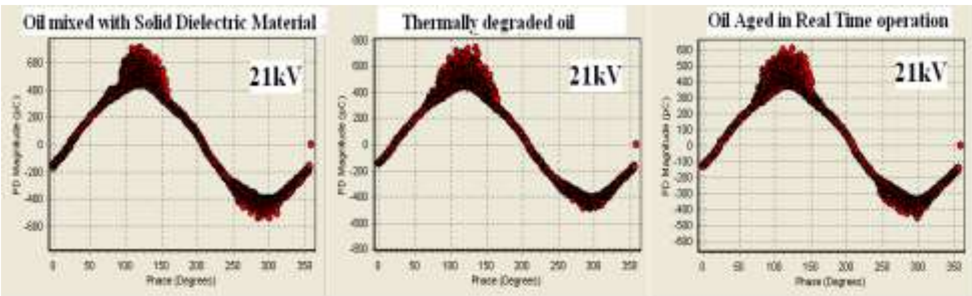

Figure 8. PD Activity in different Oil Samples

In addition to the measurement of PD activity, the state transition labels were computed from the CDHMM wherein the optimal state transition matrix for the preprocessed PD data have been computed using the Viterbi training algorithm. Since the preprocessed data represent every 10° of PD signal, it is pertaining to note from the results, that the transition of hidden state from one particular state to the other is implicitly exhibiting the transition of PD pulse from one instant to instant. The hidden states reflect the dynamism in PD pulses with respect to different oil samples. Table 3 shows the state transition map (indicted in colored shades) on each oil sample.

Table 3. State Transition Labels in different oil samples at a specific voltage level (21 kV)

Sample Type	State Transition Matrix representation with State Labels																																		
Sample 1	2	2	2	3	3	3	3	4	4	4	4	4	4	4	4	4	4	4	4	3	3	3	3	2	2	2	1	1	1	1	1	1	1	1	1	1
Sample 2	2	2	3	3	3	3	3	4	4	4	4	4	4	4	4	4	3	3	3	3	3	2	2	2	2	1	1	1	1	1	1	1	1	1	2	2
Sample 3	2	2	3	3	3	3	3	3	3	4	4	4	4	4	4	3	3	3	3	3	3	2	2	2	1	1	1	1	1	1	1	1	1	1	1	2
Sample 4	2	2	3	3	3	3	3	4	4	4	4	4	4	4	4	4	3	3	3	3	3	2	2	2	1	1	1	1	1	1	1	1	1	1	1	1
Sample 5	2	2	3	3	3	3	3	4	4	4	4	4	4	4	4	4	4	4	3	3	3	2	2	1	1	1	1	1	1	1	1	1	1	1	1	1

Table 4. Statistics of State Transition labels for Case Study 1

Sample Description	Dominant State	Transition From	Transition Probability (%)	Occurrences of dominant state	No of iterations
Sample 1	4	3 – 4	12.5	12	6
Sample 2	3	2 -3 and 4 -3	14.3 & 12.5	10	6
Sample 3	3	2-3 and 4- 3	14.3 & 14.3	13	12
Sample 4	1	2-1	20	12	6
Sample 5	1 & 4	2-1 and 3- 4	20 & 14.3	12	9

From Table 4, it is clear that among the optimal state sequence containing 4 different states, one hidden state dominates each oil sample. Domination of any one hidden state in the samples indicates that the observation probability density cluster pertaining to oil samples varies accordingly and depends on the PD activity in oil at a particular time. This clearly shows that the PD in oil is influenced mainly by its characteristics which in turn depend on the degradation mechanism and operating condition.

It is observed that there is a notable variation in the values of density estimates in new untreated oil and degraded oil. In the case of degraded oil, irrespective of the mode of degradation, the phase instant at which the maximum density value occurs remains constant, whereas the magnitude of density varies accordingly for all the samples.

