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ML-Assisted Ageing Classification of XLPE Power Cables using an Adaptive Neuro-Fuzzy Inference System

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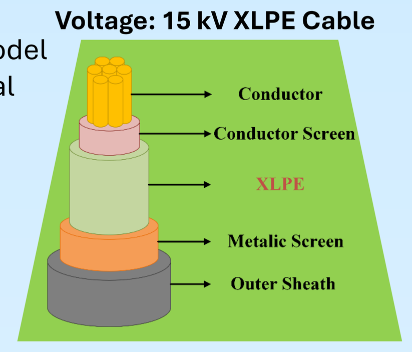
Introduction

- Cross-linked Polyethylene (XLPE) insulated power cables are crucial for reliable and efficient power delivery due to their high insulation resistance, dimensional stability, low dissipation factor, and high dielectric strength [1].
- The XLPE insulations are susceptible to ageing influenced by morphology, additives, oxidation, ions, and water [2].
- Deterioration is accelerated by thermal, electrical, mechanical, and environmental stresses, necessitating an approach to **asset management**. Central to this strategy is **condition monitoring**, which provides crucial data on cable health. This information is vital for making informed decisions regarding both **long-term expansion planning** and **immediate operational activities like system reconfiguration**, thereby ensuring the overall reliable operation [3].
- The ageing indicators like PD, space charge, IR, and $tan\delta$ can be measured through offline or online techniques [4]. However, they are insufficient to accurately reflect cable ageing due to the complex, multi-stress environment of real-world operation.
- To overcome the drawbacks of mathematical approaches, machine learning (ML) techniques with abilities like dynamic learning, generalisation, high computational speed, integration of multiple stresses, etc., can be used [5-8].
- Various ML techniques such as ANN, SVM, tree-based (decision tree, random forest, XGBoost, CatBoost and so on), etc. have been applied to classify XLPE power cable health index [5-8].
- While ML methods offer reasonable accuracy and speed, they each have limitations, including dealing with nonlinear problems, limited robustness to environmental and operational changes, low interpretability, reliance on input feature quality, and poor generalisability.
- To address the challenges of previous ML methods, ANFIS model is used to produce health index labels for unlabelled historical data with high accuracy. Eventually, creating a bigger dataset to be used for more advanced techniques in future work that can provide sequential prediction of health indexes for future years.

Voltage: 15 kV XLPE Cable



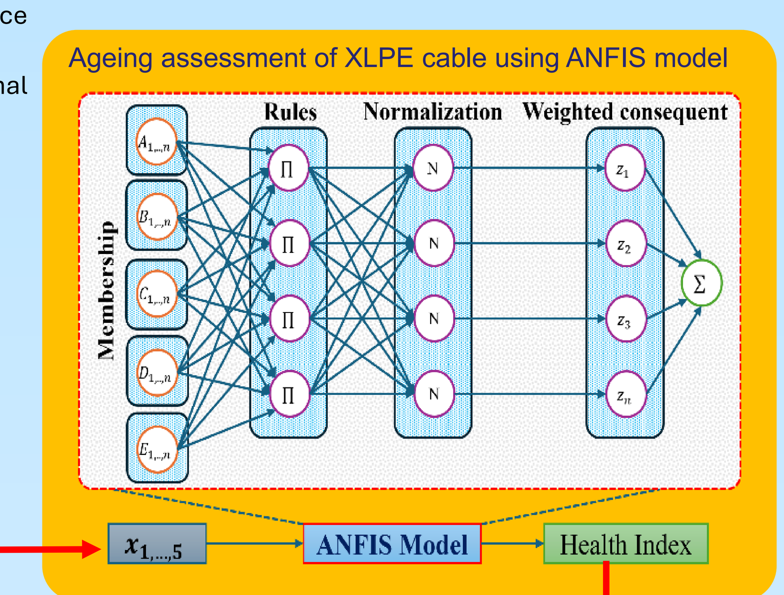
ML-Assisted Ageing Classification using ANFIS / Benefits of ML

