ABSTRACT

AI systems provide a lot of promise in the analysis and evaluation of power system data. This article shows some of the benefits of the application of AI, identifying the strengths and weaknesses of the approach, and provides a way forward to apply AI in a meaningful and controlled manner.

KEYWORDS

application, artificial intelligence, experience, machine learning, scientific machine learning

Successful application of AI techniques: A hybrid approach

The major applications of AI and ML in the transformer industry are the diagnostics and giving the predictions where and when the next transformer will fail

Introduction

There is a large push to use artificial intelligence (AI) and machine learning (ML) to help reduce the time of performing maintenance on transformers and predicting where and when the next transformer will fail [1, 2, 3]. Major companies in different industries are promoting and telling the wonders of AI and ML: managing the replacement plans of an ageing or aged fleet, reduction in maintenance while extending asset life, operational efficiency, all while capturing the expertise available so that it is not lost. These are lofty goals, and claims are already being made for the benefits of AI applications in 'the real world'. The problem we face is that AI is not perfect – it has its role in the analysis of well-described problems with sufficient data to cover all possible situations that may be found. Let us consider two things which are true in our industry:

- we are almost always faced with incomplete and possibly ambiguous data,
- the analysis of data does not take place in a vacuum as we have a history and a knowledgebase to call on to check the results.

So in simple terms, if an AI system is developed which analyses data for power transformers, then based on the data available it should be able to replicate what has already been developed as 'common knowledge' or industry expertise. For example, in DGA analysis, identifying increased levels of acetylene with increased probability of failure should be a rule which is identified [4]. If the AI is unable to state the rule in clear terms, then we may not trust other analyses described: we have to have a believable audit trail for the analysis to justify actions.

Business environment:

In an ideal world, we would have complete and detailed information on each of our transformers: maintenance history, test data, monitoring data, fault data, and so on. There would be standards and analytic tools to tell us about each individual transformer: the health, probability of failure, remaining life and so on. In practice, the data may be incomplete, inconsistent, or missing.

It is common for a subject matter expert (SME) or a technician to analyse and evaluate all available data to make decisions about actions and interventions in their region or area. Transformers would be ranked manually and grouped for prioritisation of maintenance, replacement or other intervention. Some of the analysis methods may be used only by some SMEs and not others, and they may have their own specific approaches meaning that analysis could be inconsistent based on the region and the individual involved. So, the push to more uniform approaches based on AI and ML seems both rational and sensible, especially as most experienced personnel, who understand the data, are retiring.

So, what can AI and ML do for us? Some examples of benefits include [5]:

- In weather forecasting, AI has been used to reduce human error,
- Banks use AI in identity verification processes,
- A number of institutes use AI to support helpline requests, sometimes via chatbots,
- Siri, Cortana and OK Google all build on AI apps,
- AI systems can classify well-organised data – such as X-rays.

On the downside, there are some issues [6]:

- AI may be good at interpolation within a dataset, but not at extrapolation to 'new' data,
- 'Giraffing' – the generic name for identifying the presence of objects where those objects do not exist,
- Providing bias in the analysis based on unrepresentative datasets,
- Using a black-box approach, so the reason for a 'decision' is not clear and transparent.

In fact, many of the benefits of AI application rely on having clean and well-ordered data – in terms of data mining, it is estimated that 95 % of the possible benefits can be achieved through data clean up and standard statistical methods [7]. It is, however, also noted that AI systems can work 24/7 and do not get bored with repetitive tasks.

So it would seem that an appropriate approach to apply AI tools is to use them where they are strong: analysing data to identify the majority of 'standard' or 'nor-

Figure 1. Sheep and goats

AI and ML algorithms have their pros and cons, and it is important to be aware of that in order to apply AI and ML techniques in the best possible way

mal' cases and allowing the SME's to concentrate on the data which are not clear or needs 'real attention'. Let the AI / ML interpolate but not extrapolate.

Machine learning types

In general, machine learning may be split into two similar approaches, both requiring large data sets which are split into test and training subsets [8]:

a. In **supervised** machine learning, an 'expert' classifies the data set into different cases, for example, oil samples which indicate overheating or paper degradation. A machine learning tool tries to learn from parameters within the data, for example, hydrogen content, moisture level, presence of PD, etc., and these parameters best reflect the expert classification. Then test the resulting tool against new cases to see how effective it is.
b. In **unsupervised** machine learning, a similar approach is used, but in this case, the machine learning tool groups the cases based on clusters in the many dimensions of the provided data. An expert then classifies the resulting clusters and tests them against new cases.

