# Using Machine Learning and Deep Learning for Characterizing Partial Discharge in Underground Utility Cables for Predictive Maintenance Application

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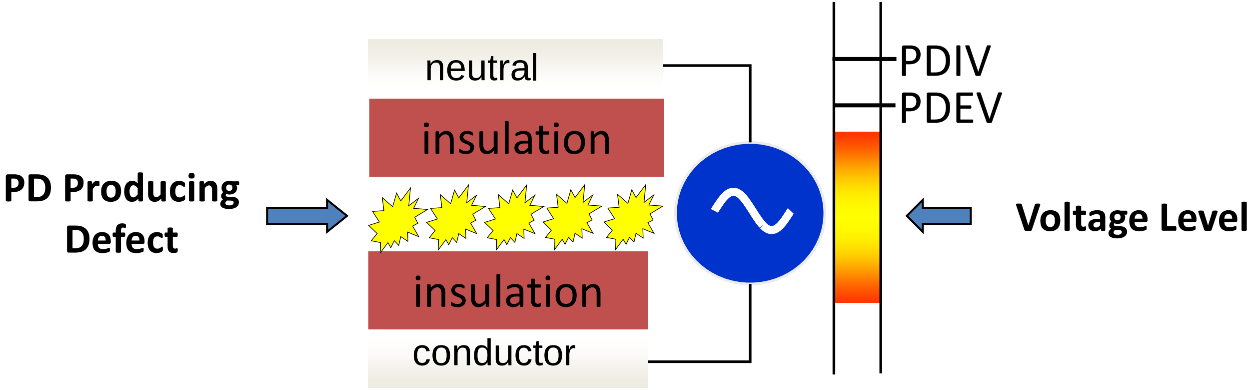
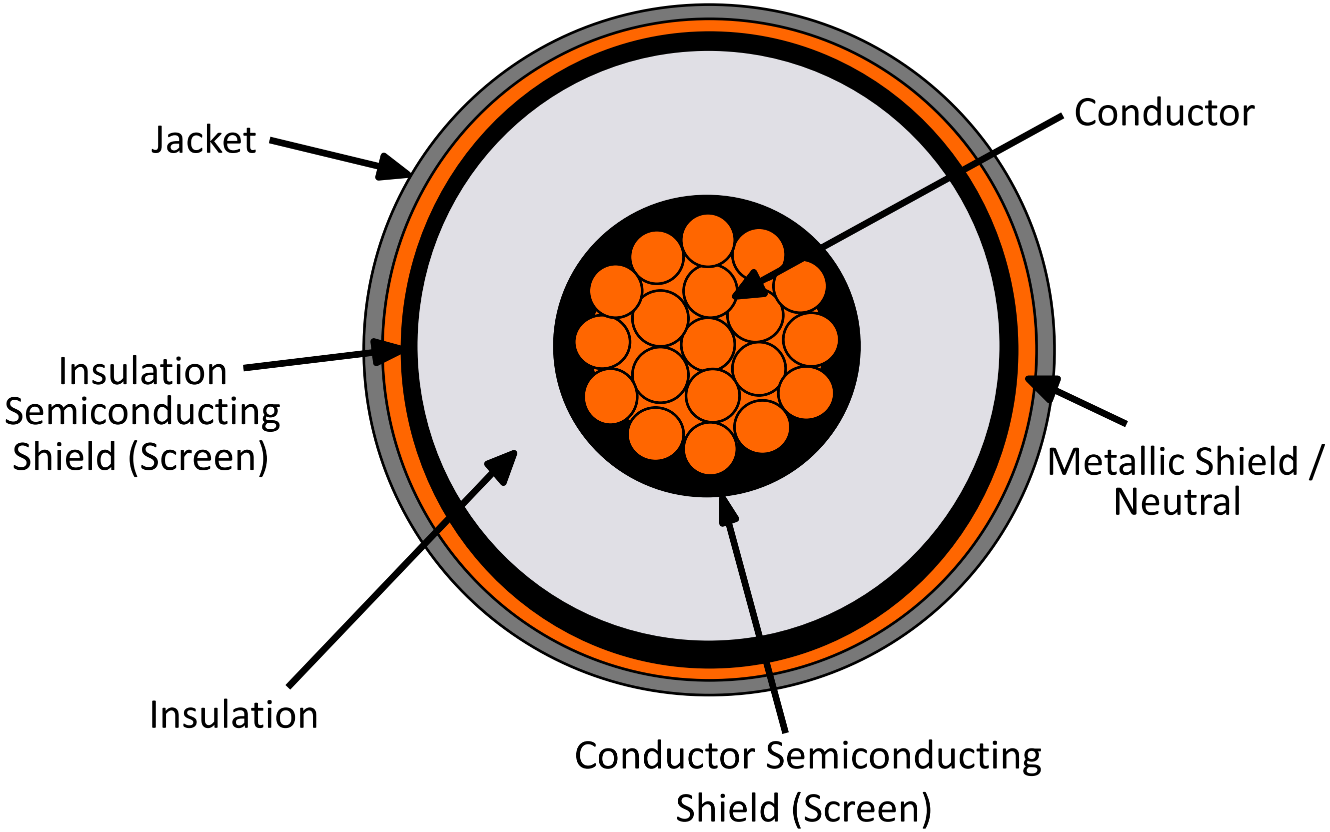
IMCORP
Power Cable Reliability

