Statistical Classification and System Identification Techniques for Partial Discharge Analysis

P. Jayasinghe [1] M. Jafari Jozani [1] B. Kordi [2]

[1] Department of Statistics

[2] Department of Electrical and Computer Engineering

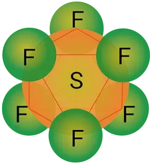
May 28, 2019

University of Manitoba

Outline

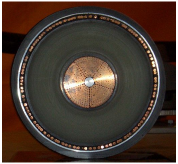
High Voltage Insulators

- Safe and reliable operation of high voltage systems highly depends on their insulation system.
- Insulators are used to isolate energized conductors from ground and one another.



(a) Gas

(b) Liquid



(c) Solid

(d) Combined

- Insulation condition monitoring is important (Cost, safety, reduced investment, etc.).

Partial Discharges (PD)

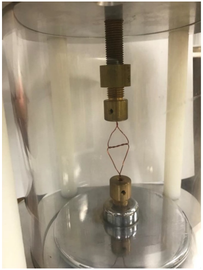
- Partial discharge: "localized electrical discharge that partially bridge the insulation" (Kuffel et al., 2000).
- PDs emit acoustic, optical, and electromagnetic energy.
- Caused by damages in the insulator
  - cracks/voids in a solid insulator
  - bubbles in a liquid insulator.
  - etc.
- Repeated exposure will lead to irreversible damage of the insulation (Gao and Noda, 2005).
- PD analysis uses symptoms of insulator deterioration to perform online/offline condition monitoring.

Motivation

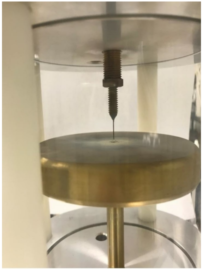
- PD source identification is a useful tool to assess the risk of insulation failure.
  - e.g. to create a system to alert of potential risks.
- Several studies have considered single PD source classification. Multiple PD source classification is not widely studied (Janani et al., 2017).
- Most methods require a skilled operator to classify the sources or extracts some key features (amplitude, rise time, etc.)
- In this work we study the problem of automatic identification of single/multiple PD sources which are not separable visually.
- Our developed methods are based on basis function approximation.

Experimental Setup

- Studied two types of partial discharge sources (twisted pair of wires and needle-plane setup).
- Partial discharge sources were connected to a high voltage source of 3 kV.
- PD measurement system, connected to an oscilloscope was employed to measure PD pulses.



(a) Twisted pair of wires.



(b) Needle-plane setup.

Collected PD Signals

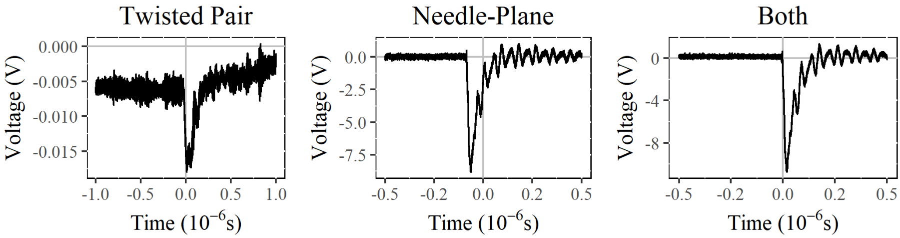
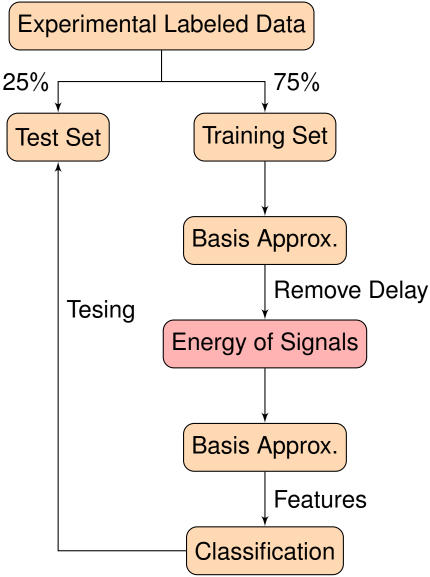
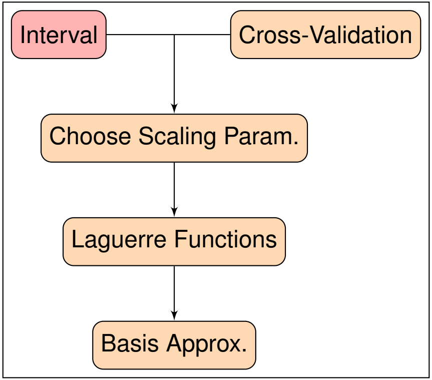


Figure: Samples of PD pulses for the three sources.