Further, the transition probability from one state to another state varies appreciably in all the samples within a range of 8 % to 20 % clearly indicating the fact that the change of hidden states is dynamic and portrays the dynamic characteristics of oil samples owing to degradation.
Also, it is worth noting that the number of iterations required to obtain the optimum state transition matrix is maximum (for a fixed computational parameters) for the sample aged under real-time conditions which has more complexity in PD data due to the combined effect of solid insulating materials and temperature.

B. Case Study 2: Influence of applied electrical stress on insulation on PD activity and its transition

In this case, PD measurement and analysis is carried out for a specific oil sample and the applied voltage is varied between 50% and 80 % of the breakdown voltage. The same procedure (as considered in Case Study 1) related to implementation of preprocessing technique, computation of the hidden state transition matrix. Table 7 and Table 8 shows the details of transition of states for the sample when subjected to different voltages and the related statistical measures respectively. It is observed from Figureure 9 that both the magnitude and the number of PD pulses has been widely increasing as the applied voltage increases. This increased in PD activity is due to the enhanced electric field across the electrode gap which orients the impurity particles and voids present in the insulating oil.

Table 7. State Transition Labels at different voltage levels (13kV to 21kV)

Applied Voltage	State Transition Matrix representation with State Labels																																		
13 kV	2	2	3	3	3	3	4	4	4	4	4	4	4	4	4	4	4	4	3	3	3	2	2	2	1	1	1	1	1	1	1	1	1	1	1	1
15 kV	2	2	3	3	3	3	3	4	4	4	4	4	4	4	4	4	4	4	3	3	3	2	2	2	1	1	1	1	1	1	1	1	1	1	1	1
17 kV	2	2	3	3	3	3	3	3	3	4	4	4	4	4	4	3	3	3	3	3	3	2	2	2	1	1	1	1	1	1	1	1	1	1	1	1
19 kV	2	2	3	3	3	3	3	3	3	4	4	4	4	4	4	4	3	3	3	3	3	2	2	2	2	1	1	1	1	1	1	1	1	1	1	1
21 kV	2	2	3	3	3	3	3	3	4	4	4	4	4	4	4	4	4	3	3	3	3	2	2	2	2	1	1	1	1	1	1	1	1	1	2	2

Table 8 Statistics of State Transition labels for Case Study 2

Sample Description	Dominant State	Transition From	Transition Probability (%)	Occurrences of dominant state	No of iterations
13 kV	1	2-1	20	13	5
15kV	1 & 4	2-1 and 3-4	20 & 12.5	11	3
17kV	3	2-3 and 4-3	20 & 16.6	13	9
19 kV	3	2-3 and 4-3	16.6 & 14.3	12	6
21 kV	3	2 -3 and 4 -3	14.3 & 12.5	10	6

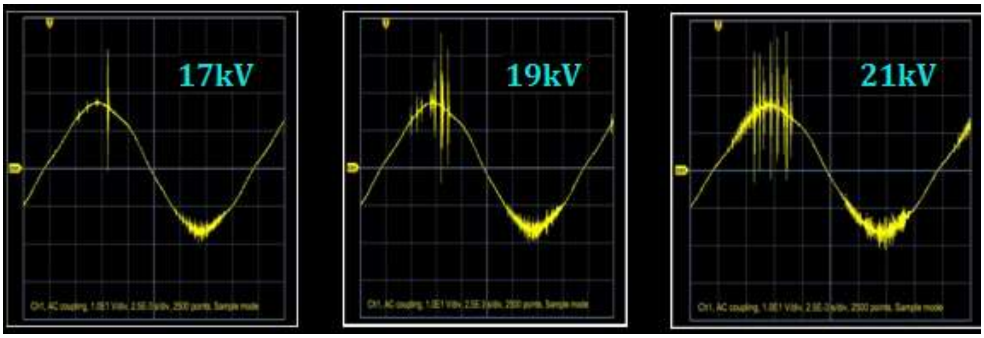

Figure 9. PD activity at different voltage levels

It is evident from the results that for a given physical condition of the oil, the changes in discharge states are obvious when the oil is stressed with varying voltage levels. The dominant state for the given oil sample and the transition between two states occurs at different probabilities. It is worth mentioning that the transition of PD pulses is unique for all the applied voltages. This indicates the influence of voltage on the PD activity in oil, but the variation in patterns of various instants of PD pulses depends on the chemical composition of the oil which has been governed by the mode and intensity of degradation.

