Diagnostic Techniques for Condition Monitoring of Insulation System of Power Apparatus- Computational Intelligence & Discrete Mathematical Tools

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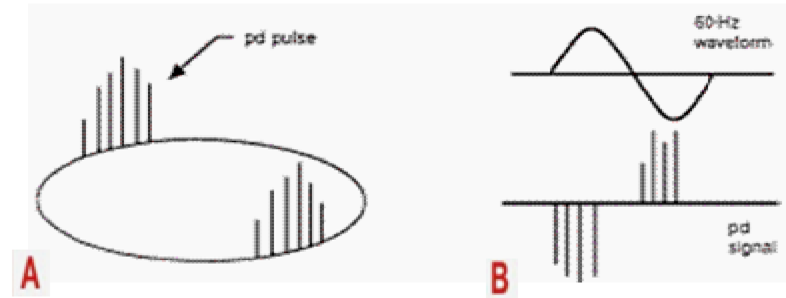
CONTENTS

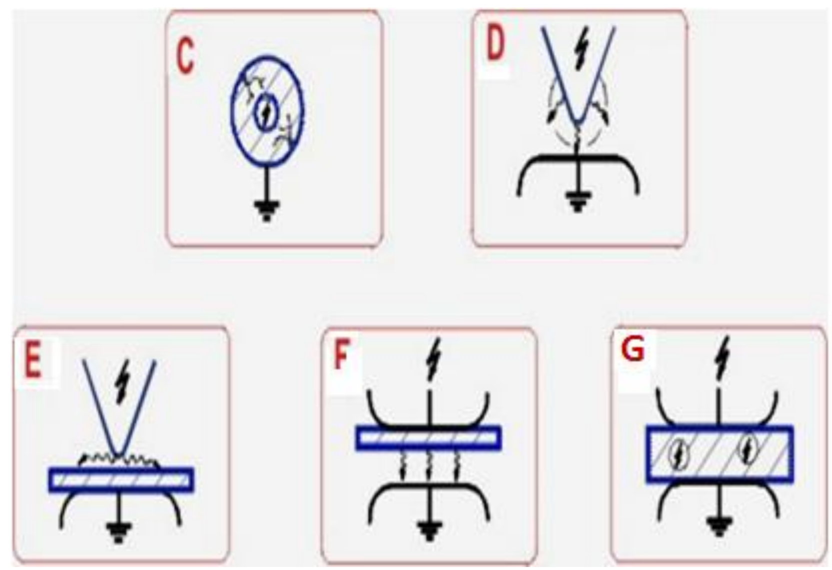
- NEED FOR PD PATTERN RECOGNITION
- SURVEY OF AI AND ASSOCIATED TECHNIQUES USED IN PD INSULATION DIAGNOSIS
- MOTIVATION FOR CARRYING OUT THE RESEARCH
- GOALS & OBJECTIVES OF THE RESEARCH
- FRAMEWORK FOR DEVELOPMENT OF HYBRID CLASSIFIER VERIONS FOR MULTIPLE SOURCE AND DYNAMIC PD PATTERN RECOGNITION AND DIAGNOSIS
- RESEARCH STUDIES FOR DEVELOPMENT OF HYBRID CLASSIFIER VERSIONS FOR MULTI-SOURCE AND DYNAMIC PD PATTERN RECOGNITION:
  - LABORATORY TESTING- BENCHMARK MODELS & INDUSTRIAL OBJECTS
  - DIGITAL PD MEASUREMENT, ACQUISITION AND PRE-PROCESSING
  - SALIENT ASPECTS OF PNN VERSIONS AND CLUSTERING ALGORITHMS
  - OBSERVATIONS, ANALYSIS & RESULTS
- INFERENCES & CONCLUSIONS

NEED FOR PD PATTERN RECOGNITION

- **Power utilities and industries have installed on-line PD diagnostic system** to assess insulation of power apparatus
  - **Caters to risk assessment** rather than providing solutions to identification of PD source
- **Identification of sources of PD is a fundamental yet vital step** towards successful diagnosis of insulation systems:
  - **Various defects influence the reliability** of insulation system **in unique ways**
  - **Comparison of PD signatures** between reference (benchmark) and experimental patterns **is largely diffused**
  - **Multiple PD sources are usually encountered during real-time/ practical measurement**



Typical PD Pattern Representation on A. Elliptical and B. Sinusoidal Base



C. **Treeing in Coaxial Configuration**
D. **Air Corona**
E. **Surface Discharge**
F. **Discharge at Dielectric Interface**
G. **Void/ Cavity Discharge**

Calibration & Measurement.wmv

ices 2013 sequence similarity presentation\samples of void with 3 varying voltages.xls

MOTIVATION FOR RESEARCH

FROM THE PERSPECTIVE OF CLUSTERING/ AI ALGORITHMS:

A major classical work in the field of data mining and AI has summarized the need for multifarious approaches for successful pattern recognition

Research Paper	Authors & Journal	Brief summary of Various Clustering Techniques Used for Pattern Recognition		Features/ Characteristics	Type of Algorithm utilized in this research
Survey of Clustering Algorithms	Rui Xu & Donald Wunsch IEEE Trans. on Neural Networks, Vol.16, No. 3, 2005	Partition Methods	Square Error Based	1. Tends to build cluster of proper convex shape 2. relates dense connected components that are flexible in terms of their shape	Versions of Vector Quantization Versions of K-means
			Density Estimation		Gaussian Mixture Density with EM-ML algorithms
		Graph Theoretic Methods	Cluster affinity search Cluster identification via connectivity kernels	Topological structure of data thro' binary relations; Learning thro' HG properties instead of Kernel functions.	Hyper-graph (HG)
		AI , NN and Evolutionary Methods	ANN Evolutionary Constraint Based	Supervised and Unsupervised learning techniques	LVQ Versions Orthogonal Least Square EM-ML algorithms
		Sequence Data	Sequence Similarity Indirect Sequence Statistical Sequence	Dynamic behaviour with time constraints	Stationary and Non-stationary Continuous Density HMM Versions
		High Dimensionality	Subspace Clustering Projection Techniques Co-clustering Techniques	Attribute and Domain decomposition	Principal Component Analysis with the following: 1. Discrete Wavelet Transformation- Diebuchies 2. S- Transform and its variants

GOALS & OBJECTIVES OF PROPOSED RESEARCH

GOAL:

- **DEVELOP HYBRID NEURAL NETWORK CLASSIFIER VERSIONS FOR DIAGNOSIS OF INSULATION SYSTEMS**
    - **Continuous Density HMM- PNN Versions**
    - **S- Transform based PNN Versions**
    - **Hypergraph based clustering with PNN Versions**

OBJECTIVES:

- **Provide solution for diagnosis of large database** exhibiting the following characteristics:
    - **High Dimensionality Input Data (Curse of Dimensionality)**
    - **Over fitting of Training Database**
    - **Fully Overlapped patterns**
- **DEVELOP CLUSTERING ALGORITHMS FOR TRAINING NNs:**
    - **Sequence Similarity based Clustering:**
        - **Continuous Density Hidden Markov Model (CDHMM):**
            - **Stationary & Non-Stationary Versions**
    - **High Dimensionality Clustering:**
        - **Discrete S- Transform: Generalized S- Transform (ST) & Hyperbolic- ST (HST)**
    - **Graph Theoretic Clustering:**
        - **Properties of Hypergraph for noise removal, segmentation and edge detection**
            - **Helly, Bonded Sets, Duality, Conformality etc**

EXPERIMENTAL STUDIES FOR DEVELOPMENT OF HYBRID PNN CLASSIFIERS FOR MULTIPLE SOURCE AND DYNAMIC PD PATTERN RECOGNITION

EXPERIMENTATION OF MULTIPLE SOURCE PD PATTERN RECOGNITION:

- **Benchmark Laboratory Models replicating:**
  - **Electrode bounded cavity (single/ multiple)**
  - **Air- Corona**
  - **Oil- Corona**
  - **Electrode bounded cavity with Air- Corona**
  - **Surface Discharge in Air and Oil**
  - **Electrical Treeing**
- **Cross Linked Polyethylene (XLPE) Cables simulating:**
  - **Electrode Bounded Cavity (single)**
  - **Gliding (surface) discharges**
  - **Multiple Source Discharges- Cavity with Surface Discharges**
- **Pollution Initiated Flashover Studies in Ceramic Insulators**
  - **Varying Salinities and varying sources of surface discharges:**
    - **Cap, pin, ribs & pin-cap**
- **Bushing in Distribution Transformer simulating:**
  - **Gliding discharges due to pollution, Corona discharges and Partially overlapped multiple sources (Gliding discharges with Air-Corona)**