# Partial Discharge (PD)

- PD is an electrical discharge that does not completely bridge the space between two electrodes.
- The voltage at which **PD** first appears is the **I**nception **V**oltage **(PDIV)**
- **PD** is extinguished when the voltage is reduced below the level called the **E**xtinction **V**oltage **(PDEV)**



# General Cable Configuration (MV and HV)



# IEEE statistics on Insulation Failures

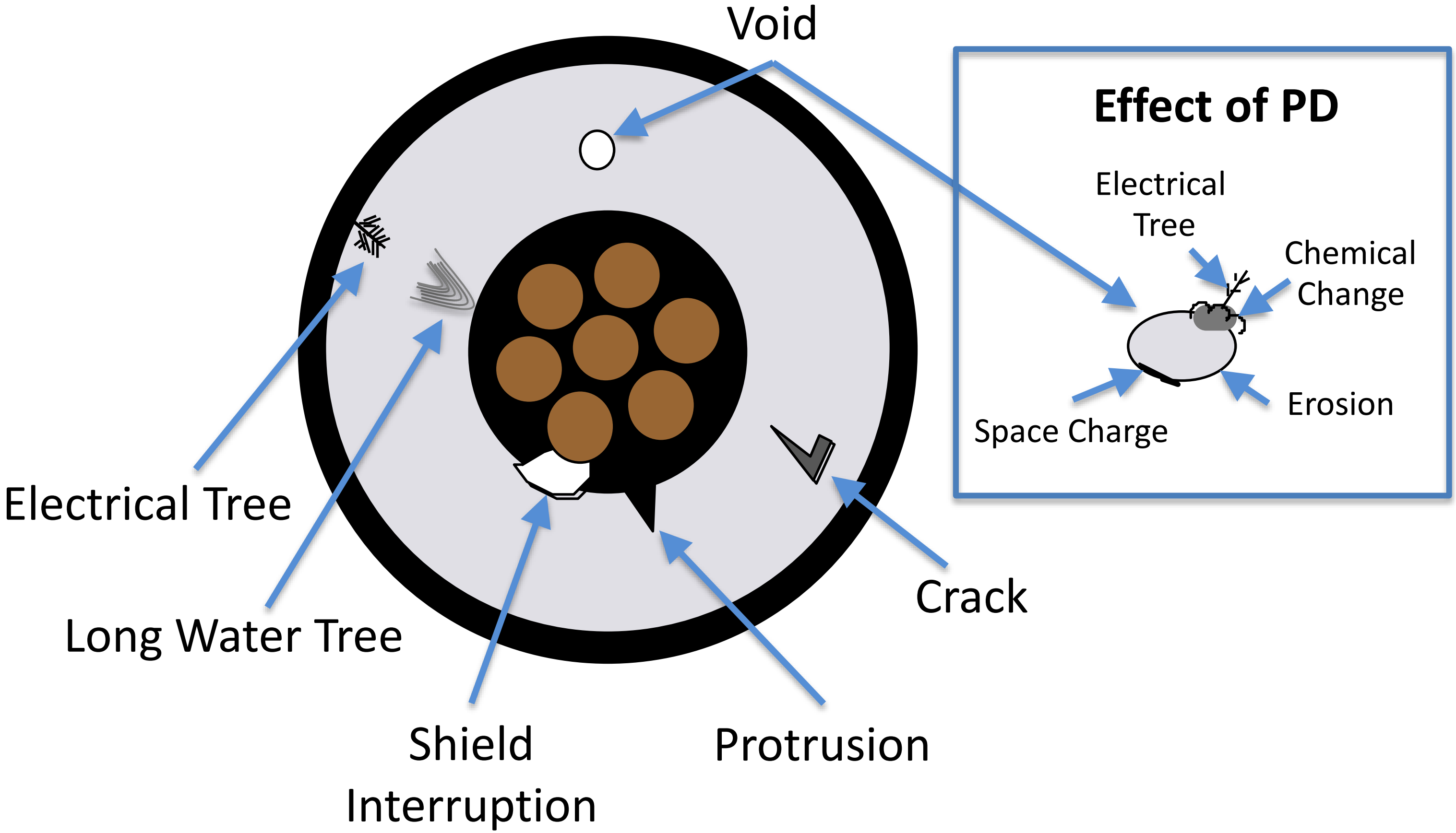
According to IEEE, insulation failure is the reason for failure of 84% of the transformers and up to 90% for Underground cables and Bus Duct and 95% for Insulated Switchgears.