C. Case Study 3: Influence of aging time on PD activity and its transition

In this segment, one virgin oil sample and aged oil samples have been subjected to a fixed electrical stress for a time duration of 4 hours continuously and PD activity has been recorded every 20 minutes time interval. The data has been preprocessed and the optimal state transition matrix has been computed as in case 1. This time based PD measurement is intended to analyze the time dependent variation of PD pulses. The following results were recorded when the PD is measured in a new oil for 4 hours at a constant test voltage across the electrode setup.

C.1. New oil under accelerated stress conditions

It is observed that, in new oil, the PD pulse magnitude is higher during the initial stages of applied voltage and as time progresses, the PD magnitude and number of PD pulses were reduced slightly. Further, there is no wide variation in the PD value during the course of time.

- When the PD is measured near DIV, it is very hard to note the sustained PD pulses during the course of test duration.
- When the oil is tested at about 60% of breakdown voltage, it is observed that there is a reduction in PD magnitude (in Pico coulomb) at about 30% at the end of 4^{th} hour when compared with the initial PD magnitude.
- When the oil is tested at about 80% of breakdown voltage, it is observed that there is a reduction of 23% in PD magnitude at the end of the 4th hour. Further, frequent rise and fall of PD pulses has been noted.

C.2. Oil aged under accelerated conditions

Variations observed in the aged samples are mentioned below and Figure. 10 shows the status of PD activity at various time instants.

- When the oil is tested near DIV, it is possible to note, sustained PD pulses for the initial hours to the final hours of testing. Approximately 10% to 25% increase in the PD pulses is noted.
- When tested at higher voltages, PD pulses are less during the initial hours of testing and it is observed, there is a substantial increase in the pulses after 3 hours duration.
- Shifting of pulses from the peak of the sine wave to zero crossing is observed.

Table 9. State Transition Labels for longer aging time of oil samples

Aging Time (Min.)	State Transition Matrix representation with State Labels																																		
0	1	1	1	4	1	4	4	4	1	4	1	4	1	1	1	1	4	4	4	1	4	4	1	4	1	1	1	4	4	4	1	1	4	4	1	4
20	1	1	1	4	1	4	4	4	1	4	1	4	1	1	1	1	4	4	4	1	4	4	1	4	1	1	1	4	4	4	1	1	4	4	1	4
40	1	1	1	4	1	4	4	4	1	4	1	4	1	1	1	1	4	4	4	1	4	4	1	4	1	1	1	4	4	4	1	1	4	4	1	4
60	1	1	1	4	1	4	4	4	1	4	1	4	1	1	1	1	4	4	4	1	4	4	1	4	1	1	1	4	4	4	1	1	4	4	1	4
80	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	2	2	2	2	2	2	2	2	2	2
100	1	1	1	2	2	2	2	2	2	2	1	1	1	2	2	2	2	2	2	2	2	2	1	1	1	1	1	1	1	1	1	1	1	1	1	2
120	1	1	1	2	2	2	2	2	2	2	1	1	1	2	2	2	2	2	2	2	2	2	1	1	1	1	1	1	1	1	1	1	1	1	1	2
140	4	4	4	4	4	1	1	1	1	1	1	1	4	1	1	1	1	1	1	1	1	1	1	4	4	4	4	3	3	3	3	3	3	4	1	4
160	3	3	3	3	1	1	1	1	1	1	1	1	3	1	3	1	3	1	3	1	3	1	1	3	3	3	1	3	3	1	1	3	3	1	3	1
180	3	3	3	3	1	1	1	1	1	1	1	1	3	1	3	1	3	1	3	1	3	1	1	3	3	3	1	3	3	1	1	3	3	1	3	1
200	4	4	4	1	1	1	1	1	1	1	1	1	1	4	1	1	1	1	1	1	4	1	1	1	4	4	4	1	4	2	2	2	2	4	1	4
220	4	4	4	1	1	1	1	1	1	1	1	1	1	4	1	1	1	1	1	1	4	1	1	1	4	4	4	1	4	2	2	2	2	4	1	4
240	4	4	4	1	1	1	1	1	1	1	1	1	1	4	1	1	1	1	1	1	4	1	1	1	4	4	4	1	4	2	2	2	2	4	1	4

