Study Committee B3

Substations and Electrical Installations

Paper ID 284

Practical Machine Learning Applications

The Doble Engineering Company

Tom RHODES[1], Imene MITICHE[2], Tony MCGRAIL[3], Falk WERNER[3], Philip BOREHAM[3]

1: Duke Energy, 2: Glasgow Caledonian Uni., 3: Doble Engineering

Introduction

- Investigate practical issues with machine learning (ML)
- ML implementations may overstate expectations
- Practical results need to support decisions
- Practical implementations need to be able to justify analyses in an auditable manner: glass box, not black box

Motivations for ML at Duke Energy

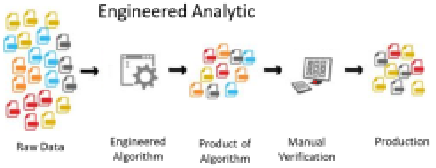
- Support Health and Risk Management analyses
- 10,000 transformers >7.5MVA
- 25,000 circuit breakers
- Lots of data, decreasing O&M dollars
- Decreasing number of people to evaluate and manage data, and experienced personnel retiring

Aims for ML at Duke Energy

- Manage replacement of aging fleet – reduce emergent issues
- Targeted maintenance to extend asset life
- Reduce customer minutes interrupted from transmission asset failures
- Capture Expertise of SMEs many of whom are retiring

Engineering Analytic Application

- Standard analyses, IEEE etc, based on decades of experience
- Note use of SME for *manual verification*

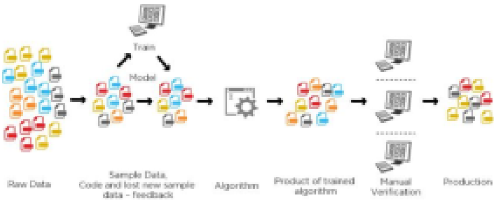


Issues faced in ML

- *"We tried it and it doesn't work for power transformers"* Duke Energy Engineer, 2017
- Data needs to be cleaned and maintained
- Expecting the ML to 'sort out' the validity and consistency issues with data did not work
- Need to have data scientists and IT professionals manage the *methods*, but Transformer SME's manage the data *interpretations*
- Failure modes may not follow expected linear progressions; transformer populations may not follow a 'bathtub curve' for asset mortality
- *"Your data must be wrong because if we use it our models don't work."* Data scientist, 2019

Supervised ML at Duke Energy

- Lots of data, classified by SMEs
- Known results based on maintenance/intervention
- Note SME still performs *manual verification* of outputs



Study Committee B3

Substations and Electrical Installations

Paper ID 284

The Doble Engineering Company

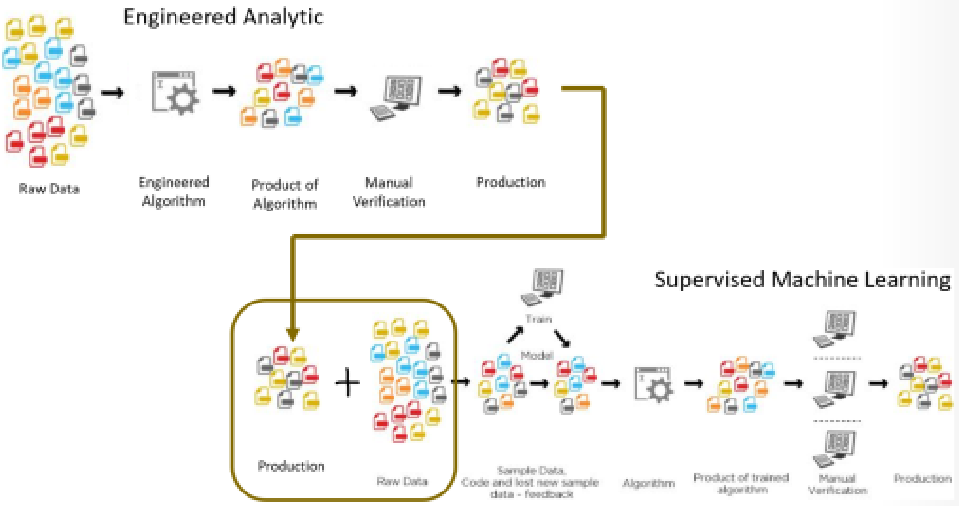
Practical Machine Learning Applications

Tom RHODES[1], Imene MITICHE[2], Tony MCGRAIL[3], Falk WERNER[3], Philip BOREHAM[3]

1: Duke Energy, 2: Glasgow Caledonian Uni., 3: Doble Engineering

Hybrid ML Approach - implementation

- Note the Engineered analytics have not 'gone away' both the raw data and the analytic outputs are input into the ML
- The system is good at identifying those cases which may be borderline or at an incipient stage