There are two basic ML learning types: supervised learning – that requires an expert for initial data classification before the learning process and unsupervised learning – where the expert evaluates data after the learning process

As an example, consider an ML tool developed to recognise sheep and / or goats in pictures supplied, as per Fig. 1. In a supervised ML approach, an expert would classify each picture, and the tool would try to find data differences between the pictures which reflects the classification. We may not know why the tool does what it does – the ML can be considered a black box. Once trained, we show the ML tool more pictures for it to classify to see how well it does – and if we just show pictures used in the training data, it will likely do very well. It is when we show it more complex pictures, or pictures of another animal, the ML tool may fail.

In unsupervised ML, the tool clusters the data and the expert classifies it afterwards. In both supervised and unsupervised ML tools, the Ml performs very well when the test cases are similar to the training cases but much less well when the supplied cases are different from the training cases. What happens if there are multiple animals in a picture? Or if there is a llama – how does that get classified? The effect called 'giraffing' where an ML tool trained to identify giraffes in supplied pictures then identifies giraffes in pictures where no giraffe is present - the effect is a result of the ML training where giraffes are over-represented in the training cases, but the cases of 'no giraffes' are underrepresented [9]. The effect can be seen in a visual chatbot which identifies the content of pictures – try asking it how many giraffes are in a picture you supply [10].

Fig. 2 shows a high-level view of an ML classification process for partial discharge EMI spectra, conducted by Dr Imene Mitiche as part of a Doble Engineering sponsored R&D project at Glasgow Caledonian University in the UK. Expert analysis of EMI spectra was initially used as a base for a supervised ML approach – features extracted from the data based on the entropy (orderliness) of the data are used to cluster the data, as shown.

The original EMI spectra cases from a number of different generator analyses taken around the world are analysed by an expert and classified; those classifications are then used to drive the supervised ML analysis based on the entropic features extracted. The supervised approach yielded an accuracy of subsequent test classification of ~75 %. An unsupervised approach was also performed, using the same entropic data, with the clusters plotted on an entropy chart to indicate the cluster independence. Subsequent classification of the unsupervised clusters yielded an accuracy in excess of 80 %. The improvement in results from the unsupervised approach demonstrates both the difficulty in classifying the spectra and benefits of not assuming perfect *a priori* knowledge from the expert. The application of the resulting ML system is being incorporated into Doble's EMI survey tools to support users in the field with their analyses.

For many analyses, there are standards and guidelines available for support, noting that these can be inconsistent and may not provide a good interpretation in all cases. In practice, there is a need to focus, as there is a large amount of data. For example, at Duke Energy, there are over 10,000 Large Power Transformers (Banks > 7.5 MVA) in their transformer fleet. These transformers have dozens of data sources from DGA to offline tests to maintenance history to condition monitoring and generate millions of individual data points. Like most companies, Duke has ever fewer people to manage that ageing fleet, and they need to be able to focus on what is most critical, most important and most relevant.

Unsupervised learning showed better results compared to supervised learning in the example of the classification of the partial discharge EMI spectra

Practicalities at Duke Energy

Duke Energy performed exhaustive research over a number of years, looking for a 'good' AI / ML tool: by 'good' we mean one which classifies cases well when they are clear but identifies those which are 'less clear' as needing further analysis. One thing in common to every ML solution they were offered or tried for predictive maintenance was an assumption that given enough data we can make accurate predictions using Gaussian modelling of the available data; unfortunately, that assumption is not true.

A Gaussian, or normal, distribution is symmetrical about an expected value. In practice, distributions of DGA values, power factor levels, PD inception voltages and other are not Gaussian, and that trend follows through the analysis to the point of classification. In addition, the realities for transformer data include:

- Limited and bad data,
- Failure to document and maintain failed asset data,
- No investment in cleaning and verifying data available,
- Data not normalised across multiple sources nor within a single source,
- Unique characteristics of data related to the manufacturing process for sister units (they are handmade),

Duke Energy has developed a hybrid model which takes the best of available analysis tools and ML systems, combined with the scientific knowledge, to make the most accurate decisions using Scientific Machine Learning