## Total Failures due to Insulation Breakdown

| Component | Percentage of insulation failure |
|---|---|
| Transformers | 84% |
| Circuit Breakers | 21% |
| Disconnect Switches | 15% |
| Insulated Switchgear Bus | 95% |
| Bus duct | 90% |
| Cable | 89% |
| Cable Joints (splices) | 91% |
| Cable Terminations | 87% |

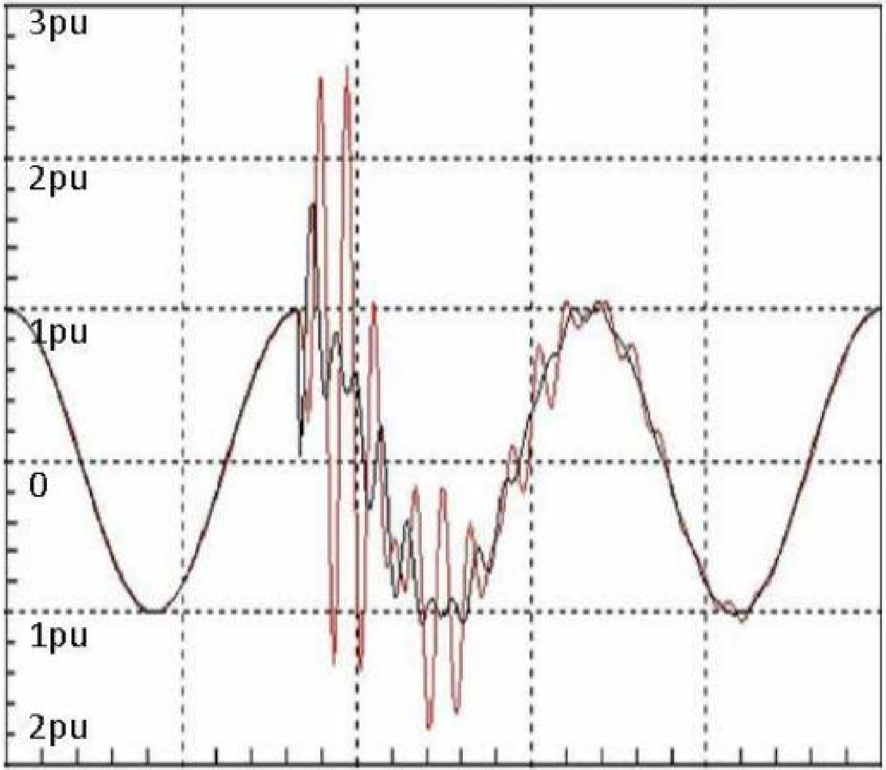
*Based on IEEE Gold Book Table 36*

# Defects: Electric Stress Enhancers



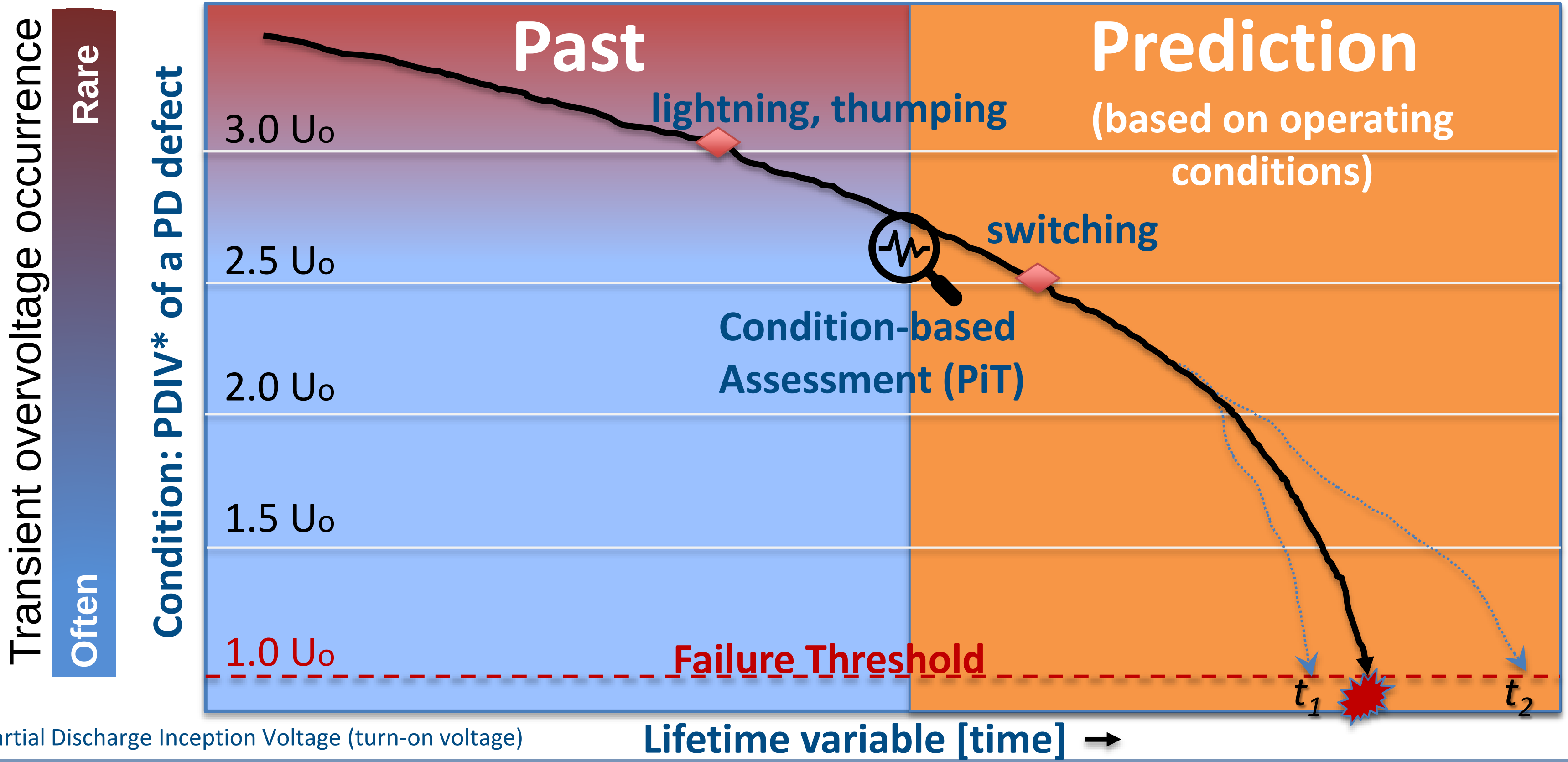
# Transient Over-Voltages (el. stress enhancers)