- ANFIS is a hybrid ML model that integrates neural networks with fuzzy logic (based on Sugano fuzzy inference systems) to create an adaptive system capable of handling nonlinear relationships between inputs and outputs.
- It comprises five layers that function sequentially to process inputs, apply fuzzy inference, and compute the final output [9-11].
- ***First layer***: Fuzzification through membership functions like the Gaussian function:
  $O_{ij}^{1} = e^{-\frac{(x_i - k_{ij})^2}{2\sigma_{ij}^2}}$
- ***Second layer***: Firing strength of each fuzzy rule by applying the T-norm operation (a fuzzy "AND" or "OR" operator that combines the degrees of truth of the input fuzzy sets):
  $O_i^2 = w_i = \prod_j O_{ij}^1 , i = 1,2, \dots , n$
- ***Third layer*** (normalization layer):
  $O_i^3 = \overline{w}_i = \frac{w_i}{\sum_{i=1}^{n} w_i}, i = 1,2, \dots , n$
- ***Fourth layer***: Defuzzification layer computes the contribution of each rule:
  $O_i^4 = \overline{w}_i f_i = \overline{w}_i (\sum_{i=1}^{n+1} p_i x_i + p_0)$
- ***Final layer***: Computes the overall output of the ANFIS model:
  $O^5 = \sum_{i=1}^{n} O_i^4$

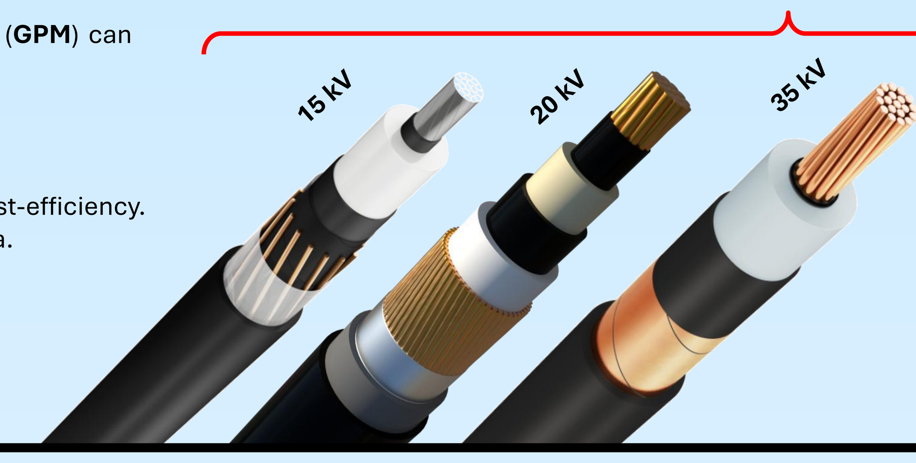
Method	Formula	Details
FCM	$J = \sum_{i=1}^{N} \sum_{j=1}^{C} u_{ij}^{m} \lVert x_i - c_i \rVert^2$	u_{ij}^m: Degree of membership of x_i in cluster j. m: Fuzziness parameter. c_i: Cluster canter. $\lVert . \rVert$: Euclidean distance.
SCM	$P(x_i) = \sum_{j=1}^{N} e^{-\frac{\lVert x_i - c_i \rVert^2}{\alpha}}$	$P(x_i)$: Potential of x_i. α: Control parameter of c_i influence.
GPM	$N_{rules} = \prod_{i=1}^{m} N_i$	N_{rules}: total number of fuzzy rules. N_i: number of fuzzy sets.

In the input layer, to obtain the parameters of the fuzzy sets, different methods such as fuzzy c-mean (**FCM**), subtractive clustering method (**SCM**) and grid partitioning method (**GPM**) can be used [11].