- 653 pulses from twisted pair and needle-plane setup.
- 512 from the combined source.
- Signals have a starting delay, which was eventually removed.



Basis Approximation

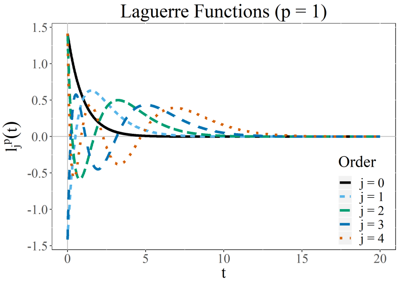


Laguerre Basis Expansion

- Laguerre basis expansion for the mathematical form of PD signals:

$$y(t) \simeq \sum_{j=0}^{k_y} y_j l_j^p(t) \quad \text{with} \quad l_j^p(t) = (-1)^j \sqrt{2p} e^{-pt} \left[\sum_{k=0}^{j} \binom{j}{k} \frac{(-2pt)^k}{k!} \right].$$

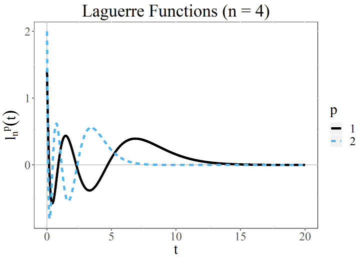
- $l_j^p(t)$ is a Laguerre function with order j, scaling parameter $p(>0)$ (Budke, 1989).
- y_j are expansion coefficients.
- Least squares, least absolute and Lasso objective functions were used to estimate y_j.



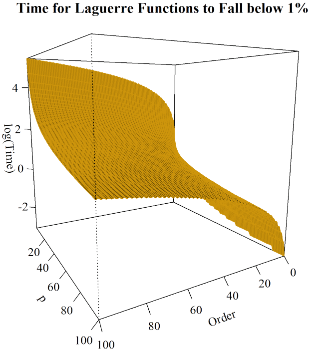
- Additionally, estimates based on the inner product were used $y_j = \int_0^\infty y(\tau) l_j^p(\tau)\, d\tau$. - Approximated numerically.
- Laguerre basis was selected due to an existing property, used in system identification.

Selecting p

- p changes the rate at which the Laguerre function goes to zero.
- Using Laguerre functions with small p will not be able to cover the entire signal.
- We improved a method proposed by Saboktakinrizi (2011) to select a suitable p.
- $f_T^{1\%}(n,p)$: time the Laguerre function with p and n takes to fall to 1% of it's peak.



(a) Laguerre functions with changing p.



(b) Relationship of n and p with $\log\left(f_T^{1\%}(n,p)\right)$.

Selecting p

- Quadratic regression model was used for the relationship of $f_T^{1\%}(n,p)$ with n and p.
- If τ is the time window of the signal that needs to be approximated, using
$$\tau \leq f_T^{1\%}(n,p),$$

We show that
$$\log(\tau) \leq 0.84 + 74.34n - 82.85p - 9.84np - 27.53n^2 + 33.35p^2.$$

- For $\tau = 1$,

n	0	40	80	120	160	200
Lower Interval	0	0	0	0	0	0
Upper Interval	2.5	43	85.7	128.4	171.1	213.8

Table: Interval for p for different orders.

Estimated PD Signals

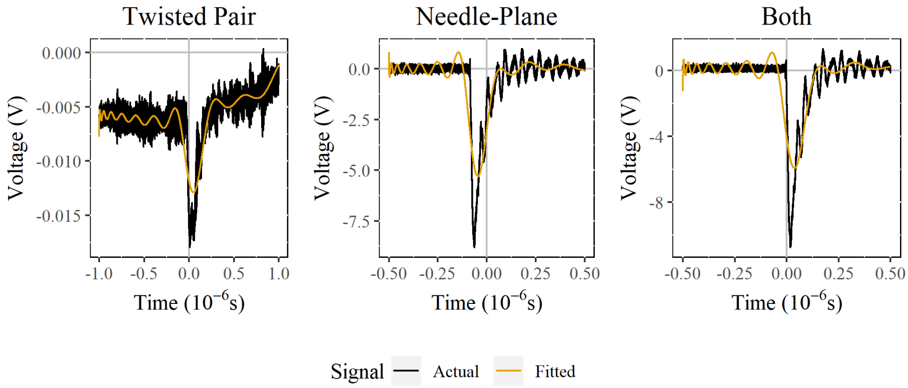


Figure: Samples of estimated PD pulses for the three sources.