FABRICATION OF BENCHMARK LABORATORY MODELS DEPICTING VARIOUS PD SOURCES

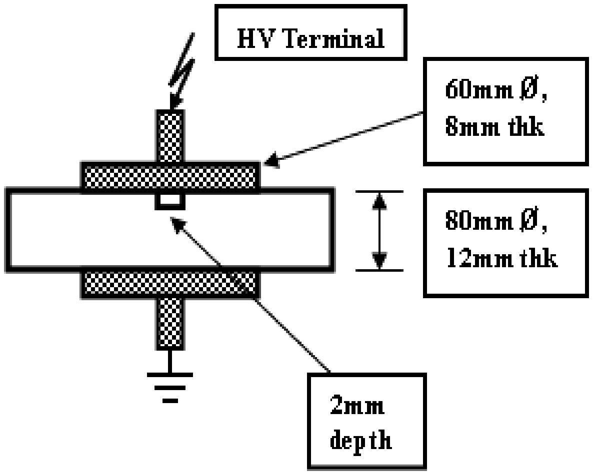


Fig. 1: Electrode Bounded Cavity

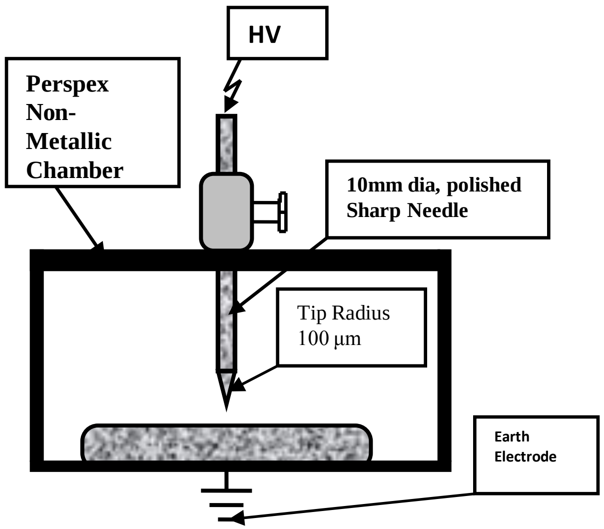


Fig. 3: Air- Corona

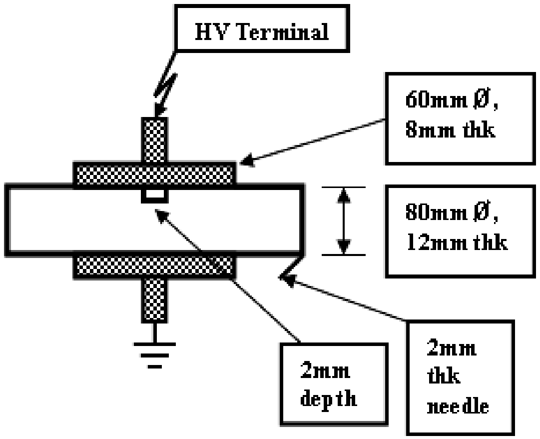


Fig. 5: Electrode Bounded Cavity with Air- Corona

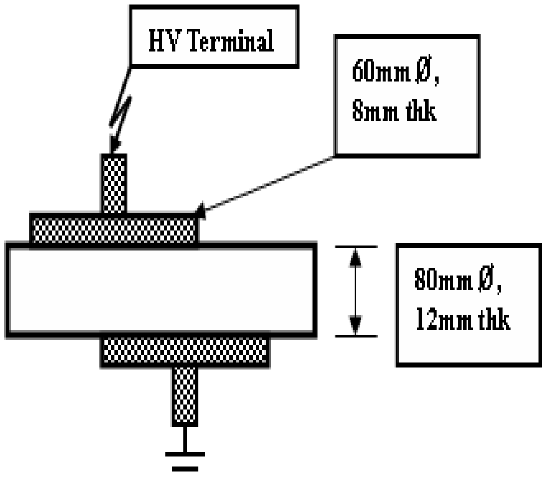


Fig.2: Surface Discharge

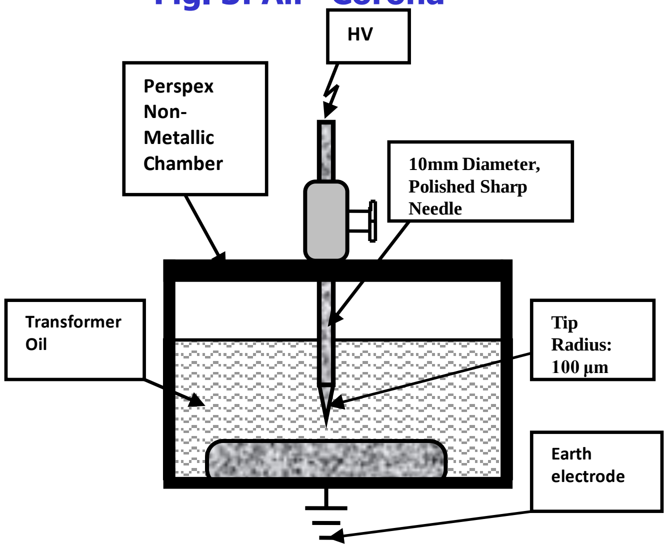


Fig. 4: Oil- Corona

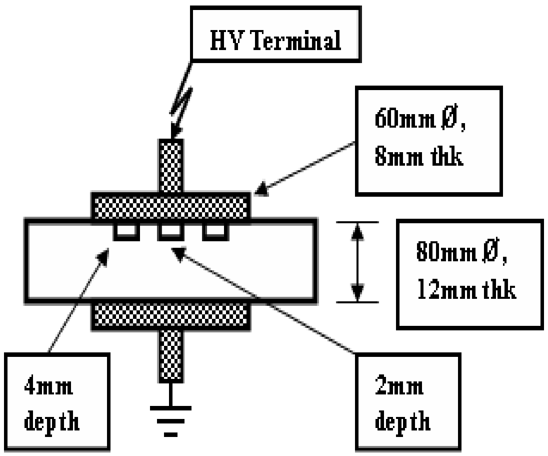


Fig. 6: Multiple Electrode Bounded Cavities

BENCHMARK LABORATORY MODELS & REAL-TIME OBJECTS DEPICTING VARIOUS PD SOURCES

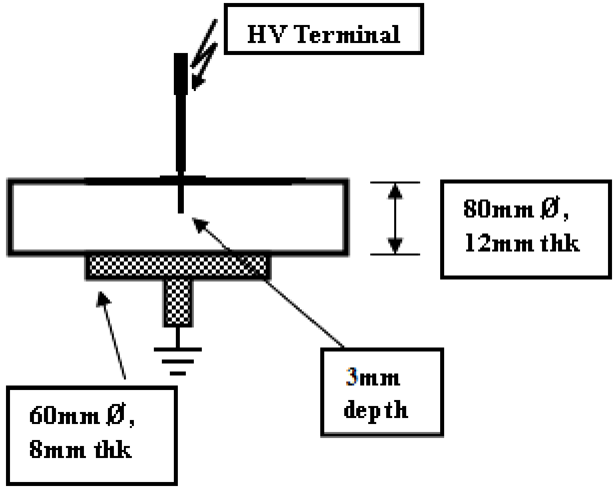


Fig. 7: Electrical Treeing

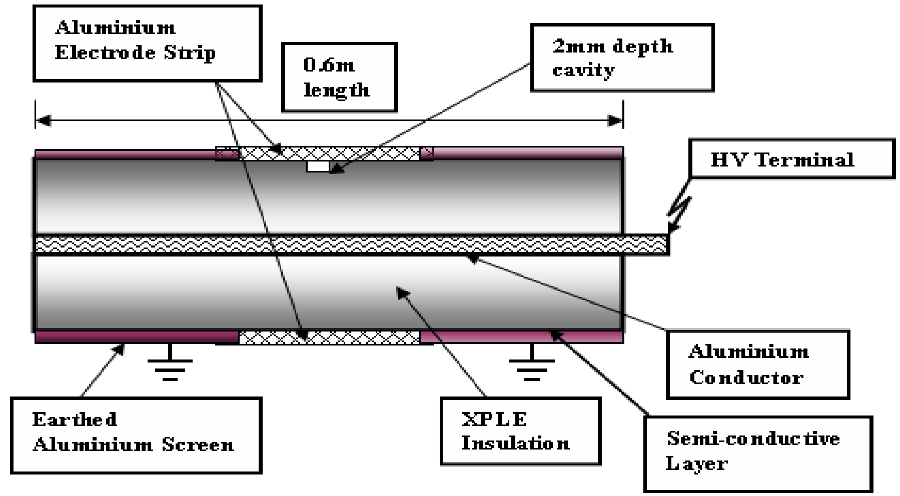


Fig. 9: Cable simulating Electrode-bounded Cavity

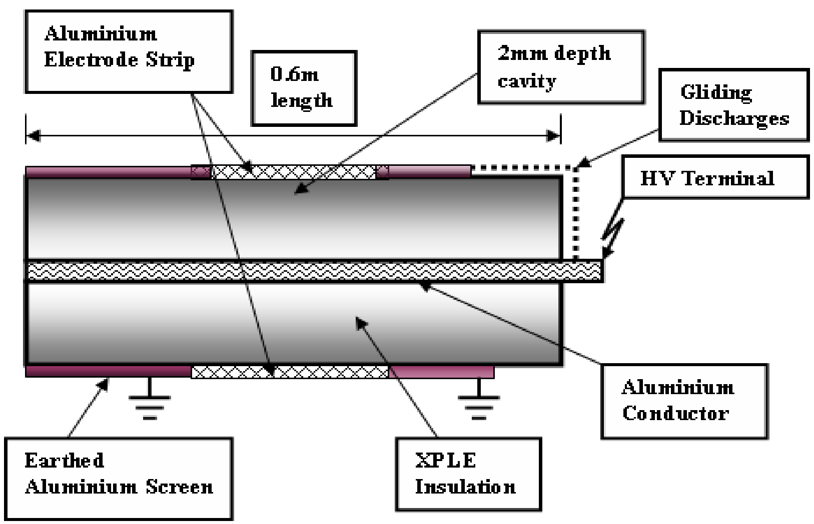


Fig. 8: Cable Sample replicating Gliding Discharges due to Missing Semi-Conductive Layer

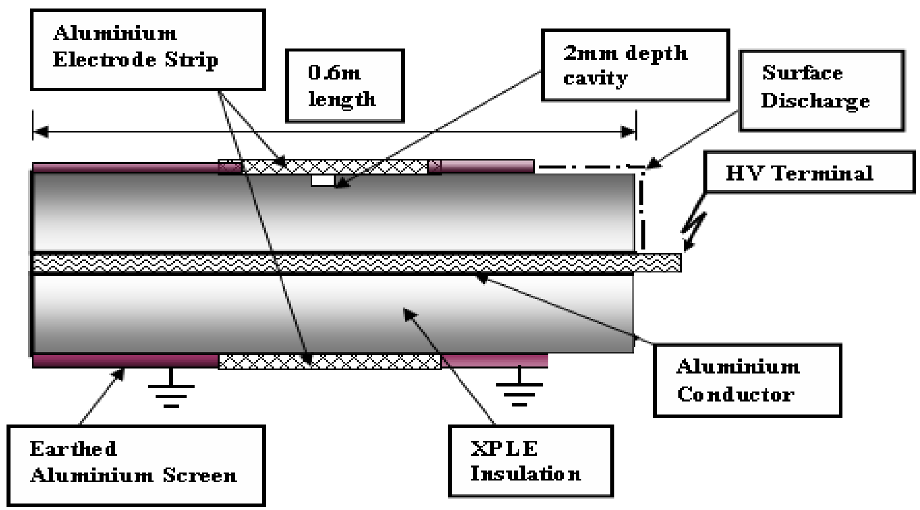
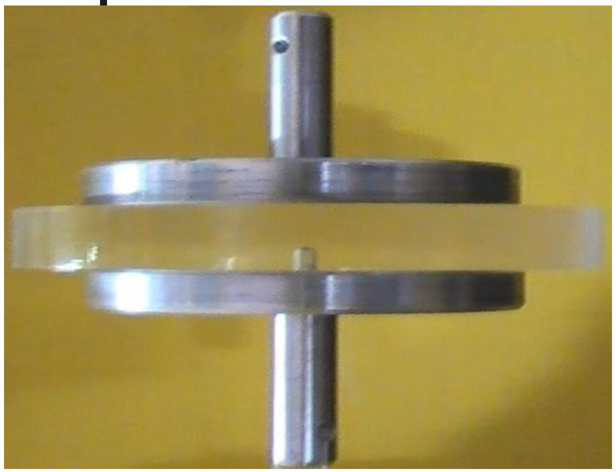


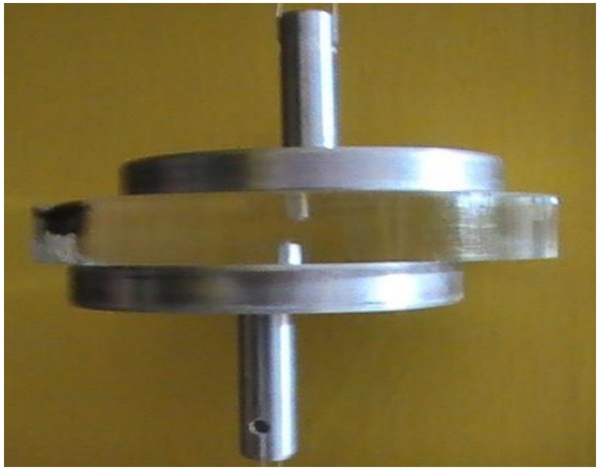
Fig. 10: Cable Sample depicting Multi-Source (Electrode-bounded Cavity with Surface Discharge)

PHOTOGRAPH OF BENCHMARK LABORATORY MODELS REPLICATING DIFFERENT PD SOURCES



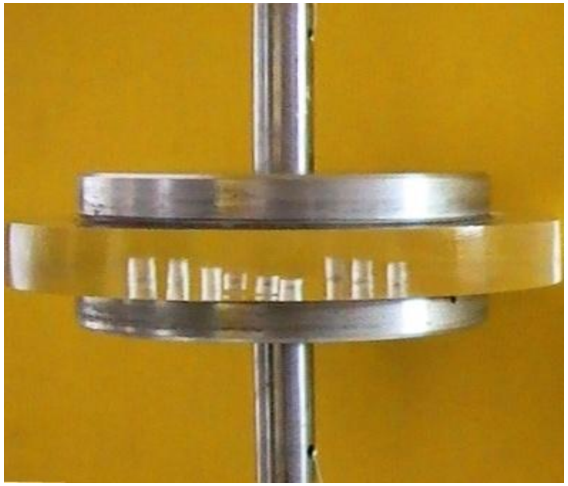
Perspex & Cast Resin Models replicating Cavity Discharges

Air & Oil Corona Model with an 85° apex angle electrode on HV bus



Model replicating Multiple Source Electrode Bounded Cavity with Surface Discharges

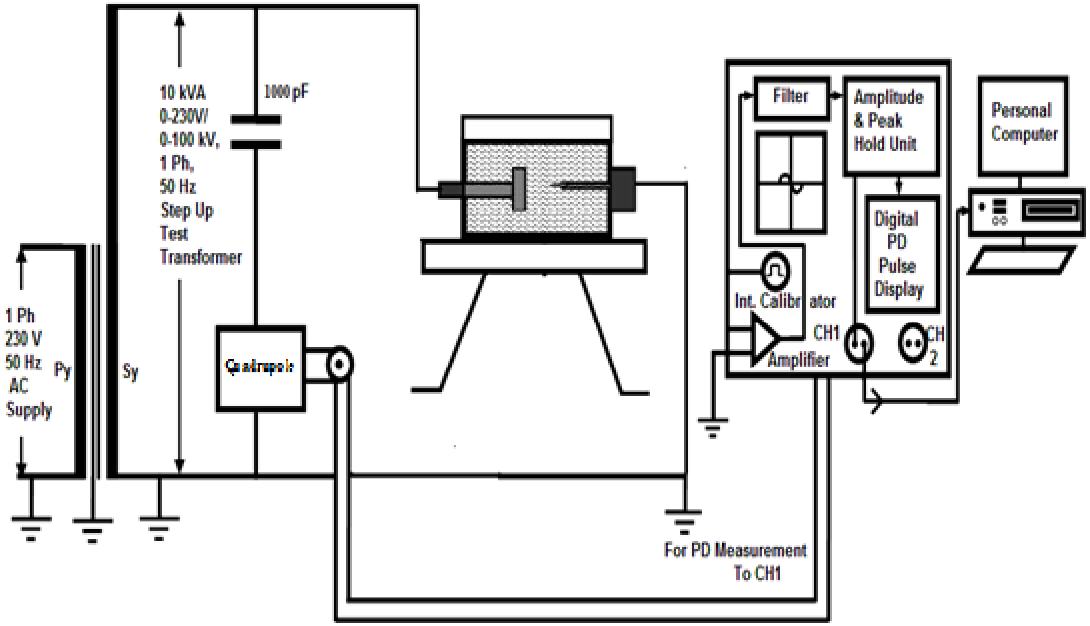
Model replicating Electrode Bounded Cavity overlapped on Air-Corona Discharges



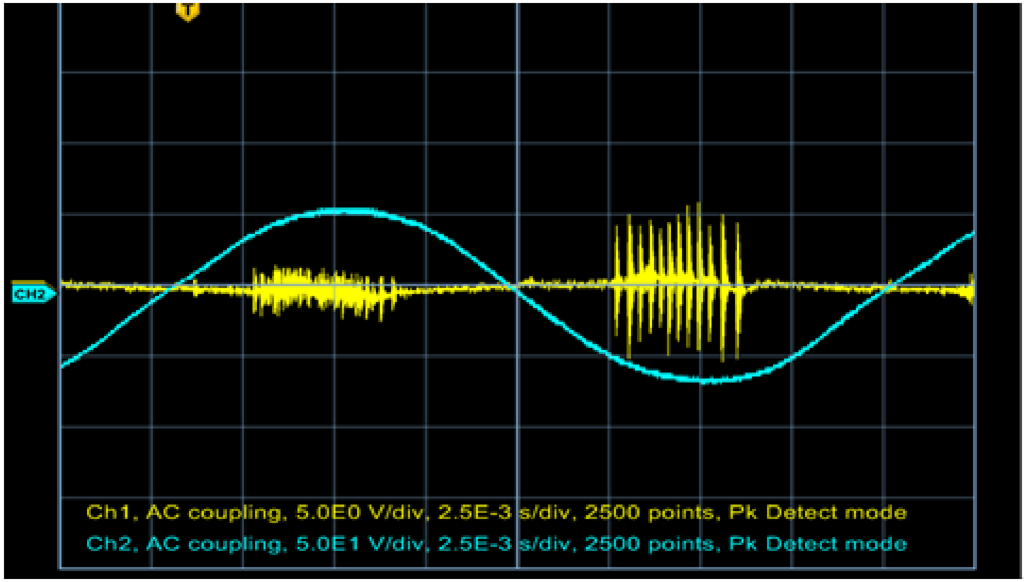
Model replicating Multiple Source Electrode Bounded Cavity