## Typical Switching Surge Effect on a Power System




Source: Thomas C. Hartman, IEEE Canada, November 2015

# Predictive Aspect – From Defect to Failure




*PDIV: Partial Discharge Inception Voltage (turn-on voltage)

# Defects developing eventually into Failures

Courtesy of General Cable

**Defects:**

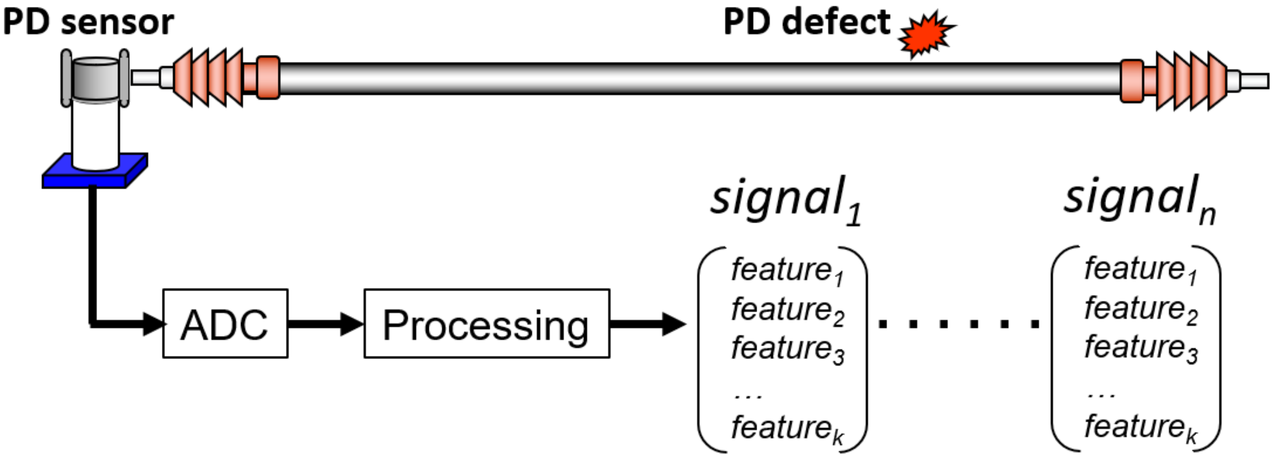
- Workmanship
- Insulation degradation
- Production (seldom)