Ageing assessment of XLPE cable using ANFIS model



Health Index Classification of Different Cable



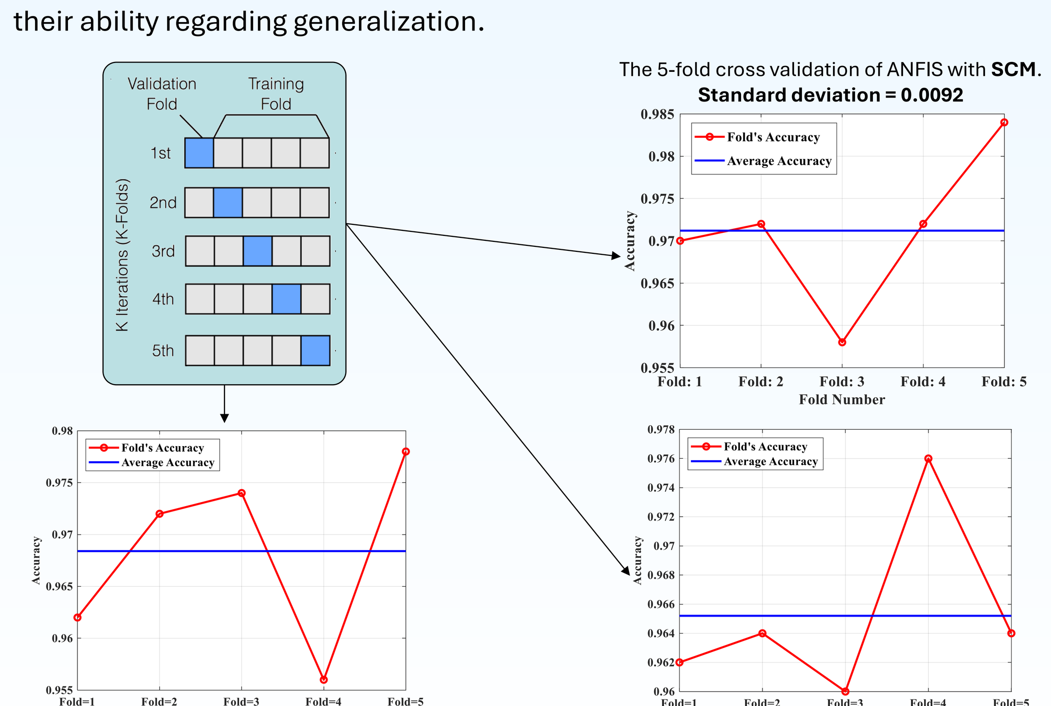
Benefits of ML techniques for real-world applications:

- Enables data-driven prioritisation of maintenance and replacement, improving reliability and cost-efficiency.
- ML models classify cable health and predict ageing trends using operational and inspection data.
- Methods like ANFIS provide interpretable rules, aiding expert decision-making.
- Using sensor/inspection data with ML methods for early fault detection.
- Enables continuous status classification and degradation prediction.
- Predicts cable behaviour under future loading or network growth.
- Detecting degradation patterns for targeted reconfiguration.

Results & Analysis & Discussion

Parameter	Range	Accuracy (%)	Best
ANFIS-SCM			
CIR	[0.05:0.01:0.95]	98.13	0.5
NP	[100:10:2000]	98.13	500
SS	[0.05:0.01:1]	98.13	0.1
ANFIS-FCM			
NC	[2:1:20]	97.33	10
NP	[20:10:2000]	97.33	400
IRSZ	[0.1:0.05:1]	97.87	0.4