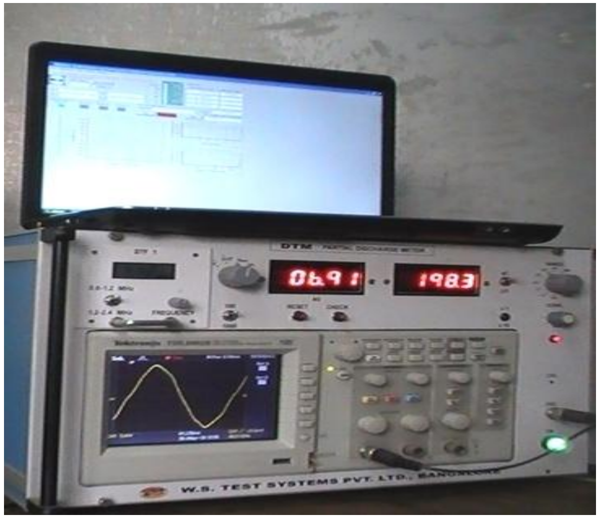
Model replicating Needle-Plane Electrode Configuration for simulating Electrical Treeing

TYPICAL EXPERIMENTAL PD TEST SETUP AND ACQUISITION SYSTEM



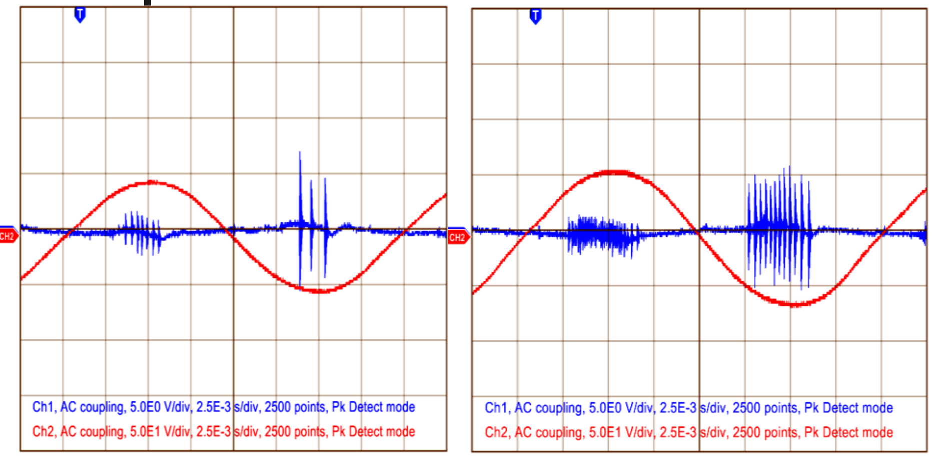
PD Test Setup.wmv



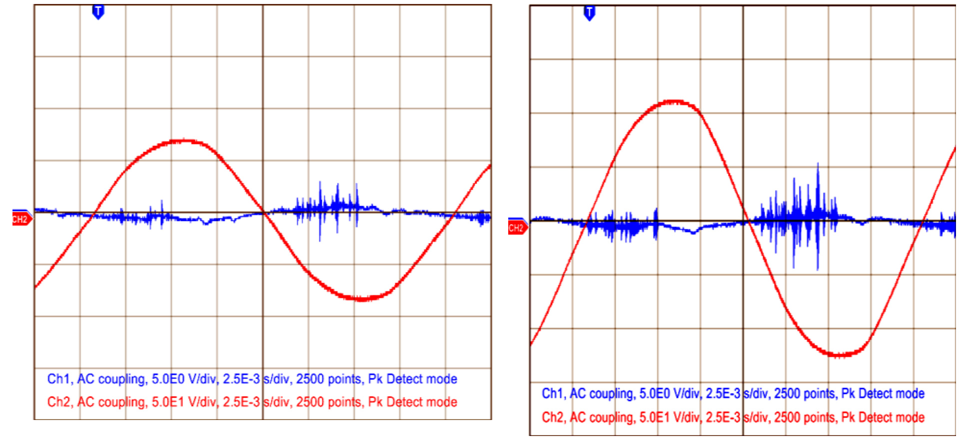


Calibration & Measurement.wmv

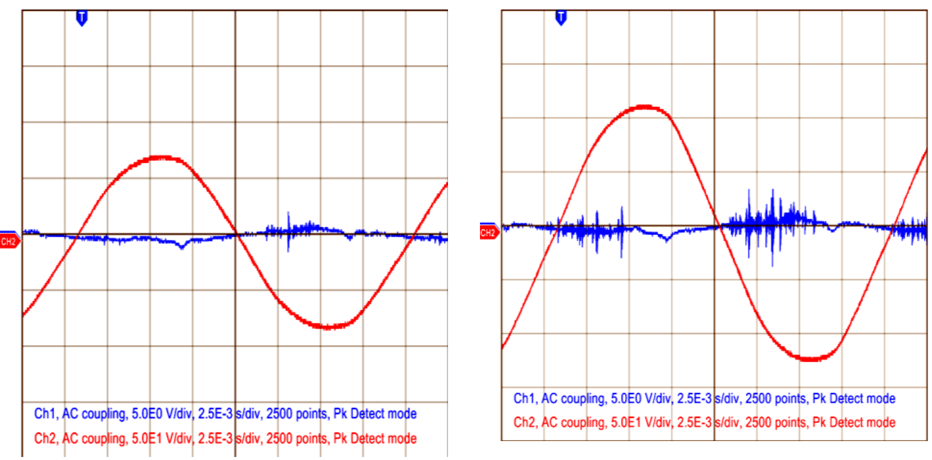
Measurement and Data Acquisition for Laboratory Models Simulating Single & Multiple Source PD Patterns



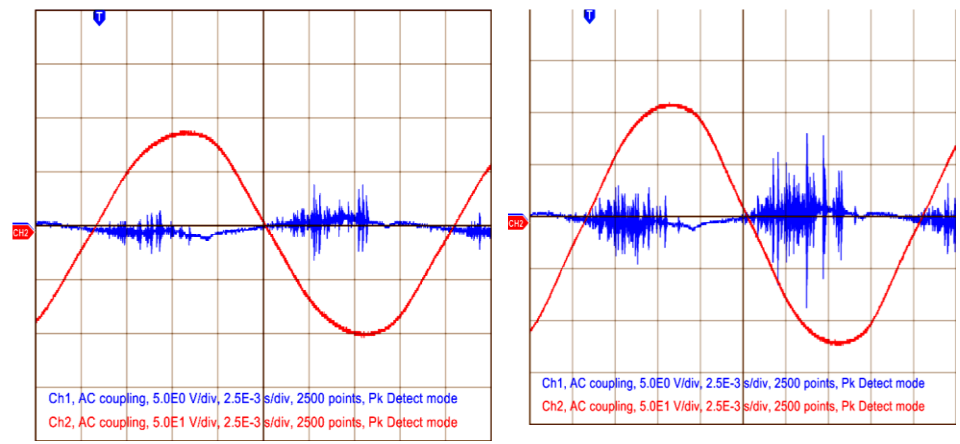
(A) Typical PD Signatures of Air Corona Discharges at Varying Applied Voltages



(B) PD Signatures of Surface Discharges in Air (gliding discharges) at Varying Applied Voltages

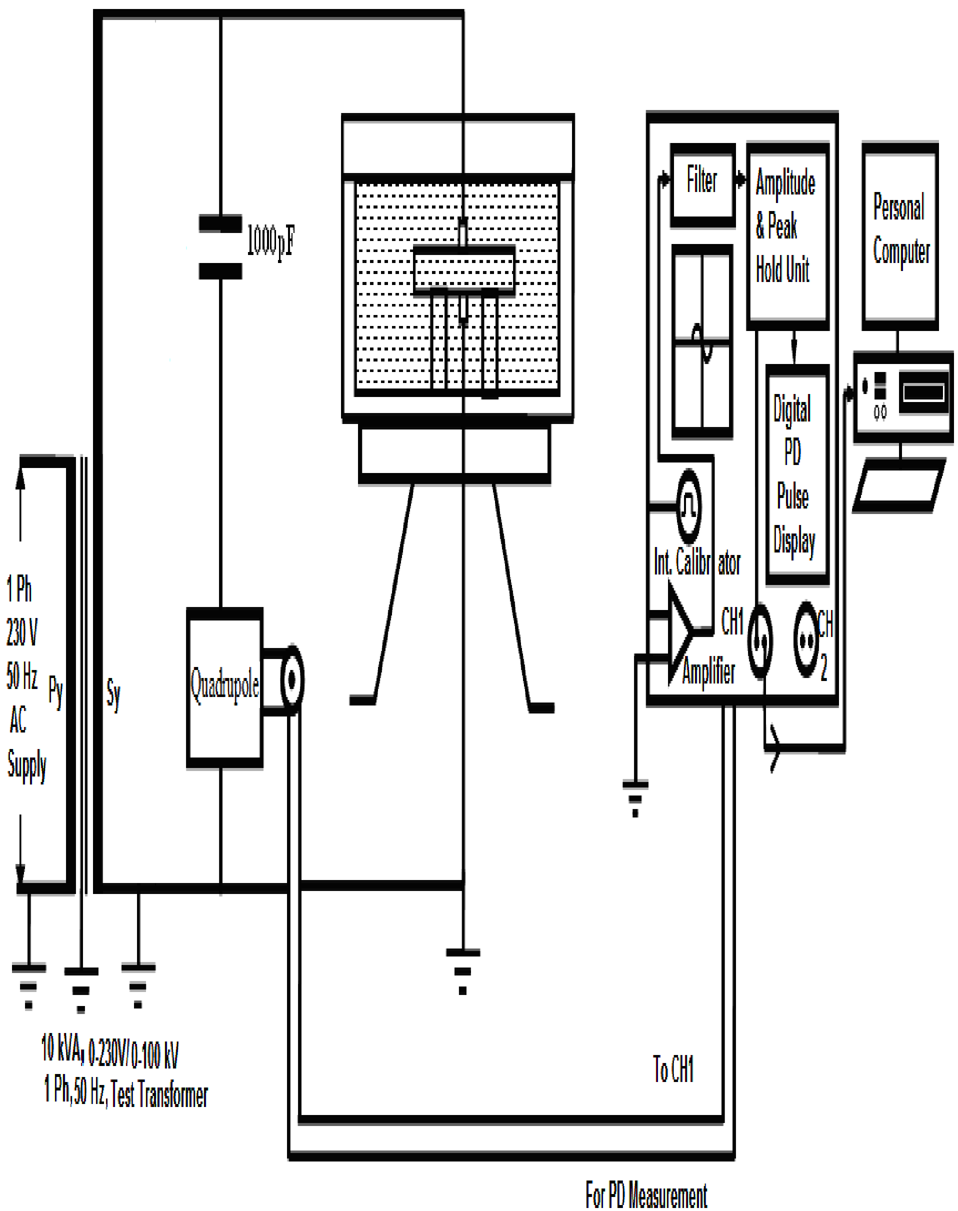


(C) PD Signatures of Electrode Bounded Cavity Discharges at Varying Applied Voltages



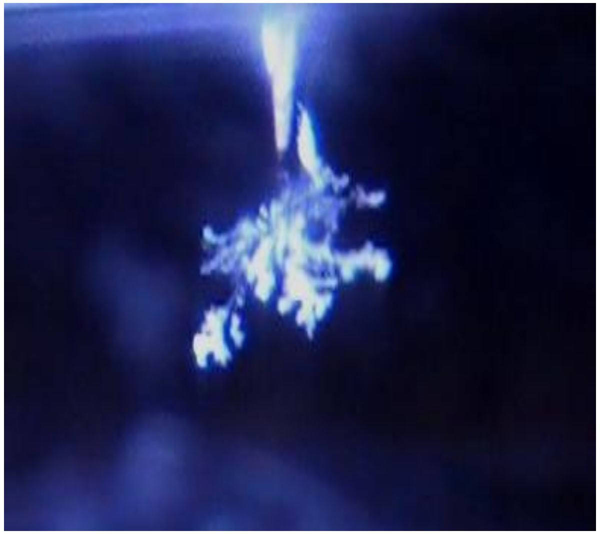
(D) PD Signatures of Multiple Source PD (Electrode Bounded Cavity with Air Corona) at Varying Applied Voltages

EXPERIMENTAL PD TEST SETUP – ELECTRICAL TREEING

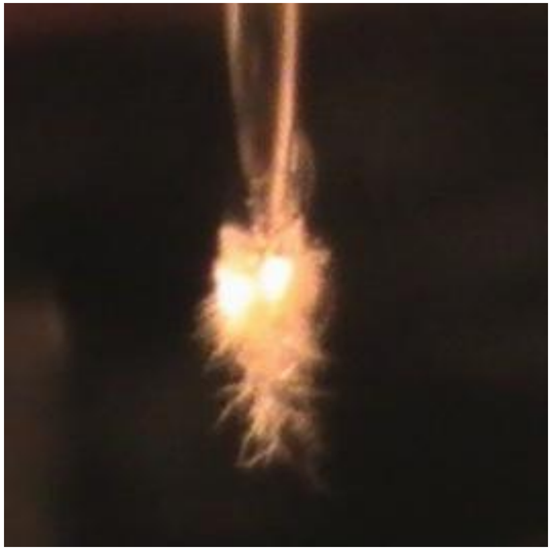


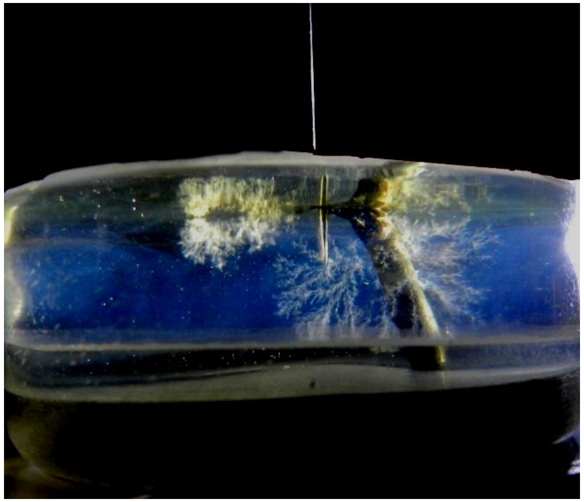
PHOTOGRAPHS OF VARIOUS BENCHMARK LABORATORY MODELS REPLICATING ELECTRICAL TREEING

Photographs of Top and Cross Sectional View of Branch-Bush Treeing-12mm thick perspex