Hybrid ML Approach - discussion

- It was estimated that 95% of the benefit of the ML application could be achieved through data clean-up, consistency and systematic standards application
- The remaining 5%, however, are borderline cases identified early enough to support intervention in a *meaningful manner*
- The ML is required to 'do well' repeatedly on well-organized data, with well-defined analyses, and has gained acceptance within the organization

ML Outcome at Duke Energy

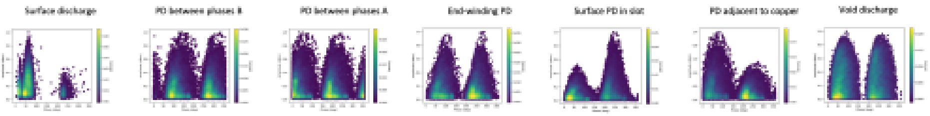
- Identification of units with incipient cooling system issues allowed for early intervention in cases which may have otherwise been missed
- Data clean up "is essential", covering 80% of initial time/effort in this application
- No 'black box' analytics allowed – SMEs can see how the ML works and what it 'considers' important

Phase Resolved Partial Discharge (PRPD)

- Partial discharge pulses recorded over multiple power system cycles, usually require expert analysis
- Some sources do have similar PRPD patterns

PRPD Implications

- Different PD sources may have different time to failure reflecting different failure modes
- Early diagnosis is often crucial to successful intervention



CIGRE PARIS 2022

The Doble Engineering Company

Study Committee B3

Substations and Electrical Installations

Paper ID 284

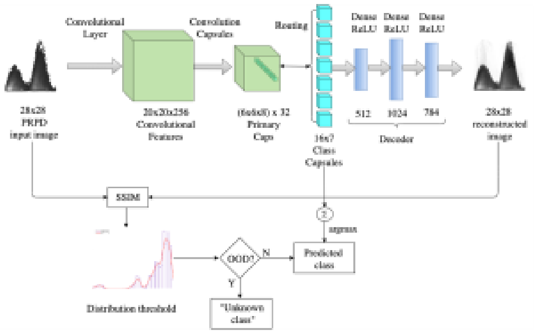
Practical Machine Learning Applications

Tom RHODES[1], Imene MITICHE[2], Tony MCGRAIL[3], Falk WERNER[3], Philip BOREHAM[3]

1: Duke Energy, 2: Glasgow Caledonian Uni., 3: Doble Engineering

PRPD Data Encoding/Decoding

- No point in classifying a PD pattern if it is not well represented in the training data set
- The data is ‘compressed’ and then reconstructed using the ‘knowledge’ within the AI based on the training data
- Poor reconstruction means the data is not well represented in the training set and may be an anomaly, an outlier, or a new data ‘class’ etc.
- “Out of distribution” (OOD) analysis helps ensure we don’t inappropriately try classify spurious data



Reconstruction Error

- Three approaches used to calculate error: Mean Absolute (MAE), Mean Square (MSE) and Structural Similarity Index Matrix (SSIM)
- Set SSIM index to 0.60 as the discriminant

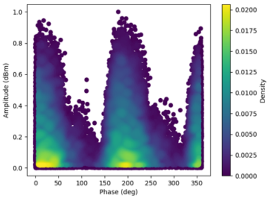
Reconstruction Error Statistics

- SSIM provides best overall accuracy

Method	Overall accuracy %	In-distribution accuracy %	OOD accuracy %
CapsNet-MAE	96.61	93.23	100
CapsNet-MSE	96.67	93.34	100
CapsNet-SSIM	**97**	**94**	100

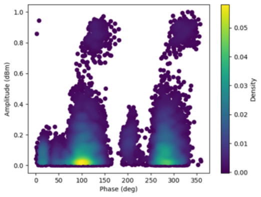
106 MVA Steam Turbine Data - 1

- Raw data shown below: SSIM at 0.94
- Data in line with training data: classified as Phase A PD



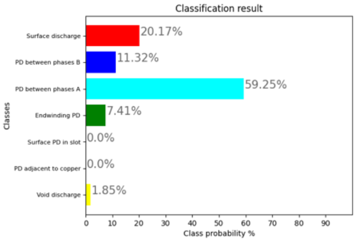
106 MVA Steam Turbine Data - 2

- Raw data shown below: SSIM at 0.38
- Data is OOD: not classified



Classification of Data - 1

- Data has similarity with a number of possible sources
- Phase A PD is ‘*closest*’ within the training data



Conclusion

- OOD detection method shows promise in identifying data which is not well represented in the original ML data set
- The SSIM metric of the original and the reconstructed PRPD images is a good indicator of OOD
- OOD detection and PD types classification in real-world data has been successful. Further work to ‘generalize’ has begun
- *“Train a ML system to distinguish between cats and dogs… and the system can **also** learn to not try to classify an alligator as it doesn’t look at all familiar…”*

http://www.cigre.org