- Entire shape of the signal is not captured by the approximation.
- An automatic procedure is introduced to remove the delay from the signal.

Automatic Removal of Signal Delay

- The objective is to find T such that $E_T = E_\infty P$.
- E_T is the energy of the signal at time T.
- E_∞ is the total energy of the signal.
- P is a desired proportion, and we showed that

$$T \geq \frac{1}{2} \log \left[\frac{2E_\infty P}{B_p C_p} + 1 \right]$$

- $E_\infty = \sum_{i=0}^{\infty} y_i^2$.
- $B_p = \left[\frac{\Gamma\left(p+\frac{1}{2}\right)}{\Gamma(p+1)\left|\Gamma\left(p+\frac{1}{2}\right)\right|} \right]^2$.
- $C_p = \sum_{i=0}^{\infty} \sum_{j=0}^{\infty} |y_i||y_j| \frac{(i+p)(j+p)\Gamma(i+p)\Gamma(j+p)}{i!j!}$.
- y_j are coefficients of the Laguerre basis approximation.

Automatic Removal of Signal Delay

Features for Classification

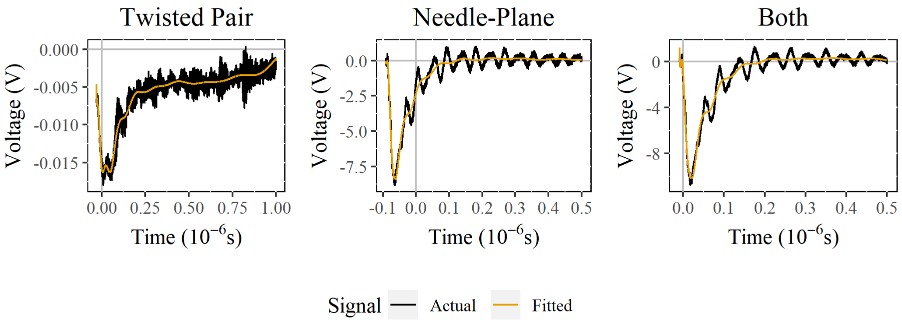


Figure: Samples of estimated PD pulses with delays removed.

- This shows an improved fit.
- Coefficients of the expansion are used as features for classification.

Classification

- First 3 basis expansion coefficients were used as our features.

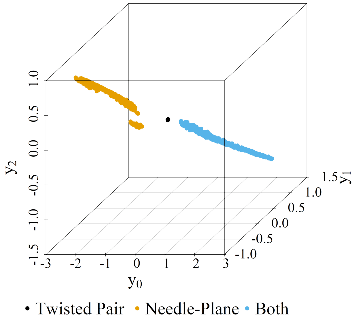


Figure: First 3 Laguerre Coefficients for all sources.

- LDA, QDA and SVM (Gaussian kernel) classifiers are used.
- 0% misclassification for QDA and SVM. 0.48% misclassification for LDA. (On test data).

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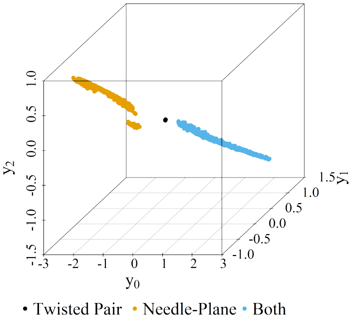


Figure: First 3 Laguerre Coefficients for all sources.

- LDA, QDA and SVM (Gaussian kernel) classifiers are used.
- 0% misclassification for QDA and SVM. 0.48% misclassification for LDA. (On test data).
- Signals from different sources are distinguishable by visual inspection.