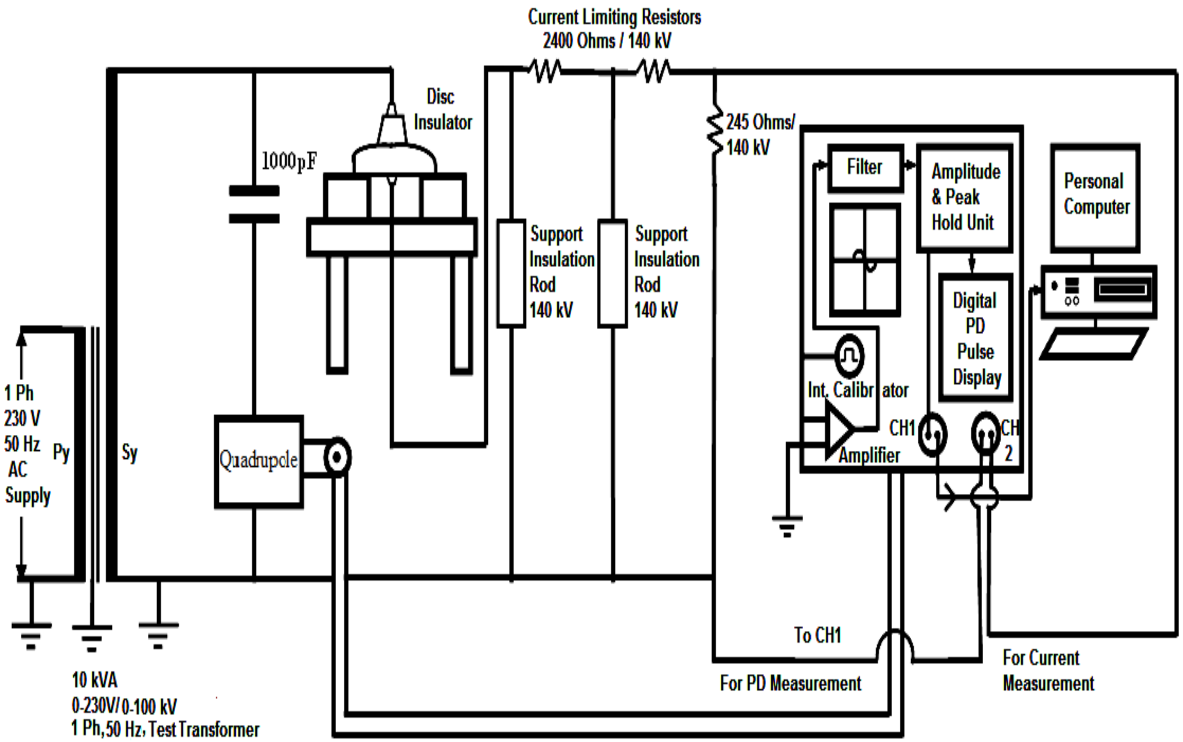
Photographs of Branch Treeing initiation and propagation in 12mm thick perspex

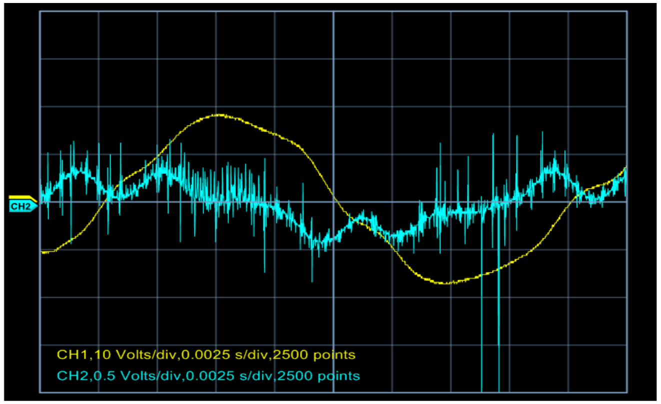




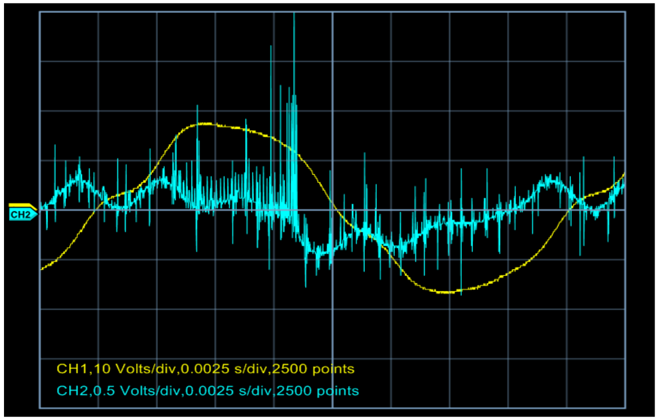
Photographs of Branch-tree initiation and breakdown in 20mm thick perspex

EXPERIMENTAL PD TEST SETUP- PREDICTION OF FLASHOVER DUE TO POLLUTION SEVERITY





A. Applied voltage 16.6kV



B. Applied voltage of 24.1 kV

Scintillations at Cap

Arcing at Cap and Pin

Flashover Initiation

PD and leakage current waveforms during Pollution Performance Test on Insulators

MVI_1462.AVI

ACQUISITION OF PD PATTERNS & PREPROCESSING/ FEATURE EXTRACTION

- **Implemented the following coding using MATLAB 6.1, Release 12:**
  - **PNN Modular Ensemble Versions for PD Pattern recognition after due verification (Fisher's Iris Plant Database) and Validation (Partial Test Set and One- Hold-One- Out)**
  - **Preprocessing/ Feature Extraction techniques for obtaining PD fingerprints**

Sl. No.	Preprocessing/ Feature Extraction Technique	Phase Window	Type of PD Fingerprint
1.	Measures Based on Maximum & Minimum Values	30º and 10º	φ-q_{max}-n; φ-q_{min}-n; φ-q-n_{max}; φ-q-n_{min};
2.	Measures Based on Central Tendency and Dispersion	30º and 10º	q_{mean}-q_{median}-q_{mode}
3.	Measures Based on Statistical Moments	30º and 10º	q_{range}-q_{dev}-$q_{qar.dev}$
4.	Measures Based on Mean Values (Types)	30º and 10º	q_{hm}- q_{gm}-q_{am}-q_{rms}
5.	Two Pass Split Window Scheme (TPSW)	30º and 10º	q-n

SEQUENCE SIMILARITY BASED TECHNIQUE

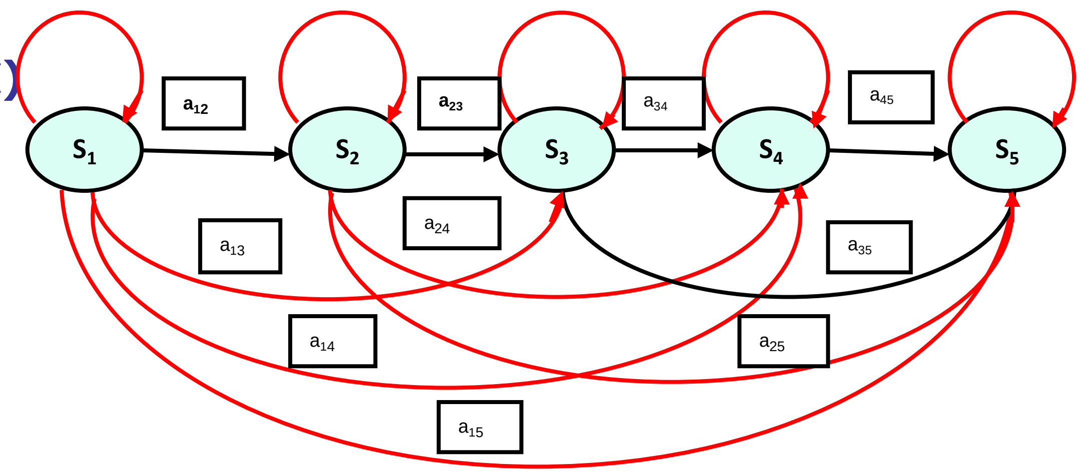
STATIONARY & NON-STATIONARY VERSIONS OF HIDDEN MARKOV MODELS

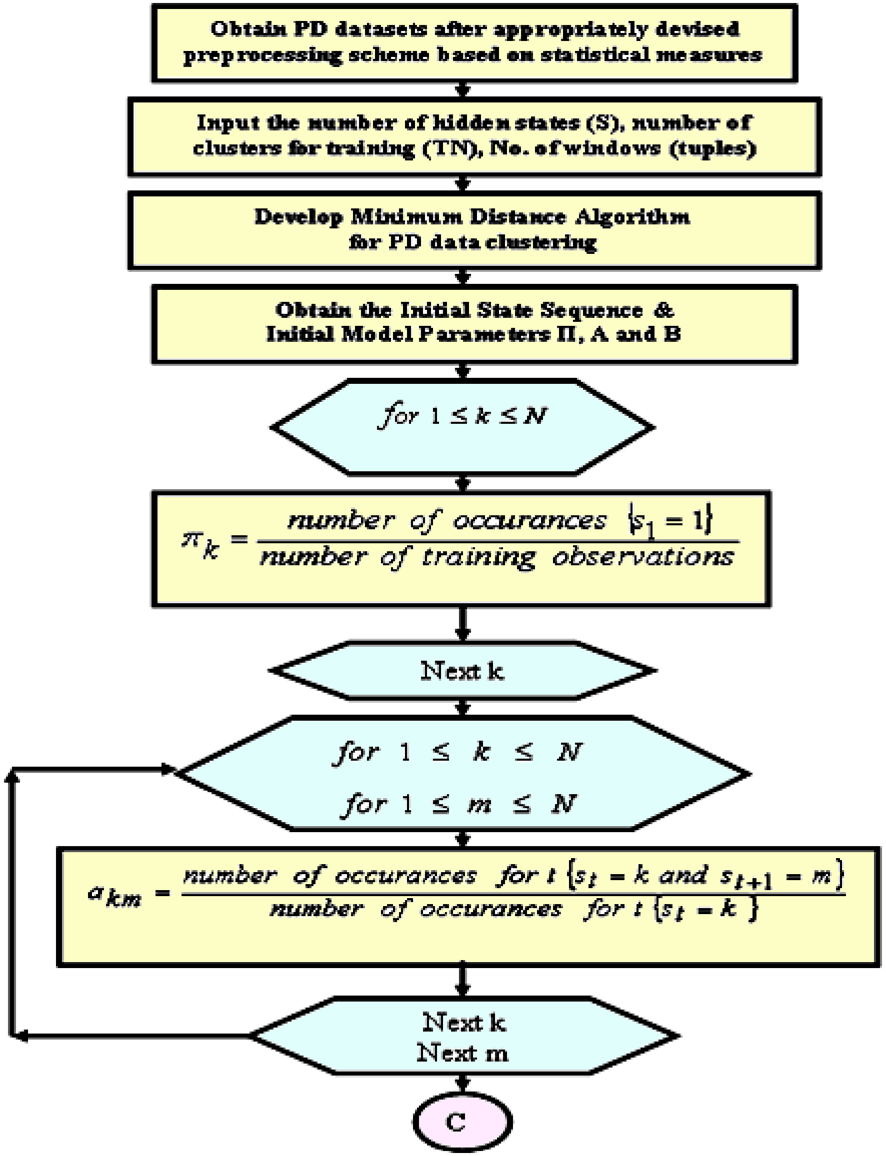
COMPARISON OF ANN & HMM

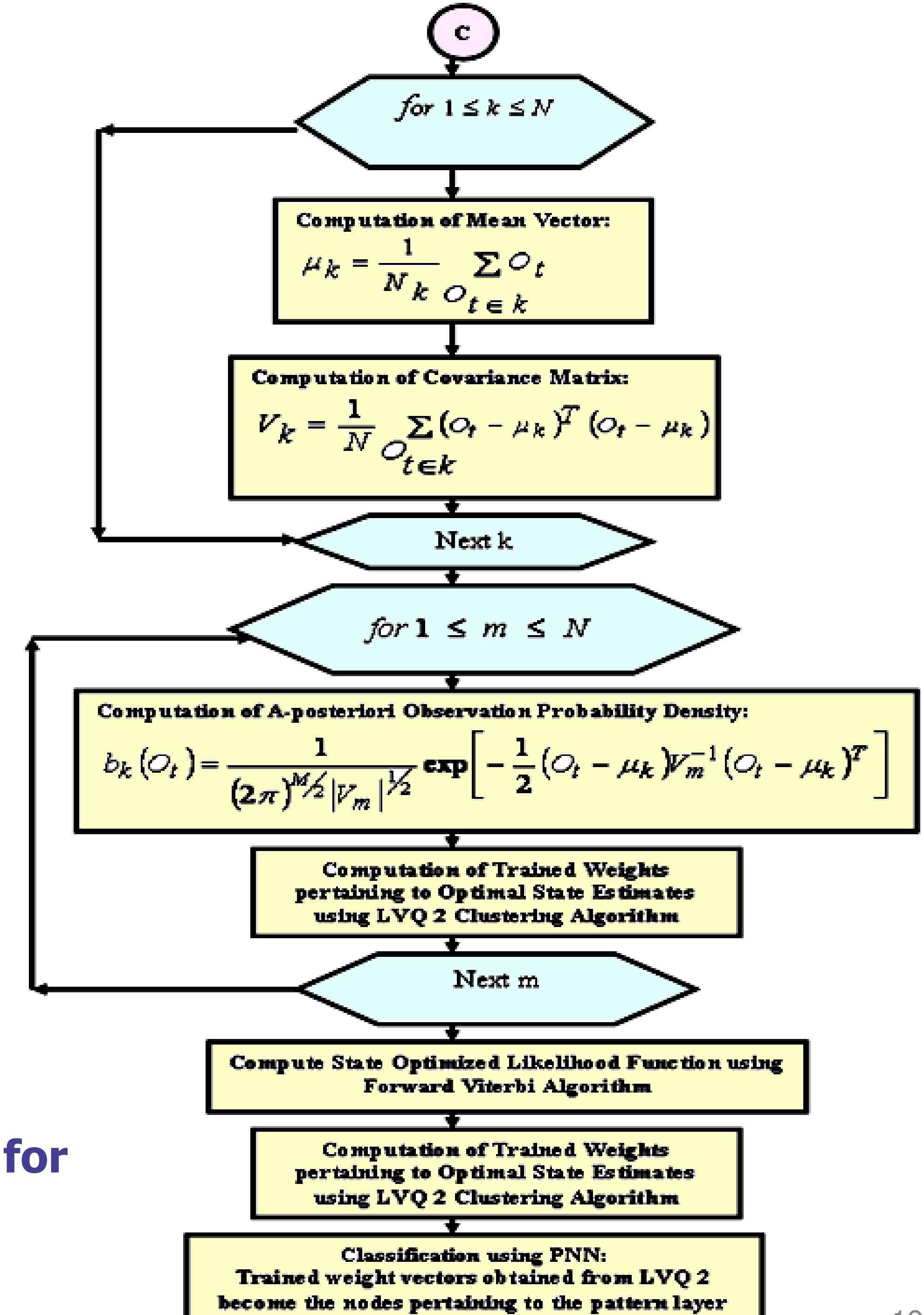
CHARACTERSTICS & SPECIFIC ASPECTS	NEURAL NETWORKS	HIDDEN MARKOV MODELS
MERITS	• Provide **discrimination based learning capabilities**	• Good adaptation in dealing with **time-sequence structures**
	• **No need for assumption of statistical distribution of datasets**	• **Capable in dealing with uncertainty**
LIMITATIONS	• **No special mechanism to deal with sequential nature of signals**	• **No global contextual information is taken into account**
	• **No 'unified theory' which explains the choice of architecture**	• **Speed during discrimination for substantial datasets may be a constraint**
TRAINING	**Separate model must be trained for each class**	**Whole dataset used for training**
TESTING	• **Produces usually binary decisions**	• **Produces a maximum likelihood for each class** in addition to classification decision
SCALABILITY	Addition of a new class/ category **implies retraining of the entire network**	Addition of a class results in a new HMM **which necessitates training of only that category**