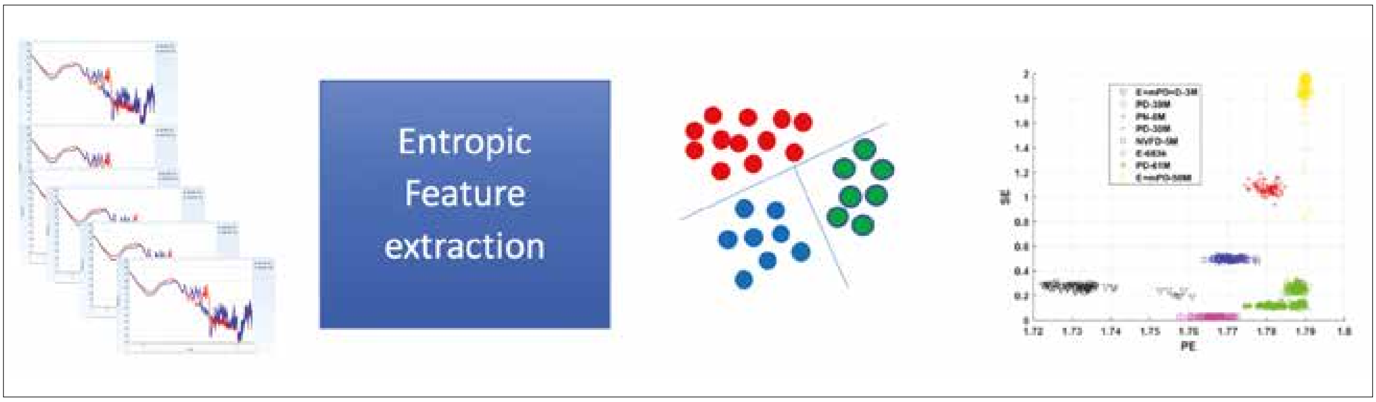

Figure 2. Feature extraction approach to partial discharge EMI Spectra Analysis

The SciML tool applies takes the best of both worlds – applying standards / guidelines and benefitting from the broad application of ML

whereas the realities for the data scientists include:

- An assumption that the answer lies in the available data, without necessarily referencing Transformer SMEs,
- ML assumes a Gaussian data distribution, but most failure modes are not based on Gaussian data,
- Major companies like Dow Chemical, Audi, and Intel have been open about predictive models for major plant assets not being effective,
- IT and data scientists do not usually understand failure modes and may not take them into account for their modelling.

Consequently, a lot of time, effort and resource can be targeted at Ml systems which do not support the 'real world'. Based on experience and SME inputs, Duke Energy has developed a hybrid model which takes the best of available analysis tools and ML systems, to allow SMEs and technicians to focus effectively, accessing data so they can make the most accurate decisions where they are needed with fewer things 'slipping through the cracks'.

Duke's hybrid model methodology development occurred at the same time as biologists and other scientific groups were developing similar techniques, finding that pure machine learning was not producing accurate results in practice. The hybrid approach is now termed 'Scientific Machine Learning' (SciML), where actionable decisions are made based on reliable data supported by subject matter expertise.

SciML is noted for needing less data, being better at generalisation, being more interpretable, and more reliable, than both unsupervised and supervised machine learning [11]. Duke's use of SciML went into effect in January 2019, while the terminology and papers on the concept from academic and commercial AI / ML platforms did not come into common use until late 2019 / 2020.

The SMEs are regularly asked by the asset / finance group to "Provide a list of transformers most likely to fail, or in the poorest condition, for our proactive replacement project." The response was regionally based, with different spreadsheets and different analyses and different collations as some SMEs have over 1,000 transformers to evaluate. Then there is a call coming in about a transformer that failed and that is not on any of the supplied lists. Such failures are inevitable: not every failure is driven by condition related failure modes and not every failure is predictable.