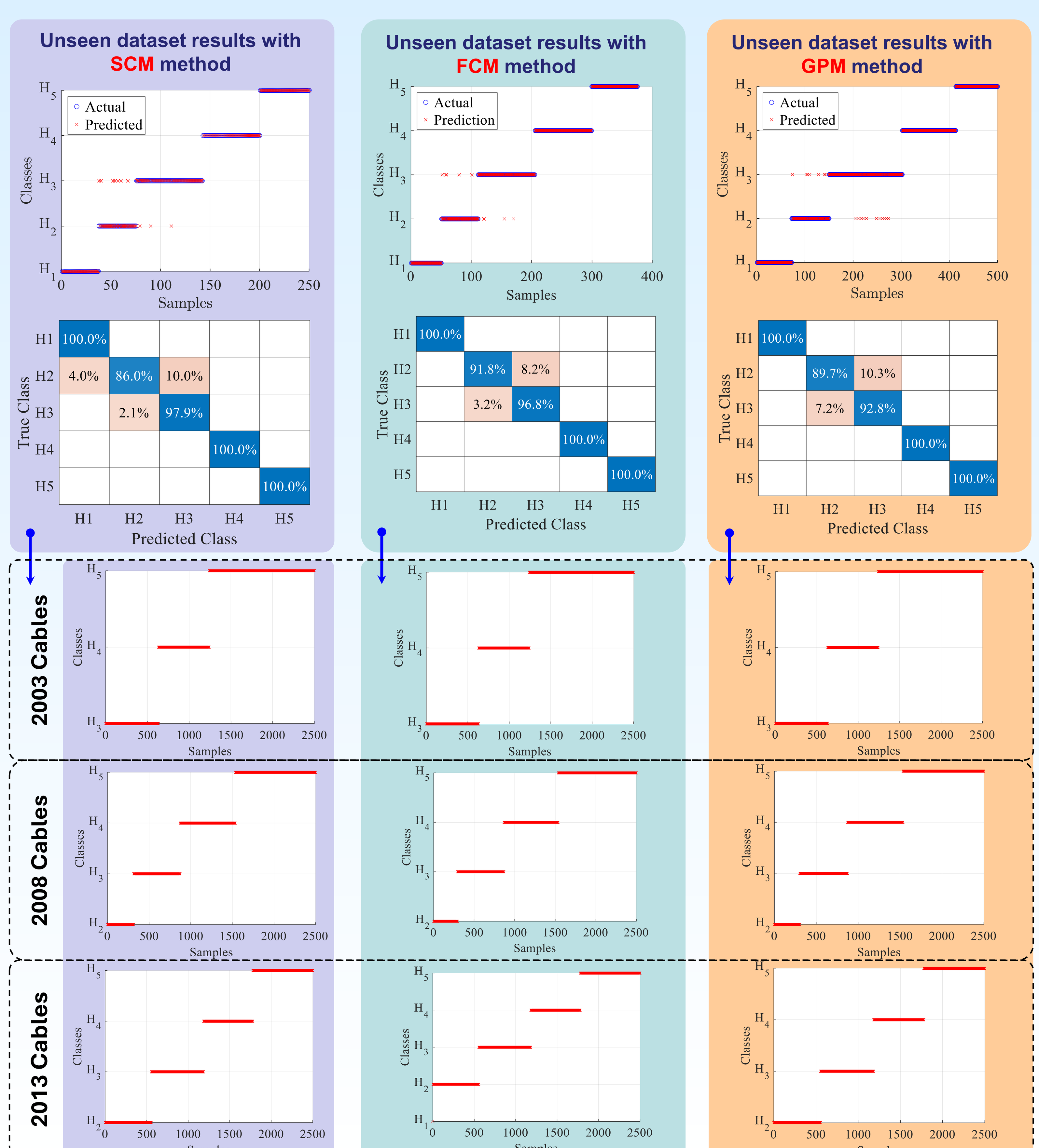
- Sensitivity of model to its major controlling parameters or so-called "**hyperparameters**" should be tested for all health indexes, making sure the best setup has been proposed for the final ANFIS.
- Therefore, the best combination of the hyperparameters of ANFIS are obtained through the ***sensitivity analysis*** method with SCM and FCM clustering methods to ensure accuracy. In the SCM method, cluster influence range (CIR), number of epochs (NP), and step size (SS) were chosen as the important hyperparameters. The same parameters for FCM are evaluated; with the number of clusters (NC) instead of CIR.
- **Cross-validation** to ensure their correct performance across the dataset and, their ability regarding generalization.



The 5-fold cross validation of ANFIS with **SCM**. **Standard deviation = 0.0092**

The 5-fold cross validation of ANFIS with **FCM**. **Standard deviation = 0.0083**

The 5-fold cross validation of ANFIS with **SCM**. **Standard deviation = 0.0063**



- To ensure the performance of the model, the 2018 cable dataset is split into main (80%) and **unseen** (20%) datasets. It can be concluded that the model is capable of classifying unseen data, effectively (**97.72%**).
- **The model's predictions on the historical data (2003-2013) exhibit a clear trend correlating with cable ageing.**
- Proportion of samples classified as hazardous increased over time, with **15%** reaching the most severe condition by 2018, which implies that ANFIS model effectively captured the temporal dynamics of cable ageing.
- Proposed method dealt with the nonlinearity of the dataset and showed excellent accuracy and generalization ability for **unseen** samples classification that had been missing from previous studies analysis on different ML models [5-7].

	Model	Acc.	Pre.	Rec.	F1	Training time	Testing time
ANFIS	**FCM**	***97.87***	97.72	97.94	97.82	12.70s	0.0013s
	SCM	***98.13***	97.77	98.52	98.10	22.49s	0.0018s
	GPM	***97.73***	97.23	98.05	97.60	194.3s	0.0905s

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Conclusion & Acknowledgement

- An ANFIS technique was implemented for health index classification of aged 15kV XLPE underground power cables.
- The performance of the ANFIS for classifying and predicting the health index of aged cables was presented.
- Different clustering methods, such as FCM, GPM and SCM, have been investigated.
- The ANFIS model classified the health index of cables with an accuracy of more than 98%.
- The model produced new labels for historical datasets, leading to the creation of a bigger dataset.
- ***For future work***, a model for the prediction of the next years of ageing based on the existing dataset and the historical dataset will be developed, capable of classifying health indexes alongside the estimation of power cables' ages. It will also include a wide range of cables (XLPE, PVC, PILC, etc.) with various voltage levels, creating a comprehensive framework for ageing prediction and lifetime monitoring of power cables.

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