SUMMARY OF KEY ASPECTS OF HYBRID HMM-PNN

- **HMM is a doubly stochastic process <u>consisting of an underlying stochastic process that is not directly observable</u>**
  - May be visualized through another set of stochastic processes that produces a sequence of observations
  - Model characterized by a collection of hidden states connected by transitions
- Comprises two types of model representations
  - **Ergodic (fully connected) Model**: Every state can be reached from every other state of the model
  - **Non- ergodic (Left-Right) Model: State index may increase as time increases (states proceed from left to right)**
- **Five state labels are utilized in this research**
  - PD patterns are best characterized by two zones -"discharge pulses" and "background"
- **Model denoted by λ = (A, B, Π)**







Flow Chart of Hybrid CDHMM-PNN for PD Pattern Recognition and Classification

Performance of Hybrid CDHMM-PNN for Multiple Source PD Laboratory Models

Feature Extraction Scheme	Phase Window	No. of Tuples	Training Patterns	Total Number of Testing Patterns	Classification Hybrid CDHMM Versions (%)	
					Stationary	Non-Stationary
Measures based on Maximum Value	φ-q_{max}-n (10°)	36	108	400	**94.8**	**96.8**
Measures based on Minimum	φ-q_{min}-n (10°)	36	108		94.2	95.5
Measures based on Types of Mean Values	AM-GM-HM-RM (10°)	36	108		94.7	96.2
Measures based on Mean-Slope-Angle	Mean- Slope-Angle (10°)	36	108		92.95	97.44

pseudo code for viva voce\classify1hmmtrainingwithoutclusteringalgorithm.m

Comparison of Optimal State Sequence in Stationary and Non-stationary Versions of CDHMM- Case Study 1

PD Source	Optimal State Sequence: Stationary CDHMM	Optimal State Sequence: Non-stationary CDHMM
Electrode Bounded Cavity	1 1 4 4 1 1/3 3 5 2 5 2 1 1	1 3 1 1/3 3 2 3 2 1 3 4 5 4 2 1
	1 1 4 1 1/4 1 1/2 2/3 3 5 3 1 -	1 2 1/4 1 3 1 1/4 4 1 1/3 3/4 3 5 3 2
	1 1/4 2 2/3 2/1 2/3 3 1 4/3 4/5 3/4 3 1	1 1/2 4/5 2/3 2/1 3 1 4/3 4/5 4/3 3/4 3/2 2/1 1 -
Air Corona	1 1/2 2 5 5 2 5 - - - - - - -	3/1 2/4 4/1 5 2/1 1 2 5 1 2 5 1 5 1 -
	1 1/4 4/5 1/4 1 1//4 4/5 4 2 5 3 1 1/4	1 1/2 4/1 4/5 1 2 1 3 1 4/5 4/3 2 5 1 -
	1 1/4 4/5 2 2 1 2/4 4 4/5 4/3 3 3 5 2	1 2 2/4 2/5 3/2 2 3 1 2 4 5 3 5 3 1
Oil Corona	1 1/3 3 3/5 3 - - - - - - - - -	1 2 1 2 3 2 3 2 1 2 1 4 3 4 2 5 2
	1 1/3 3/5 2 2/5 2 4 2 - - - - -	1 2 1/3 4/5 2 2/3 1 3 2 1 2/3 3/5 3 4 2 1
	1 5/4 2 4 3 1 1/2 5/4 3/2 3 3 4 5 3 3/1	1 4/2 4/5 2 2/3 2 4 3 1 2 4/5 5 3 4 2 1
Electrode Bounded Cavity with Air Corona	1 4/1 4/2 2 5 5/1 2 5 - - - - - -	1/3 2/4 1/2 3/5 5 1 1/3 3/5 5/2 5 1 5 1 1 - -
	1 2 2/4 1 2 1/3 4 5 1 1/2 1 - - -	1 2 2/4 1/4 1/3 4/3 4 1 3/1 3/4 3 5 3 1 - -
	1 2 3 4 5 3 4 5 3 1/4 2 3 1 -	1 2 4 5 4 5 4 5 2 5 4 5 4 1 - -

Performance of Hybrid CDHMM-PNN during pollution studies in ceramic insulators

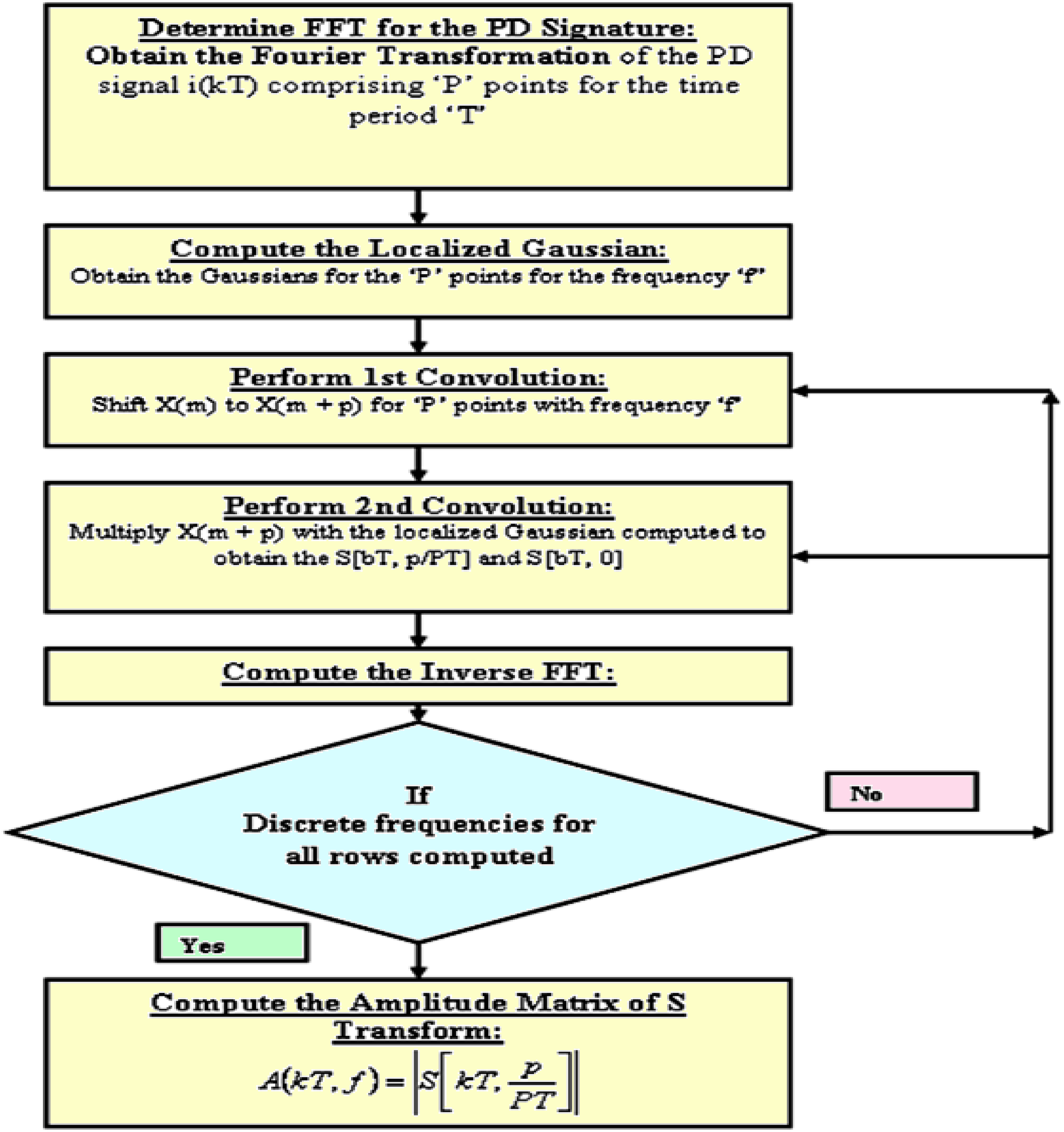
Feature Extraction Scheme	Phase Window	No. of Tuples	Training Patterns	Total Number of Testing Patterns	Classification Hybrid CDHMM Versions (%) in Pollution Performance Studies			
					Sample 2 (Salinity 67 g/l)		Sample 3 (Salinity 57g/l)	
					Stationary	Non-Stationary	Stationary	Non-Stationary
Measures based on Maximum Value	φ-q_{max}-n (10°)	36	60	200	90.5	92.67	94	95.5
Measures based on Mean-Slope-Angle	Mean-slope-angle (10°)	36	60		91.6	94.4	95	96

pseudo code for viva voce\dynamichmmtraining.m

HIGH DIMENSIONALITY BASED TECHNIQUE VERSIONS OF S- TRANSFORM

COMPARISON OF WAVELET & S- TRANSFORMS

CHARACTERSTICS/ FEATURES	FOURIER TRANSFORM	WAVELET TRANSFORM	S – TRANSFORM
DOMAIN	• **Decomposes signal into frequency components** and provides excellent frequency resolution • Does not describe about time distribution	• **Decomposes signal based on dilation of a basis function** (mother wavelet) **with a scaling parameter** (fixed number of cycles/ scale) • Enables multi-resolution studies	• **Intermediate step between STFT and wavelet transform** • Enables use of the frequency variable as well as multi-resolution strategy
KERNEL	• **Exponential function** (particular case provides decomposition of signal using cosine and sine kernels)	• **Arbitrary Kernel**- The mother and the primary wavelet functions act as dual; • Initial kernels are necessary to be specifically defined	• Operates utilizing **Exponential function** • Variables in the exponential function are also scaled-down according to the sample
NATURE OF ANALYSIS	• Multi-resolution analysis not addressed; • Limitation related to time-variant signals	• Multi-resolution (time-frequency) analysis addressed	• Frequency resolution is addressed in a procedure that allows extrapolation
WINDOWING/ SIGNAL SAMPLING	Windowing and sampling does not exist	$\psi\left(\frac{t-b}{a}\right)$ serves as changing window of the sample signal where "b" is translation (shifting) parameter and "a" is the scaling parameter	Sample elements are scaled by sample size in addition to translation
MATHEMATICAL REPRESENTATION	$F(ix)=\sum_{n=-\infty}^{\infty} f\left(\frac{x}{N}\right)e^{\frac{isx}{N}}$	$W_{\psi} f(a,b)=\lvert a\rvert^{-1/2}\iint f(x,t)\psi\left(\frac{t-b}{a}\right)dx\,dt$	$S\left[bT,\frac{p}{PT}\right]=\sum_{m=0}^{P-1} X\left[\frac{m+p}{PT}\right]e^{\frac{-2\pi^2 m^2}{p^2}}e^{\frac{j2\pi mk}{P}}$ for p ≠ 0; $S[bT,0]=\frac{1}{P}\sum_{m=0}^{P-1} x\left[\frac{m}{PT}\right]$ for p=0;



Flow Chart of Discrete S- Transform for Multiple Source PD Pattern Recognition

Comparison of Wavelet Transform-PNN & S Transform- PNN in Classifying Multiple Source PD

Classification Capability of Wavelet Transform-PNN

Feature Vector	No. of Tuples	Total No. of Windows for Statistically Extracted Features	Total Number of PD Signatures	Classification Capability (%)			
				OPNN without Clustering	APNN without Clustering	LVQ2 Clustering	
						OPNN	APNN
Daubechies Coefficients (Order 7 and Level 3)	192	16	480	92	93.1	94.2	94.7
	264	9	480	90.2	91.3	92.3	93.1