**Failure:**

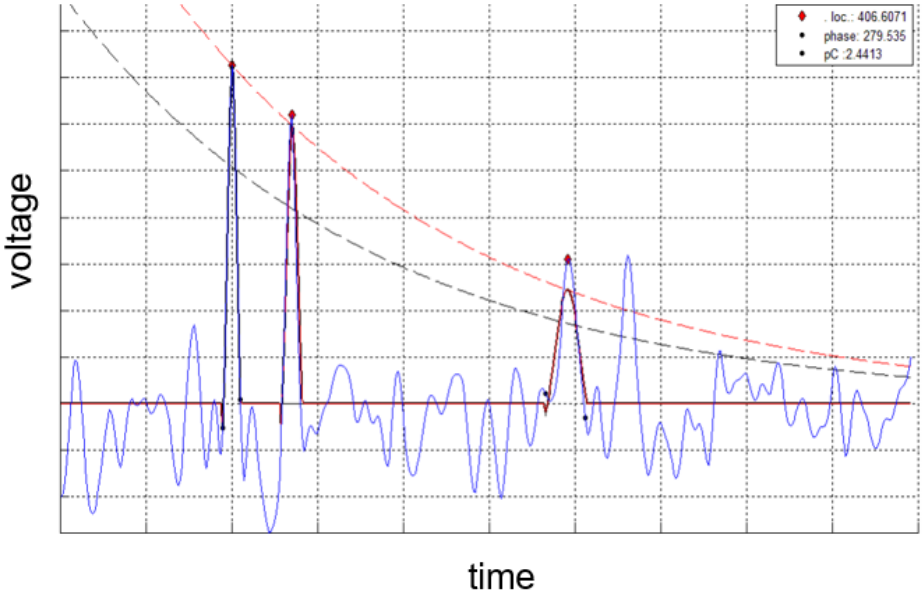
- Outage (unexpected)
- Safety Hazard
- O&M expense

# Capturing time series signals from a defect

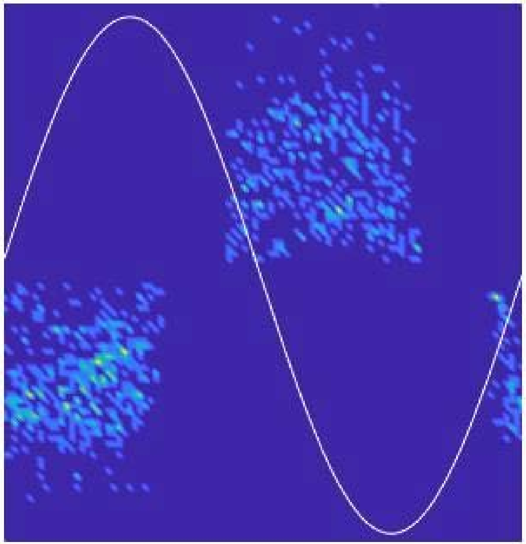
**Time-Capturing time series signals from an underground power cable**



# Partial Discharge (PD) Signal and PRPD



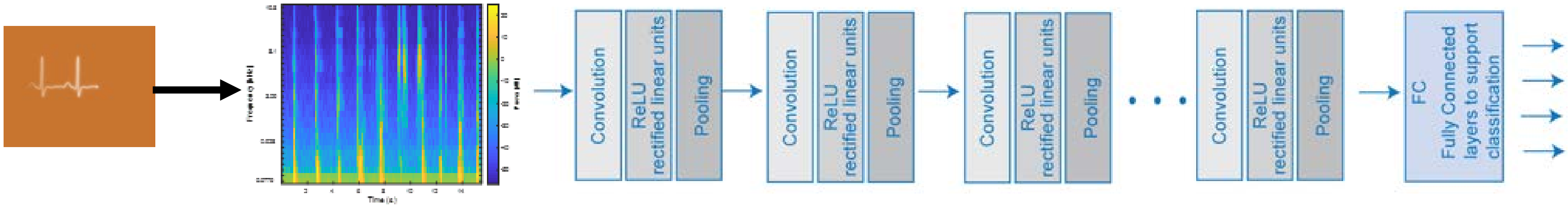

Time-resolved Partial Discharge signal



Phase-resolved PD (PRPD)

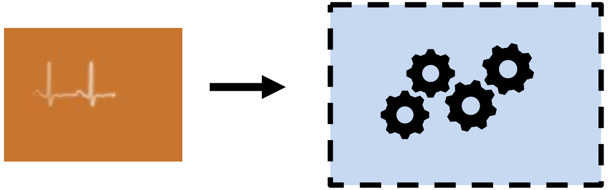
# Deep Learning Workflow for Signal Applications