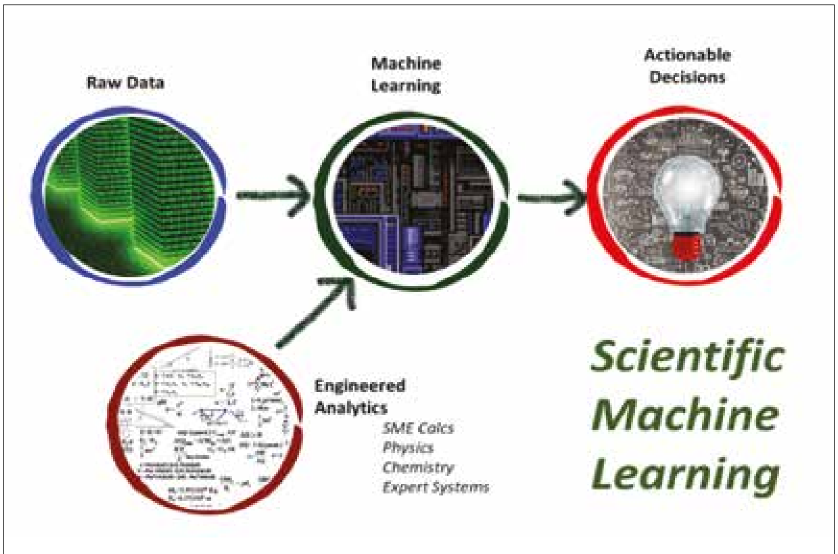

Figure 3. Overview of hybrid engineering ML transformer fleet analysis tool – now called SciML

The first step in the development of a useful Health and Risk Management (HRM) tool was to invest in data clean up and subsequent data hygiene management – this is an ongoing task and needs constant vigilance to prevent rogue data errors causing false positives in the analyses. Data is made available through a single-user interface, and standard engineering algorithms are applied to identify issues and data which need a deeper analysis: condition-based maintenance data (CBM), load variation, oil test, electrical test, and work order data all provide the context in one interface for decision support. Analytics such as the Doble Frank scores, TOA4 gassing scores / severity, EPRI PTX indices are applied initially, and the results are normalised as a linear feature set which can be analysed with a supervised ML tool. The combination of approaches allows data related to each transformer to be classified into one of the several predefined classifications or states: Normal, Monitor, Service, Stable, Replace, and Risk Identified.

The approach is shown, at a high level, in Fig. 3.

The SciML tool takes the best of both worlds – applying standards / guidelines and benefitting from the broad application of ML. The process at Duke has reduced time for SMEs to perform annual fleet evaluations in a few days rather than several weeks, consistently across the organisation. The number of 'bad actors' slipping through the cracks is lower, but not yet zero.

One of the features of the Hybrid system is the ability of the system to automatically change some states:

- a state may be automatically changed to 'Monitor' or 'Service' based on raw data,
- the state may be changed to 'Risk Identified' based on engineering analytics and ML classification,
- no transformer state can be automatically changed to 'Stable' or 'Replace': that requires SME intervention. After reviewing the data, the SME determines if a transformer is 'Stable' or should be 'Replaced', with comments recorded.

Duke Energy's hybrid model of engineered analytics and machine learning has proven to be an excellent but imperfect tool, being far more 'accurate' than either pure AI / ML tools have proven or engineered analytics alone. The transformer state, as updated by SMEs is now far more useful in making sound planning decisions.

Success, in terms of uptake and use of the Hybrid model, has been based on a number of activities: data hygiene, collation of data sources, application of standards / guidelines for engineered analytics, data normalisation for features to feed the ML, continuous SME input and refinement in a closed-loop evaluation.

The benefits of the hybrid approach have been to allow SMEs and field technicians to focus on important and critical cases. The system is not perfect, but it has identified bad actors more consistently and more accurately than any previous approach used at Duke Energy.

Conclusions

AI / ML tools can provide benefit in the interpretation and classification of complex data, but they can be fooled by data inconsistent with their training set. The application of ML tools requires input from the SMEs who can guide the development in specific applications. Understanding the raw data and making the best use of data hygiene / management activities is a base for building an overall analysis system which combines the best practice, application of standards / guidelines, and targeted use of AI / ML systems. Doble Engineering has shown the development of targeted AI / ML tools can bring benefit in practical data analysis in the field; Duke Energy has shown that application of targeted ML tools can support SMEs in their asset performance analyses.

Acknowledgements

The authors would like to thank our colleagues at Duke Energy and at Doble Engineering Company, and many more across the industry who have provided comment, feedback and discussion of the application of AI techniques. And many thanks to Dr Mitiche at Glasgow Caledonian University for sharing her results of AI analysis of PD / EMI data.

AI / ML tools can provide benefit in the interpretation and classification of complex data, but they can be fooled by data inconsistent with their training set, which is why the ML tools require inputs and check from the expert

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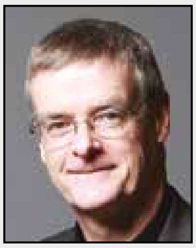

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