Classification Capability of S Transform-PNN

Total Number of Classes for Discrimination	No. of Tuples		Taper Parameter (for HST)		Training Patterns for each Class	Total Number of Testing Patterns	Classification Hybrid S-Transform Variants with PNN (%)	
	ST-PNN	HST-PNN	g_f	g_b			ST-PNN	HST-PNN
4 Classes (3 Single Source and 1 Multi-Source PD)	150	100	0.5	1.5	90	480 for 4 Classes & 600 for 5 Classes	96.25	96.6
5 Classes (3 Single Source and 2 Multi-Source PD)							92	94
4 Classes (3 Single Source and 1 Multi-Source PD)	500	40	0.5	1.5	90		96.3	99.79
5 Classes (3 Single Source and 2 Multi-Source PD)							95.5	99.83

pseudo code for viva voce\hypstranswithoutpreoprocessingandwithPCA.m

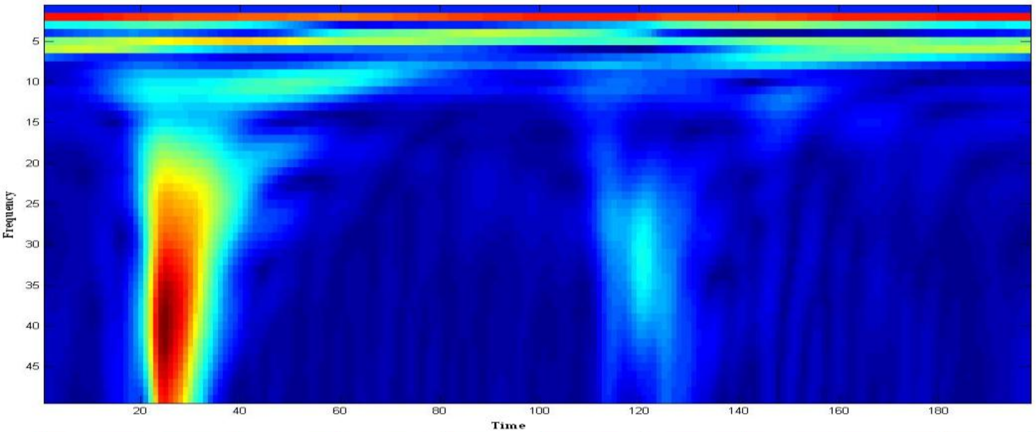
Capability of Hybrid S-Transform PNN Variants in Classifying Multi-Source PD Signatures in 33kV XLPE Cable Samples

Total Number of Classes for Discrimination	No. of Tuples		Taper Parameter (for HST)		Training Patterns for each Class	Total Number of Testing Patterns	Classification Hybrid S-Transform Variants with PNN (%)	
	ST-PNN	HST-PNN	g_f	g_b			ST-PNN	HST-PNN
4 Classes (3 Single Source and 1 Fully Overlapped Multi-Source)	150	40	0.5	1.5	90	480	95.25	96.67
4 Classes (3 Single Source and 1 Fully Overlapped Multi-Source)	150	40	0.5	1.5	90	600	94.5	96.17

Performance of Hybrid S-Transform PNN Variants in Classifying Multiple Source PD Signatures in 11kV Bushing of 11kV/ 415V Distribution Transformer

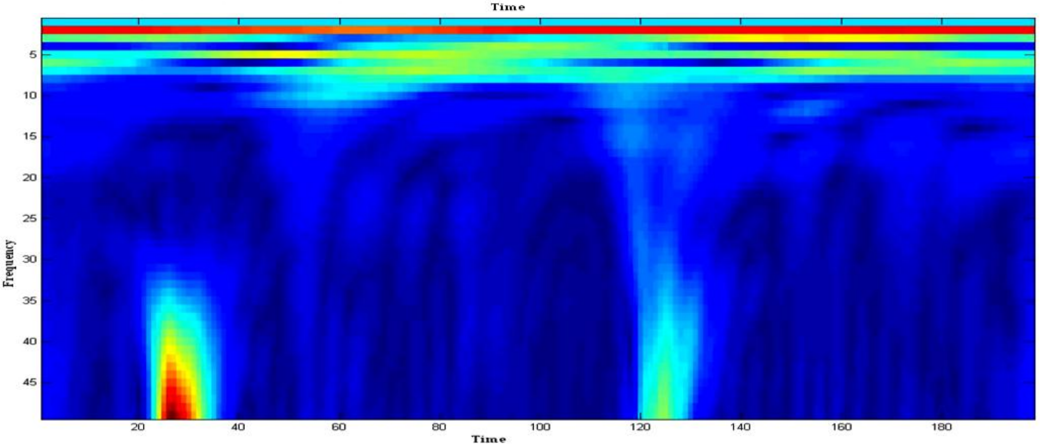
Total Number of Classes for Discrimination	No. of Tuples		Taper Parameter (for HST)		Training Patterns for each Class	Total Number of Testing Patterns	Classification Hybrid S-Transform Variants with PNN (%)	
	ST-PNN	HST-PNN	g_f	g_b			ST-PNN	HST-PNN
3 Classes (2 Single Source and 1 Partially Overlapped Multi-Source)	150	40	0.5	1.5	90	360	93.4	95.2
3 Classes (3 Single Source and 1 Partially Overlapped Multi-Source)	150	40	0.5	1.5	90	450	92	94.2

Analysis plot of HST Time-Frequency Amplitude Characteristics



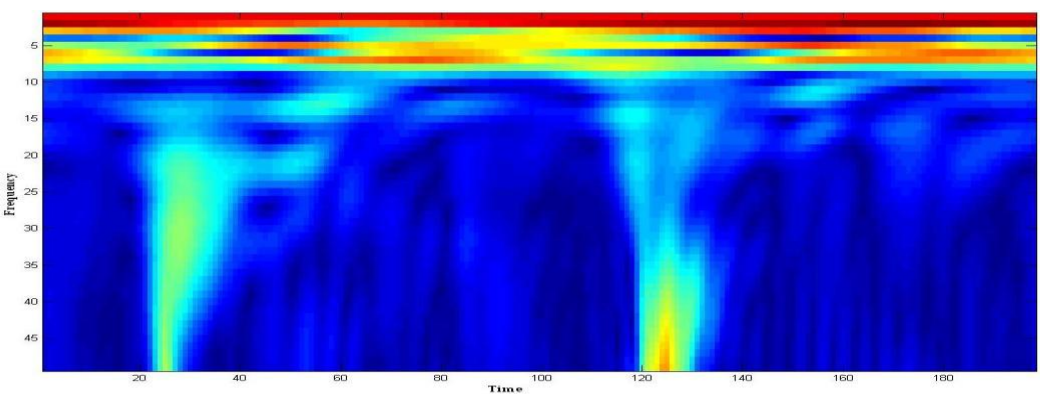
Electrode bounded Cavity Discharges

There is a **substantial increase in frequency at time points ranging from 20-30**, while small variations are **observed in the range 110-120**.



Air Corona Discharges

Variations are observed with a **considerably lower band of frequency during the time range varying from 22-38** and finer changes in the time period **122-130.**



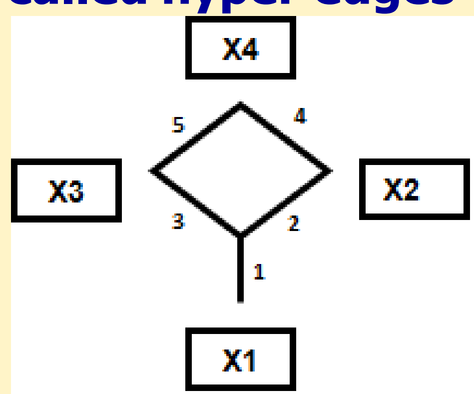
Electrode bounded Cavity Discharges

It is interesting to note that in the case of electrode bounded cavity with air corona (multiple-source) discharges, **the complex non-stationary behaviour and overlapped characteristic of signature patterns is evident**

GRAPH THEORETIC TECHNIQUE
HYPERGRAPH BASED FEATURE EXTRACTION

RATIONALE BEHIND HYPER GRAPH APPROACH FOR CLUSTERING/ CENTER SELECTION

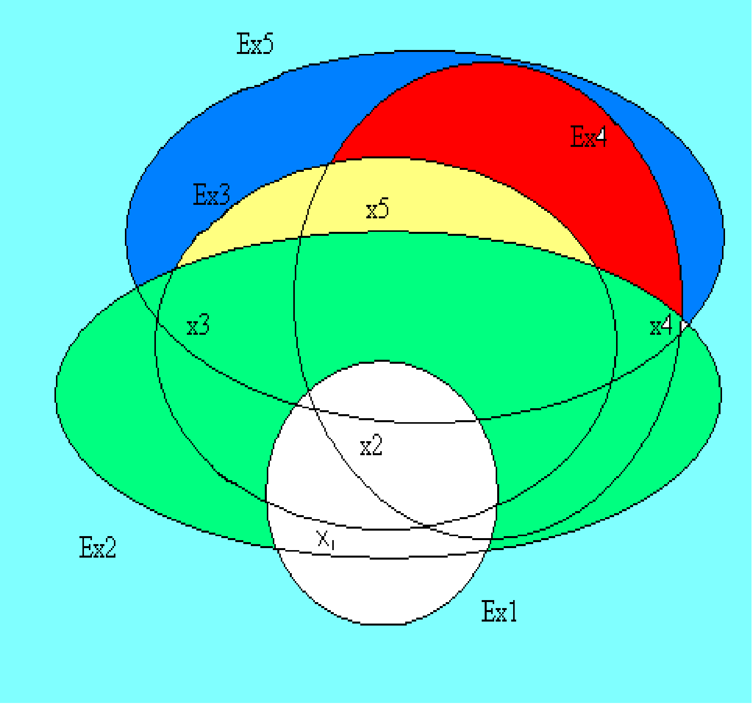
Graph	Hyper Graph (HG)
• **Implementation of binary relationship between vertices .** • **DOES NOT express simultaneously both geometry and topology relationship**	**Enhancement of Geometric notion of data** • **Utilizes various distance metrics for building neighborhood, stars etc** for geometric visibility
Focus on the topological aspects **rather than the geometrical aspects such as contour, symmetry, homogeneity etc**	**Implements SET THEORETIC concepts for topological operations**
• A graph G is a pair (V,E), where V is a set of vertices, and E is a set of edges between the vertices E = {(u,v) | u, v ε V}. • All graphs will be considered as connected with no isolated vertex. We denote it by G =(V, E). • Given a graph G, we denote by Γ (x) the neighborhood of a vertex x.	• Hyper graph 'H' on a set **S is a family $(E_i)_{i \in I}$** of **non-empty subsets of S called hyper edges** with $\cup E_i = S$



$$E_{x_1} = \{x_1, x_2, x3\}$$
$$E_{x_2} = \{x_1, x_2, x_3, x_4\}$$
$$E_{x_3} = \{x_2, x_3, x_5\}$$
$$E_{x_4} = \{x_2, x_4, x_5\}$$
$$E_{x_5} = \{x_3, x_4, x_5\}$$

RATIONALE BEHIND HYPER GRAPH APPROACH FOR CLUSTERING/ CENTER SELECTION

- **Properties of HG such as Helly, Duality etc provide:**
  - **Feature detail preservation capability**
  - **Ability to cluster data**
  - **Capacity to handle noisy data**
  - **Reduction of computational complexity (processes only star centers of HG)**
  - **Efficient algorithms to process/detect edges and sharp/ overlapped boundaries, identifying homogeneous regions etc.**



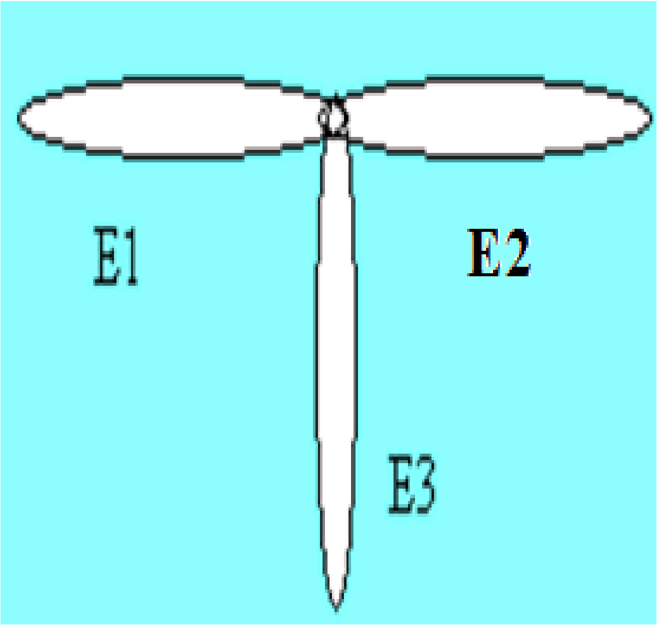
NEIGHBORHOOD HYPERGRAPH

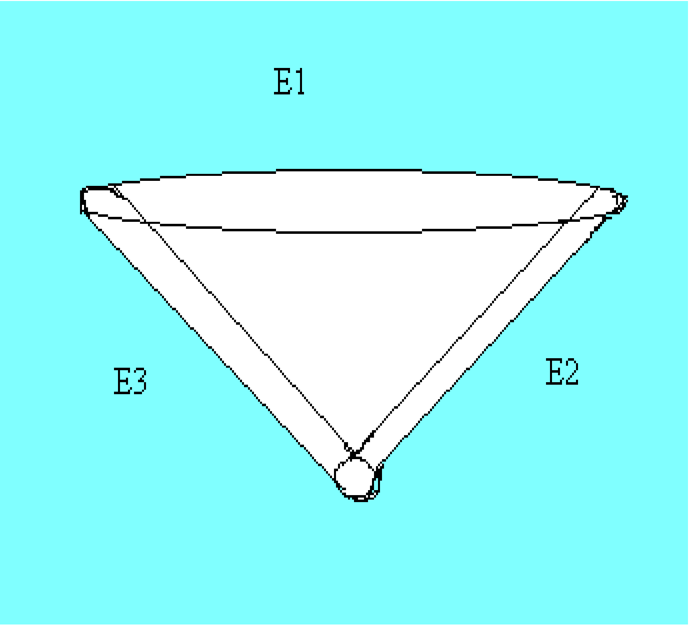
- Given a graph G, **the hyper graph (H_G) having vertices of G and neighbourhood of these vertices as hyper-edges (including these vertices) is called the neighbourhood HG** of G.
- To each graph **we can associate a neighbourhood hyper graph:**

$$H_G = \{ S, (E_\alpha = \{x\} \cup \Gamma(x) \}.$$

NEIGHBOURHOOD HG

- **INTERSECTING FAMILIES AND HELLY PROPERTY**
  - **A family of hyper edges from this family intersects two by two.** Distinguishes two types of interesting families:
    - **Intersecting family with an empty intersection**
    - **Intersecting families with a non-empty intersection (belongs to a star)**





Classification Capability of HG based PNN Version for Moderate Dataset PD Signature