Normalized Signals

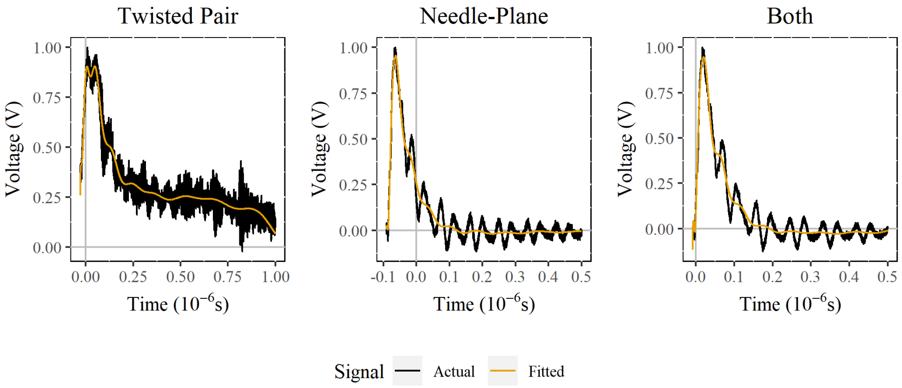


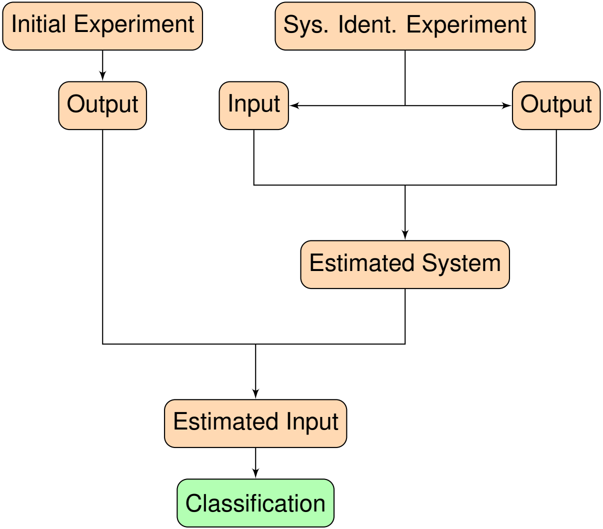
Figure: Sample of normalized PD pulses.

- 5.97%, 2.63% and 0.95% for LDA, QDA and SVM.
- If 7 Laguerre coefficients are used, a perfect classification can be observed.

System Identification

Figure: A Blackbox representation of a system.

- A known input $x(t)$ and an output $y(t)$ were used to estimate the system $h(t)$.
- If some conditions are satisfied, $y(t) = h(t) * x(t)$.
  - $*$ is the convolution operator.


Initial Experiment
Sys. Ident. Experiment
Output
Input
Output
Estimated System
Estimated Input
Classification

System Identification

- Write all functions using Laguerre expansion.

- Developed
  1. a recursive formula

$$h_m = \frac{1}{x_0}\left(\sqrt{2p}y_m - \sqrt{2p}\left(\sum_{j=1}^{m}(-1)^{m+j}y_{j-1}\right) - \sum_{i=0}^{m-1} h_i x_{m-i}\right),$$

  2. used group Lasso (Friedman et al., 2010) objective function, to estimate the system.

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  2. used group Lasso (Friedman et al., 2010) objective function, to estimate the system.
- No improvement in classification when classifying based on the input.

Conclusions

- In this research we developed methods to
  - identify the source of a PD using Laguerre basis approximations,
  - remove the delay from a signal,
  - identify the underlying system.

Conclusions

- In this research we developed methods to
  - identify the source of a PD using Laguerre basis approximations,
  - remove the delay from a signal,
  - identify the underlying system.
- Selecting a proper p is essential.
- There were many numerical limitations especially when generating Laguerre functions with small time gaps.
- Singular design matrices when least squares objective functions are used.
- Further research includes to find the effect of the group sizes in group Lasso.

References I

Budke, G. (1989, dec). On a Convolution Property Characterizing the Laguerre Functions. *Monatshefte für Math. 107*(4), 281–285.

Friedman, J., T. Hastie, and R. Tibshirani (2010, jan). A Note on the Group Lasso and a Sparse Group Lasso.

Gao, C.-F. and N. Noda (2005, apr). Effects of Partial Discharges on Crack Growth in Dielectrics. *Appl. Phys. Lett. 86*(16), 162904.

Janani, H., B. Kordi, and M. J. Jozani (2017, feb). Classification of simultaneous multiple partial discharge sources based on probabilistic interpretation using a two-step logistic regression algorithm. *IEEE Trans. Dielectr. Electr. Insul. 24*(1), 54–65.

Kuffel, J., P. Kuffel, and W. Zaengl (2000). *High Voltage Engineering Fundamentals* (2nd ed.). Elsevier.

Saboktakinrizi, S. (2011). *Time-Domain Distortion Analysis of Wideband Electromagnetic Field Sensors Using Orthogonal Polynomial Subspaces Master of Science*. Ph. D. thesis, University of Manitoba.

Questions?

Find this presentation at `https://github.com/sachijay/SSC19`

Thank You.