Convolutional Neural Networks (**CNN**)
*Signals can be converted into images*

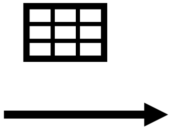


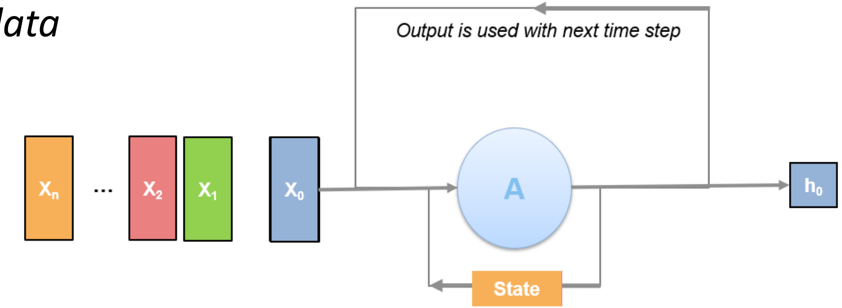

Time-Frequency Transformation

Long-Short-Term-Memory (**LSTM**) Networks
*Time-series data*



Feature Engineering






Courtesy of MathWorks®

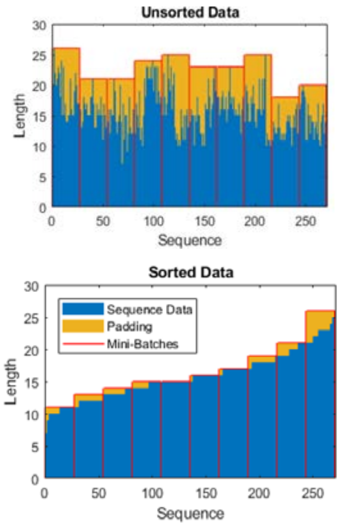
# PD classification with different classifiers

## Classification of PD into “PD” and “non-PD”

| Classifier | Accuracy | Precision | Recall | F1-score |
|---|---|---|---|---|
| Random Forest | 0.90 | *0:* 0.97<br>*1:* 0.70 | *0:* 0.90<br>*1:* 0.90 | *0:* 0.94<br>*1:* 0.79 |
| Logistic Regression | 0.91 | *0:* 0.95<br>*1:* 0.74 | *0:* 0.93<br>*1:* 0.82 | *0:* 0.94<br>*1:* 0.78 |
| Support Vector Machine | 0.91 | *0:* 0.95<br>*1:* 0.74 | *0:* 0.93<br>*1:* 0.82 | *0:* 0.94<br>*1:* 0.78 |
| Ensemble Learning (AdaBoost) | 0.91 | *0:* 0.93<br>*1:* 0.83 | *0:* 0.96<br>*1:* 0.71 | *0:* 0.95<br>*1:* 0.77 |
| Neural Network | 0.95 | *0:* 0.97<br>*1:* 0.86 | *0:* 0.96<br>*1:* 0.87 | *0:* 0.97<br>*1:* 0.87 |