Type of Feature	Number of Optimal Centers from HG Algorithm				Training Patterns	Classification (%)
	Electrode bounded cavity	Air	Oil	Multiple Source		
φ-q_{max}-n (30°)	8kV-26 10kV-13 12kV-7	7kV-17 9kV-15 11kV-8	15.04kV-18 17.36kV- 17 20.08kV- 14	6.9kV- 3 8kV- 10 10kV- 17	165	98
φ-q_{max}-n (10°)	8kV- 6 10kV-16 12kV-10	7kV-8 9kV-12 11kV-10	15.04kV-15 17.36kV- 16 20.08kV- 14	6.9kV- 7 8kV- 12 10kV- 17	170	96.67
φ-q_{min}-n (10°)	8kV-12 10kV-18 12kV-8	7kV-16 9kV-18 11kV-17	15.04kV-12 17.36kV- 13 20.08kV- 15	6.9kV- 18 8kV- 21 10kV- 17	188	94.3
AM-GM-HM-RM (10°)	8kV-9 10kV-26 12kV-9	7kV-15 9kV-18 11kV-17	15.04kV-17 17.36kV- 17 20.08kV- 19	6.9kV- 18 8kV- 19 10kV- 15	190	91.3

pseudo code for viva voce\HYPERGRAPHvoid10 kvtensam.m

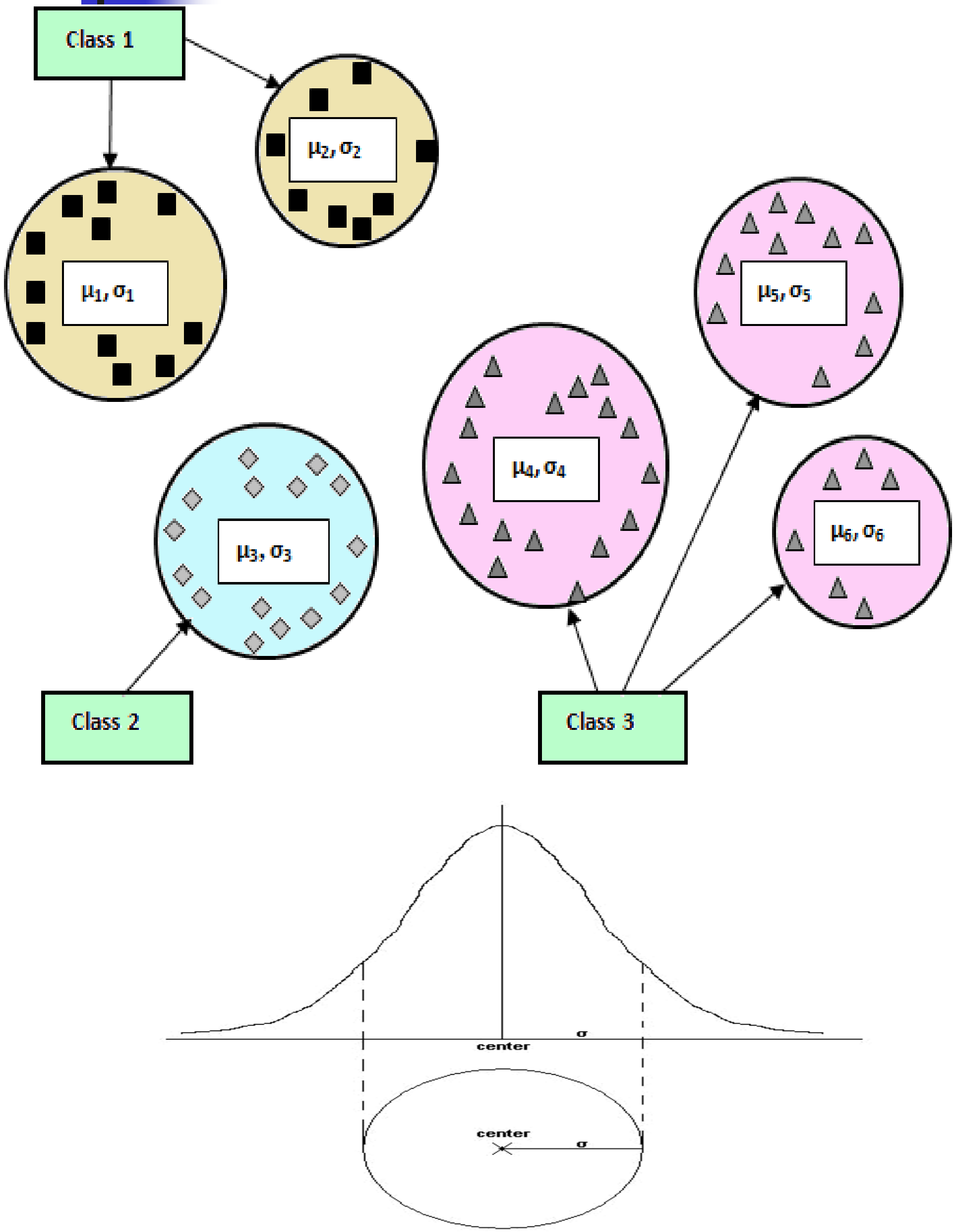
LARGE DATASET CLUSTERING

FOR GAUSSIAN MIXTURE DENSITY KERNEL NEURAL NETWORKS

EM-ML ALGORITHM

EM-ML WITH JACKNIFE ALGORITHM

FUNDAMENTAL CONCEPTS OF HRPNN



- **HRPNN CONCEPTS:**
  - **Over-training and its impact due to individual mean vectors.**
    - Desirable to employ a smaller set of kernel functions.
  - **Expectation Maximization (EM) algorithm to derive an optimal Maximum Likelihood (ML) training algorithm** for Gaussian mixture PNN for training **two fundamental kinds of Gaussian PNNs:**
    - **Homoscedastic PNN-** "same scatter"
    - **Heteroscedastic PNN-** "different scatter"
  - HRPNN allows having **a smaller set of Gaussian function with different variance (scatter)** enabling a much more parsimonious PNN.

MATHEMATICAL ASPECTS OF HETEROSCEDASTIC PNN

- First layer accepts input patterns.
- Second layer nodes are divided into *k* groups, one for each class.
  - Also called as a Pattern Layer or Exemplar Layer
  - The i^{th} kernel in the j^{th} group, is defined as a Gaussian basis function

$$\mathrm{p}_{i,j}(x) = \frac{1}{\left(2\Pi\sigma_{i,j}^{2}\right)^{\frac{d}{2}}}\exp\left(-\frac{\left\|x - c_{i,j}\right\|^{2}}{2\Pi\sigma_{i,j}^{2}}\right)$$

where $c_{i,j}$ is the centre or the mean vector and $\sigma_{i,j}^2$ is the positive variance parameter or smoothening parameter.

- The third layer has k nodes and estimates a class conditional PDF f_j using a mixture of Gaussian kernels,

$$f_j(x) = \sum_{i=1}^{M_j}\beta_{i,j}\,p_{i,j}(x)$$

where $M_{i,j}$- number of pattern units for class j and

$\beta_{i,j}$- positive mixing coefficient satisfying the condition

$\Sigma\,\beta_{i,j} = 1,\ 1 \le j \le k.$

MATHEMATICAL ASPECTS OF HETEROSCEDASTIC PNN

- **Fourth layer of the HRPNN makes the decision** according to the equation:

$$\boxed{g_{Bayes}(x) = \arg\left(\max_{1 \le j \le K}\{\alpha_j f_j(x)\}\right)}$$

α_j refers to the class a-priori probability.

EXPECTATION MAXIMIZATION (EM) ALGORITHM:

- **E-STEP:**
  - Computes expected value of the 'unobserved' data using the current parameter estimate and the observed data.
  - At each iteration computes the weights for $1 \le m \le M_i$, $1 \le n \le N_i$ and $1 \le i \le K$:

$$\boxed{w_{m,i}^{(k)}(x_{n,i}) = \frac{\beta_{m,i}\Big|^{(k)} p_{m,i}^{(k)}(x_{n,i})}{\sum_{l=1}^{M_i} \beta_{l,i}\Big|^{(k)} p_{l,i}^{(k)}(x_{n,i})}}$$

MATHEMATICAL ASPECTS

Contd…

$$p_{l,i}^{(k)}(x_{n,i}) = \frac{1}{\left(2\prod \sigma_{l,i}^{2}\Big|^{(k)}\right)^{\frac{d}{2}}} \exp\left(\frac{-\left\| x_{n,i} - c_{l,i}\Big|^{(k)} \right\|^{2}}{2\prod \sigma_{l,i}^{2}\Big|^{(k)}}\right)$$

- **M-step:**
  - **Forms a likelihood function and determines an ML estimate of the parameter.**
  - Updates the parameters for $1 \leq m \leq M_i$, $1 \leq n \leq N_i$ and $1 \leq i \leq K$:

$$c_{m,i}\Big|^{(k+1)} = \frac{\sum_{n=1}^{N_i} w_{m,i}^{(k)}(x_{n,i})\, x_{n,i}}{\sum_{n=1}^{N_i} w_{m,i}^{(k)}(x_{n,i})}$$

$$\sigma_{m,i}^{2} = \frac{\sum_{n=1}^{N_i} w_{m,i}^{(k)}(x_{n,i}) \left\| x_{n,i} - c_{m,i} \right\|^{2}}{d \sum_{n=1}^{N_i} w_{m,i}^{(k)}(x_{n,i})}$$

pseudo code for viva voce\hopnn

CLASSIFICATION CAPABILITY OF HOPNN AND HRPNN- MULTIPLE SOURCE PD

Input Feature	No. of Tuples	Total No. of Testing Datasets	Randomly Chosen Initial Centers- 144 Nos. (36 Sets for each class): No. of PDF labeled sequentially as EC, AC, OC and ECC (Set 1 only) – HOPNN	Randomly Chosen Initial Centers- 144 Nos. (36 Sets for each class): No. of PDF labeled sequentially as EC, AC, OC and ECC (Set 1 only) – HRPNN	No. of Iterations	Classification Capability EM-ML Algorithm (%) – HOPNN	Classification Capability EM-ML Algorithm (%) – HRPNN
φ-q_{max}-n (30°)	36	621	24,22, 20,21	20,18, 18,20	28	88.6	89.5
φ-q_{min}-n (30°)	36	621	22,25, 24,18	18,17, 16,18	30	87.6	87.9
φ-q_{max}-n (10°)	108	624	12,14, 15, 14	10,12, 13,9	36	90.2	91.3
φ-q_{min}-n (10°)	108	624	16,11, 16,12	13,11, 9,8	43	88.2	88.5
Traditional Statistical Operators (30°)	48	621	14,16, 14,10	12,15, 11,10	11	94.1	94.6
Traditional Statistical Operators (10°)	144	621	12,14, 18,11	14,11, 15,13	9	94.8	95.1

Input Data:
1. Number of Classes (R)
2. Dimensionality of Input Data (d)
3. Number of Patterns of Class (E)
4. Number of Training Samples (N)
5. Input for Testing (x)

ML with EM Algorithm:
Obtain the Maximum Likelihood (ML) Estimate of the Weights, Centers and Variance of each Class (using Lagrangier Multiplier Operator):

1. **Weight (w):** $w^{R}_{E,i}(x_{n,i}) = \dfrac{\beta_{E,i}|^{(R)}\, p^{(R)}_{E,i}(x_{n,i})}{\sum_{m=1}^{E} \beta_{m,i}|^{(R)}\, p^{(R)}_{m,i}(x_{n,i})}$

2. **Center (c):** $c_{E,i}|^{(R+1)} = \dfrac{\sum_{n=1}^{N_i} w^{R}_{E,i}(x_{n,i})\, x_{n,i}}{\sum_{n=1}^{N_i} w^{R}_{E,i}(x_{n,i})}$

3. **Variance (σ):** $\sigma^2_{E,i}|^{(R+1)} = \dfrac{\sum_{n=1}^{N_i} w^{R}_{E,i}(x_{n,i}) \left\| x_{n,i} - c_{E,i}|^{(R)} \right\|^2}{d \sum_{n=1}^{N_i} w^{R}_{E,i}(x_{n,i})}$

4. **Mixing Coefficient (β):** $\beta_{E,i}|^{(R+1)} = \dfrac{1}{N_i} \sum_{n=1}^{N_i} w^{R}_{E,i}(x_{n,i})$

Jack-Knife Procedure:

Computing the Pseudo Value Estimates of Centers, Variance and mixing Coefficient:

1. Pseudo Estimate for Center:

A. $c_{E,i}|^{(R+1)} = \dfrac{\sum_{n=1}^{N_i} w^{R}_{E,i}(x_{n,i})\, x_{n,i}}{\sum_{n=1}^{N_i} w^{R}_{E,i}(x_{n,i})}$

B. $c_{E,i}|^{(R+1)}_{-j} = \dfrac{\sum_{n=1, n\neq j}^{N_i} w^{R}_{E,i}(x_{n,i})\, x_{n,i}}{\sum_{n=1, n\neq j}^{N_i} w^{R}_{E,i}(x_{n,i})}, 1 \le j \le N_i$

C. $\hat{c}_{E,i}|^{(R+1)} = N_i c_{E,i}|^{(R+1)} - \dfrac{N_i - 1}{N_i} \sum_{j=1}^{N_i} c_{E,i}|^{(R+1)}_{-j}$

C

C

2. Pseudo Estimate for Variance:

A. $\sigma^2_{E,i}|^{(R+1)} = \dfrac{\sum_{n=1}^{N_i} w^{R}_{E,i}(x_{n,i}) \left\| x_{n,i} - \hat{c}_{E,i}|^{(R)} \right\|^2}{d \sum_{n=1}^{N_i} w^{R}_{E,i}(x_{n,i})}$

B. $\sigma^2_{E,i}|^{(R+1)}_{-j} = \dfrac{\sum_{n=1, n\neq j}^{N_i} w^{R}_{E,i}(x_{n,i}) \left\| x_{n,i} - \hat{c}_{E,i}|^{(R)} \right\|^2}{d \sum_{n=1, n\neq j}^{N_i} w^{R}_{E,i}(x_{n,i})}$