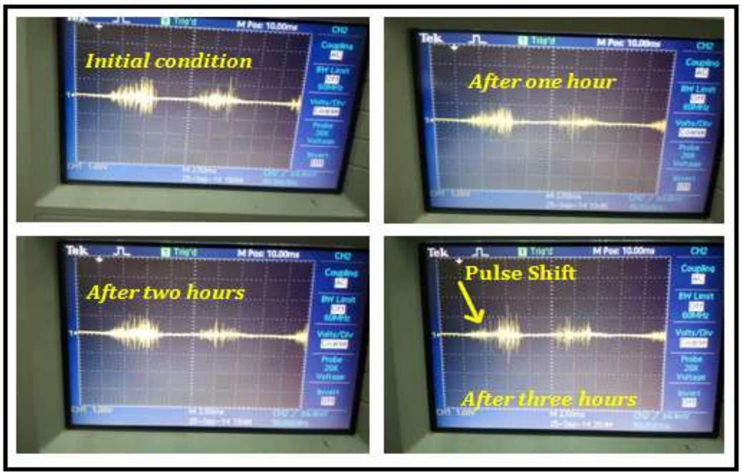

Figure 10. PD Activity in Aged Oil Sample for Longer Duration

Table 9 shows the state transition label for a virgin sample at every 20 minute time interval. From the transition label, it is evident that there is an appreciable change in the state of PD activity after every 60 minutes time interval.

From the above analysis, it is evident that the PD activity depends on the physical characteristics of the insulation and magnitude of applied stress level. Further, it has been observed that, the discharge activity exhibits time dependent variations with unique pulse transitions. The optimal state transition labels computed for each case show the phase instant of the applied sinusoidal wave where exactly the transitions are prevalent. The PD pulse transitions and state transition labels have been correlated to characterize the dynamics of PD under different voltages and aging time.

6. Conclusion and Future Scope

In this research, the feasibility of Continuous Density Hidden Markov Model has been verified to assess the dynamics of time varying PD signal in oil insulation system. The computational part of this research includes the measurement of PD in different insulations samples at different voltages and aging time, preprocessing of PD data for the extraction of dynamical features and determination of optimal state transition matrix. From the combined experimental and computational investigations carried out on the oil samples, significant conclusions have been deciphered by correlating the variations in state transition matrix and time varying PD signal.

- The state transition matrix for each sample is very unique. It is obvious that due to the variation in PD signals, the same has been reflected in the HMM parameters.
- The transition between one state to the other is distinct in each oil sample with varying probability percentage.
- The time dependent changes in PD pulses have been identified by correlating the PD pulse with state transition labels.
- HMM parameters are exceedingly capable of displaying the variations occurring in PD signals due to different applied voltages and the phase instant where the transition is prevalent.
- With this CDHMM approach, the complexity in analyzing the PD data for understanding its dynamics has been reduced.

The future studies will focus on implementing the other versions of HMMs since this methodology may provide more viable analysis in time variant state estimation procedure and yield more plausible solutions in dealing with the dynamic aspects of insulation oil.

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