# Workflow for model training

## LSTM Model Training for PD classification in Matlab ®




Data Pre-processing and Augmentation

Training Options for the network

Sorting

Normalize Sequence Data

Mini-Batch Size

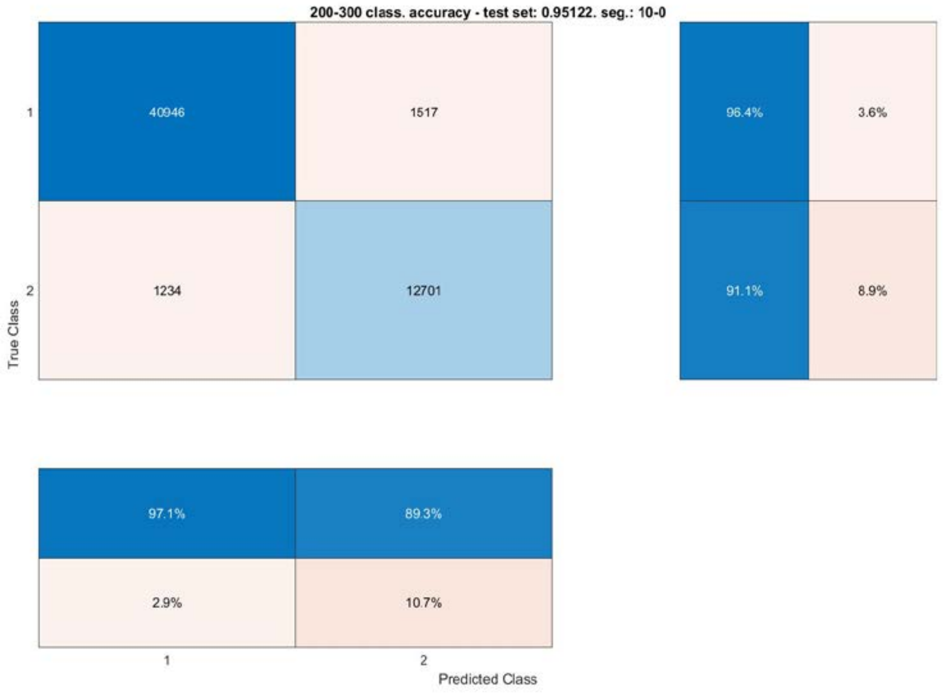
Shuffle

Final trained network

# Partial Discharge Identification

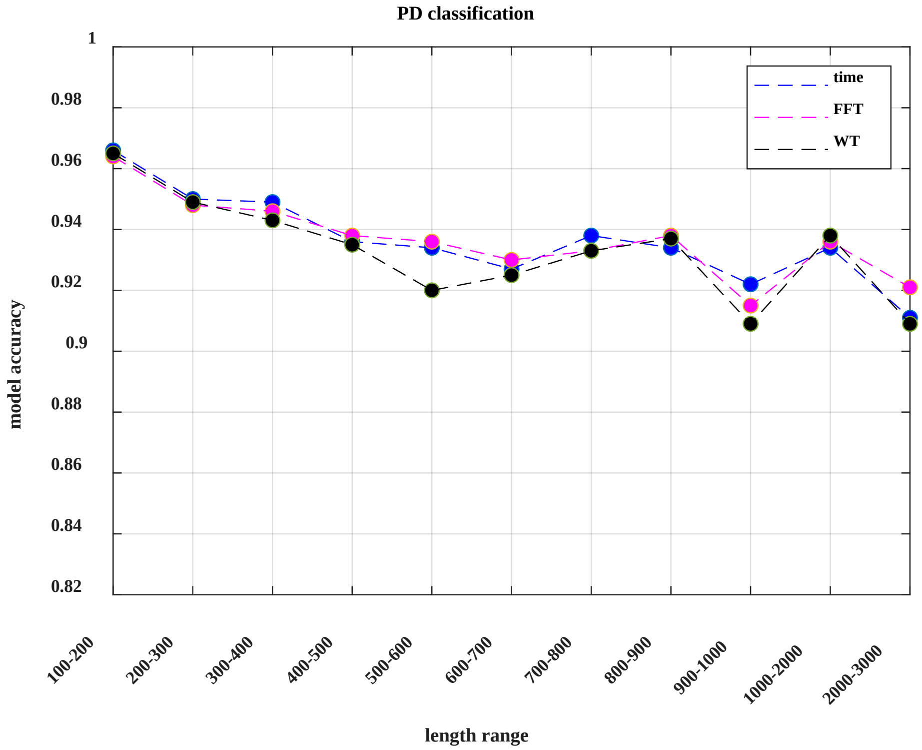
## Deep Learning on Partial Discharge Signals with LSTM

- 281,989 labeled PD time series (signals)
- 69,173 true instances, 212,816 false instances
- Methodology: Recurrent Neural Network (LSTM)
- Overall Accuracy: **95.1%**.



# Binomial Classification results for PD identification

Binomial Classification results with and without data augmentation



# Partial Discharge Location Characterization

## Deep Learning on Partial Discharge Signals with LSTM

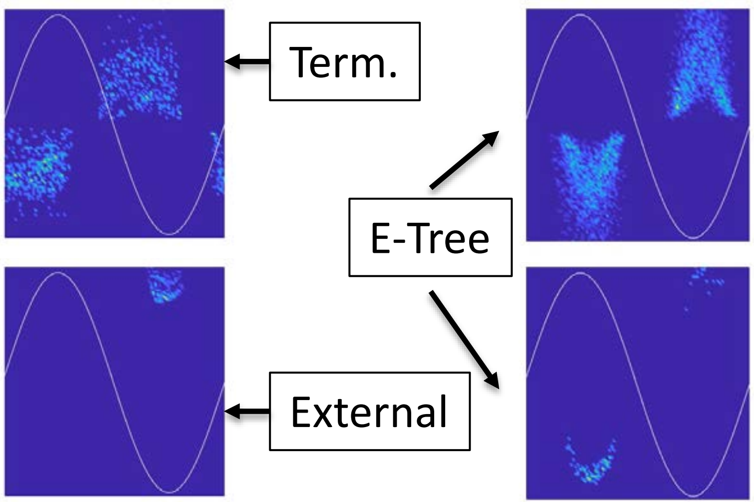
- 281,989 labeled PD time series (signals)
- 69,173 true instances, 212,816 false instances
- Methodology: Recurrent Neural Network (LSTM)
- Overall Accuracy: **93.27%**.