C. $\sigma^2_{E,i}\Big|^{(R+1)} = N_i \sigma^2_{E,i}|^{(R+1)} - \dfrac{N_i - 1}{N_i} \sum_{j=1}^{N_i} \sigma^2_{E,i}|^{(R+1)}_{-j}$

3. Pseudo Estimate for Mixing Coefficient:

A. $\beta_{E,i}|^{(R+1)} = \dfrac{1}{N_i} \sum_{n=1}^{N_i} w^{R}_{E,i}(x_{n,i})$

B. $\beta_{E,i}|^{(R+1)}_{-j} = \dfrac{1}{N_i - 1} \sum_{n=1, n\neq j}^{N_i} w^{R}_{E,i}(x_{n,i}), 1 \le j \le N_i$

C. $\beta_{E,i}|^{(R+1)}_{-j} = \dfrac{1}{N_i - 1} \sum_{n=1, n\neq j}^{N_i} w^{R}_{E,i}(x_{n,i}), 1 \le j \le N_i$

D. $\hat{\beta}_{E,i}|^{(R+1)} = N_i \beta_{E,i}|^{(R+1)} - \dfrac{N_i - 1}{N_i} \sum_{j=1}^{N_i} \beta_{E,i}|^{(R+1)}_{-j}$

Compute Probability Density Function Estimate:

$$p^{(R)}_{E,i}(x_{n,i}) = \frac{1}{\left(2\Pi \sigma^2_{E,i}|^{(R)}\right)^{d/2}} \exp\left(\frac{-\left\| x_{n,i} - c_{E,i}|^{(R)} \right\|^2}{2\sigma^2_{E,i}|^{(R)}} \right)$$

Class Conditional Probability Density Function Estimate:

$f_j(x) = \sum_{i=1}^{E} \beta_{i,j}\, p_{i,j}(x), 1 \le j \le R$

Bayes Classifier Decision:

$O_{Bayes}(x) = \arg\left(\max_{1 \le j \le R} \{\alpha_j f_j(x)\} \right)$

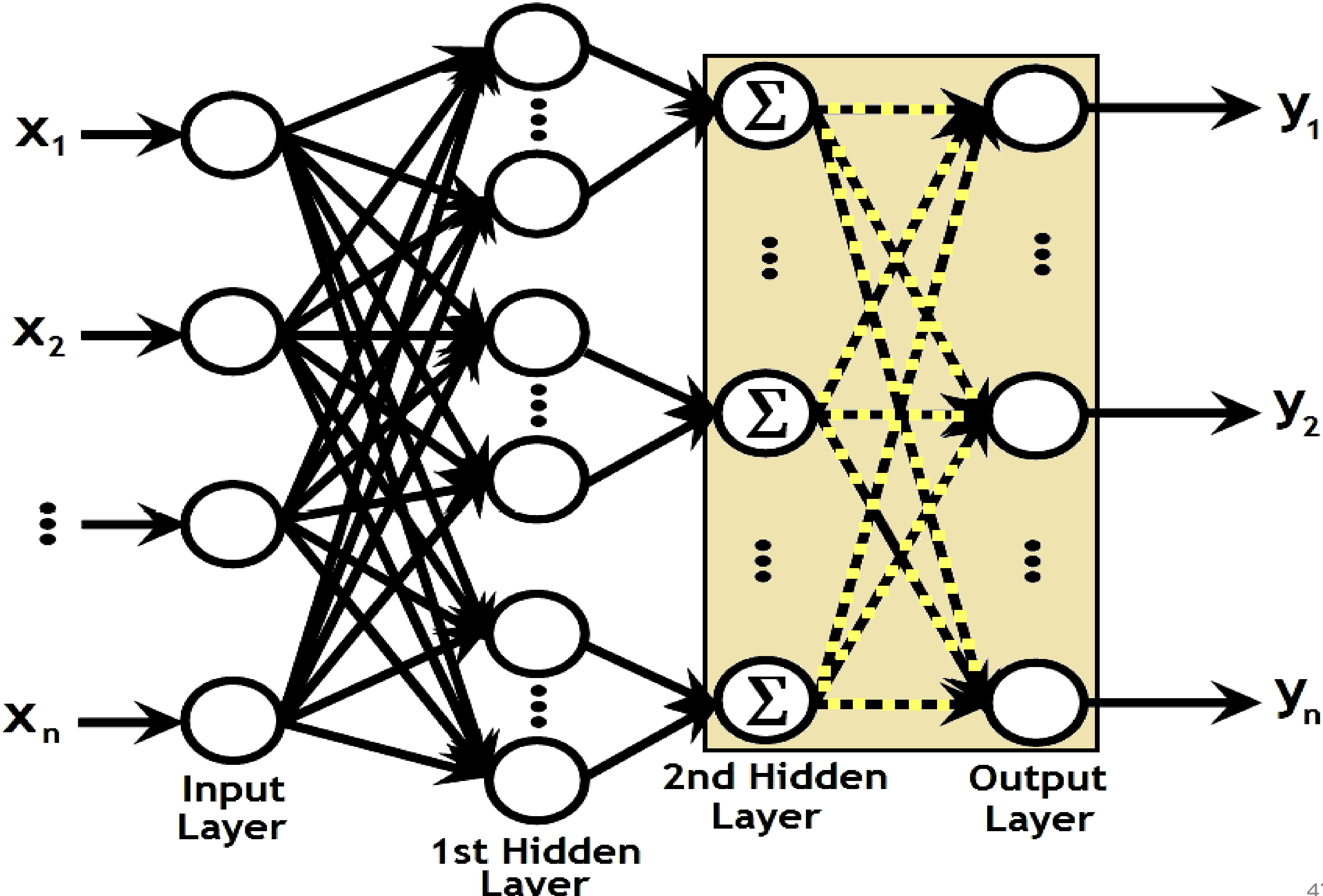
Training Algorithm for Robust Heteroscedastic Probabilistic Neural Network Using EM-ML with Jack-knife Procedure

pseudo code for viva voce\Rhpnn-autopdf

CLASSIFICATION OF HRPNN AND RHRPNN IN MULTIPLE SOURCE PD PATTERN CLASSIFICATION

Input Feature Vector	PD Types		Total No. of Training Datasets	Testing Datasets	No. of Centers (PDFs) labeled sequentially as V, S, OC, VC and VS		No. of Iterations		No. of Misclassifications		Classification Capability	
					HRPNN	RHRPNN	HRPNN	RHRPNN	HRPNN	RHRPNN	HRPNN	RHRPNN
Φ-q_{max}-n (30°)	Single Source	3	90 (30 sets/ type)	120	22,20,21	20,20,20	26	14	8	6	93.33%	95%
	Multi-Source: Partially overlapped	4	120 (30 sets /type)	160	24,22,20,21	20,18,18,20	28	12	12	8	92.5%	95%
Φ-q_{min}-n (30°)	Single Source	3	90 (30 sets/ type)	120	24,21,18	20,18,18	24	16	10	8	91.67%	95%
	Multi-Source: Partially overlapped	4	120 (30 sets /type)	160	20,25,24,18	18,17,16,18	30	15	10	7	93.75%	95.63%
Φ-q_{max}-n (10°)	Single Source	3	90 (30 sets/ type)	120	20,25,28	20,18,16	25	11	5	2	95.83%	98.75%
	Multi-Source: Partially overlapped	4	120 (30 sets /type)	160	10,12,13,8	5,3,6,7	36	15	7	3	94.17%	97.5%
q-n (30°): TPSW Scheme	Single Source	3	90 (30 sets/ type)	120	15,12,14	4,7,8	12	7	5	3	95.83%	97.5%
	Multi-Source: Partially overlapped	4	120 (30 sets /type)	160	14,16,14,10	5,4,7,3	8	5	4	2	97.5%	98.75%
q-n (10°): TPSW Scheme	Single Source	3	90 (30 sets/ type)	120	8,14,12	3,4,3	10	8	3	2	97.5%	98.75%
	Multi-Source: Partially overlapped	4	120 (30 sets /type)	160	12,14,18,11	3,4,4,6	7	6	6	4	96.25%	97.5%

ARCHITECTURE OF RBPNN



CLASSIFICATION CAPABILITY OF RBPNN - MULTIPLE SOURCE PD (NO. OF CENTERS)

Classification Capability of FOLS-RBPNN for Different Number of Centers

Type of Preprocessing Scheme	Sequence in Phase Window	Total No. of Patterns presented during Training	No. of FOLS Centers as Patterns		Classification Capability (Total No. of Patterns: 480)	
			Automatically generated centers	Manually modified centers	Automatically generated centers	Manually modified centers
Measures Based on Maximum Values	φ-q_{max}-n (30º)	180	112	128	81%	76%
	φ-q_{max}-n (10º)	180	94	114	89%	78%
Measures Based on Central Tendency	φ-q-n (30º)	180	104	124	85%	75%
	φ-q-n (10º)	180	72	108	92%	86%

CLASSIFICATION CAPABILITY OF RBPNN - MULTIPLE SOURCE PD

Classification Capability of FOLS-RBPNN for all types of Preprocessing Schemes

Type of Preprocessing Scheme	Sequence in Phase Window	No. of patterns during Training	No. of Patterns as FOLS Centers	Classification Capability (Total No. of Patterns: 480)
Measures Based on Maximum Values	φ-q_{max}-n (30°)	180	112	81%
	φ-q_{max}-n (10°)	180	94	89%
Measures Based on Minimum Values	φ-q_{min}-n (30°)	180	126	80%
	φ-q_{min}-n (10°)	180	108	84%
Measures Based on Central Tendency	φ-q-n (30°)	180	104	85%
	φ-q-n (10°)	180	82	92%
Measures Based on Dispersion	φ-q-n (30°)	180	114	83%
	φ-q-n (10°)	180	88	89%

Classification Capability of Enhanced Kernel Clustering based PNN Modular Version for Large Dataset PD Signature

Feature Vector	Classification Capability (%)				
	Decision based on Modular HOPNN Version	Decision based on Modular HRPNN Version	Decision based On Modular RHRPNN Version	Decision based on Modular RBPNN Version	Decision based on Combined Kernel Clustering based Modular PNN Versions
φ-q-n (measures for 10^{o} phase window): 1. Measures based on Maximum Values 2. Measures based on Statistical Operators & Higher Order Moments 3. Measures based on Types of Mean Values	93.4	95.2	97.2	93.6	96.8

INFERENCES & CONCLUSIONS

Sl. No.	PNN Modular Version	Clustering/ Center Selection Algorithm	Characteristic Features	Inferences
1.	**PNN Module I (Basic Versions)** ▪ OPNN ▪ APNN ▪ HOPNN	▪ OPNN and APNN does not utilize clustering algorithms ▪ HOPNN utilizes ML with EM Algorithm for clustering	▪ Utilizes same 'scatter' (σ) with different centers 'μ' ▪ More appropriate for small training datasets	▪Appropriateness of prototype centers becomes vital ▪ Restrictions on the credibility of the structure when the dataset lacks veracity
2.	**PNN Module II (Improved Partition Clustering Versions)** ▪ LVQ-PNN Versions ▪ K MEANS- PNN Versions	▪ Labelled Clustering: LVQ Versions-1, 2 & 3 ▪ Unlabelled Clustering: K-Means: Forgy & Standard	▪ Clusters obtained by training using reference (codebook) vector ▪ More appropriate for moderate datasets	▪Random centers of selected initial seed data as codebook vectors may lead to overtraining ▪ Appropriate for training validated sets of known sources of single source PD
3.	**PNN Module III (Enhanced Kernel Clustering Versions)** HRPNN RHRPNN RBPNN	▪ Maximum Likelihood with Expectation Maximization Algorithm (EM & ML) ▪ ML & EM with Jackknife procedure ▪ Forward Orthogonal Least Square (FOLS) Algorithm	▪ Utilizes different 'scatter' with different centers 'μ' ▪ Useful for large training datasets	▪Jackknife technique provides a more parsimonious yet effective sets of centers ▪ Counters the effect of 'outliers' effectively

INFERENCES & CONCLUSIONS

Sl. No.	PNN Modular Version	Clustering/ Center Selection Algorithm	Characteristic Features	Inferences
4.	PNN Module IV (Dynamic Pattern Recognition) ▪ Stationary CD-HMM ▪ Non-stationary CD-HMM	▪ LVQ 2 for training the density estimates of optimal state labels	▪ Utilizes Veterbi Algorithm for obtaining optimal state transition density estimates	▪ Provides a mechanism for discriminating PD sources based on non-stationary version of HMM - Correlated through the changes in the optimal state transition labels ▪ Provides an interesting opportunity for dynamic pattern recognition which in turn provides plausible mechanism to distinguish and characterize ageing of insulation systems
5.	PNN Module V (Hybrid Versions) ▪ Generalized S-Transform ▪ Hyperbolic S-Transform	▪ Principal Component Analysis (for dimensionality reduction)	▪ Clusters obtained by training using reference (codebook) vector ▪ More appropriate for moderate datasets	▪Offers an exciting and a viable alternative to WT in the context of providing a distinct methodology to associate the time-frequency relationship of the non-stationary behaviour of PD signatures ▪Capability of HST variant in providing plausible solutions to discriminate PD sources buried in noise during real-time studies

CONCLUSIONS & FUTURE SCOPE

- **Devising a strategy for Dynamic PD pattern recognition and classification utilizing the novel technique of non-stationary CDHMM-PNN version**
    - **Provides plausible avenues to understand the dynamics of the discharge mechanism due to the non-stationary behaviour of PD signatures**
    - **May prove to be useful in PD analysis for discharge initiated ageing in dielectric materials**

- **Formulation and development of a novel approach of utilizing the Hyperbolic S- Transform as a hybrid PNN Ensemble Classifier:**
    - **Provides a viable alternative to the more complex wavelet transformation**
    - **Easy yet effective time- frequency representation of PD signatures**
    - **Provides fresh opportunities in discriminating**
        - **Non-stationary and complex non-Markovian multiple source PD signatures**
        - **Discrimination of discharge signatures buried in noise**

- This study makes obvious the **capability of the HST variant in providing possible solutions to discriminate PD signatures buried in noise** during practical real-time measurements

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THANK YOU