confusion matrix for 20 cable segments

| True Class \ Predicted Class | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 5103 | 17 | 8 | 4 | 1 | 1 | 2 | 1 | 2 | 8 | 17 | 22 | 2 | 1 | 3 | | | | 1 | 220 | 94.3% | 5.7% |
| 2 | 18 | 109 | 4 | 2 | 1 | 1 | 3 | 1 | 3 | 2 | 3 | 2 | 6 | 2 | 2 | | 1 | 1 | 3 | 4 | 64.9% | 35.1% |
| 3 | 5 | 11 | 121 | 4 | | | | | 1 | 2 | | 1 | | | | | 1 | | | 1 | 82.3% | 17.7% |
| 4 | 4 | 2 | 4 | 62 | 3 | | | | | | 1 | 1 | | 1 | 4 | | | | | 4 | 72.1% | 27.9% |
| 5 | 1 | | | 3 | 23 | 1 | | | | 1 | | | | | 5 | | | 2 | 1 | | 62.2% | 37.8% |
| 6 | | 1 | | | 3 | 118 | 6 | | | | 1 | 1 | 1 | | | | | | | | 90.1% | 9.9% |
| 7 | | | | | | 13 | 63 | 4 | 1 | 1 | | 1 | | | 1 | | | | | 2 | 73.3% | 26.7% |
| 8 | 3 | | | 1 | 1 | | | 29 | 3 | 1 | | | | | 2 | | | | | 2 | 69.0% | 31.0% |
| 9 | 2 | 2 | | | | | | 6 | 165 | 3 | | | | | | | | | | 7 | 89.2% | 10.8% |
| 10 | 1 | 2 | | | 2 | | | | 14 | 161 | 6 | | 1 | | 5 | 1 | | | | 3 | 82.1% | 17.9% |
| 11 | 1 | | | | | | | | | 17 | 103 | 12 | | | 1 | | | | | 1 | 76.3% | 23.7% |
| 12 | | | | | | | | | | | 13 | 181 | 1 | | | | | | | 2 | 91.9% | 8.1% |
| 13 | | 2 | | | | | | | 2 | | | 4 | 286 | 3 | | | | | | 2 | 95.7% | 4.3% |
| 14 | | | | | | | | | | | | | 7 | 184 | 14 | | | | | | 89.8% | 10.2% |
| 15 | 1 | 1 | | | 4 | | | | 1 | 1 | | | | 5 | 268 | 4 | | | | | 94.0% | 6.0% |
| 16 | 1 | | | 1 | 2 | | | | | | | | | | 18 | 82 | 25 | | 1 | 2 | 62.1% | 37.9% |
| 17 | 1 | | | | | | | | 1 | | | | | | | 4 | 249 | 2 | | 2 | 96.1% | 3.9% |
| 18 | 1 | | | | | | | | | | | | | | | | 6 | 35 | 8 | 1 | 68.6% | 31.4% |
| 19 | 2 | 2 | 1 | | | | | | | | | | | | | | | 2 | 402 | 10 | 95.9% | 4.1% |
| 20 | 180 | 6 | | 3 | 2 | 1 | | | 1 | 2 | | | 2 | | 2 | | 1 | | 5 | 5196 | 96.2% | 3.8% |
| | 95.8% | 70.3% | 87.7% | 77.5% | 54.8% | 87.4% | 85.1% | 70.7% | 85.1% | 80.9% | 71.5% | 80.4% | 93.5% | 93.9% | 82.5% | 90.1% | 88.0% | 83.3% | 95.5% | 95.2% | | |
| | 4.2% | 29.7% | 12.3% | 22.5% | 45.2% | 12.6% | 14.9% | 29.3% | 14.9% | 19.1% | 28.5% | 19.6% | 6.5% | 6.1% | 17.5% | 9.9% | 12.0% | 16.7% | 4.5% | 4.8% | | |

# Phase-Resolved PD classification

- Defect type classification
- **Risk factor assignment** for defects
- 5 classes, 3007 images
- Classification accuracy: **96.7%**




**class accuracy on test set: 96.7%**

| True Class \ Predicted Class | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| 1 | 27 | 3 | | 4 | 1 |
| 2 | 1 | 21 | | | |
| 3 | 1 | | 8 | | |
| 4 | 1 | | | 250 | |
| 5 | | | | | 20 |

# Conclusion

- Automated workflow for risk assignment of PD defects has been developed
- Deep Learning models successfully classify and characterize PD measurements
- Risk prioritization and risk factor assignment to assets allows for optimal asset operation and maintenance

# Working at the intersection of Power Systems and Artificial Intelligence

**Biography: Steffen Ziegler**

Steffen Ziegler holds a Master of Science degree in Electrical Engineering from the Karlsruhe Institute of Technology - Germany. With over 20 years of engineering management experience and research and development experience in the field of Power Systems, Steffen is currently leading a team of engineers in the field of Signal Analysis and Artificial Intelligence. Steffen received a one-year scholarship to study at the University of Connecticut. At the University of Connecticut, he studied in the field of electrical engineering, which included the successful completion of an independent study in the field of Power Systems with Prof. Dr. Matthew Mashikian.

Since 1999 Mr. Ziegler is working for IMCORP and is currently the Director for Signal Analysis and Artificial Intelligence. Past positions include Manager for Research and Development. He has specialized in the field of digital signal processing applications and machine learning and deep learning applications for Underground Power Cable Systems. Mr. Ziegler published peer-reviewed papers for Jicable, Cired and IPST. He presented at numerous conferences, including PES-ICC, EUEC, Grid Modernization Forum and MathWorks Energy Speaker Series. He is a member of the IEEE Power & Energy Society and regularly attends and contributes as a working group member at Insulated Conductors Committee (ICC) meetings. He is also a member of the VDE in Germany. Past memberships include the Cigré B1.28 working group.

Since 2015, Mr. Ziegler is a member of the Industrial Advisory Board of the ECECS department at the University of New Haven in Connecticut.