Towards intrusive non-destructive online ageing detection of transformer oil leveraging bootsrapped machine learning models

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***Abstract*— Transformers play a crucial role in power networks, ensuring that generated electricity is delivered to consumers at the safest voltage level, reducing losses, and enabling metering and grounding. The insulation system is critical for ensuring that the function of the power transformer is carried out safely, at the expense of its gradual deterioration over time. Most conventional oil ageing detection methods are offline and, as a result, are best suited for scheduled maintenance practices which cause risk to life, sample contamination, loss of man-hour, and risk of missing critical incipient ageing responses outside the maintenance cycle window. Oil quality index (OQIN) data sets were bootstrapped to develop robust machine learning models for online ageing classification (class A to class G). Correlation models from existing mineral oil dataset was develop to predict the refractive index (RI), breakdown voltage value (BDV), dielectric dissipation factor (DDF), dissolved decayed products (DDP), total acid number (TAN), interfacial tension (IFT), and oil quality index (OQIN) using the optical fibre sensor transduced output voltage (OFSTOV) of intensity modulated optical fibre. The existing mineral oil dataset also validates the developed OQIN machine learning model. The high correlative models presented in this paper have the potential to enable the transition from traditional offline scheduled maintenance ageing detection methods to online/IoT-based prescriptive ageing detection solutions. This paper also lays the groundwork for revolutionising in-situ transformer oil ageing detection to include digital-twinning capability, thereby improving reliability, reducing risks, and reducing operational costs.**

Keywords*— *Ageing, Bootstrap, Fibre Optic Sensor, High Voltage, Machine Learning, Online, Transformer Oil

I. Introduction

Electricity is produced for the sole purpose of satisfying the needs of consumers, who can be found in settings as diverse as homes and factories. Transformers are typically the devices used to supply consumers with the required voltage. Transformers are expensive but necessary components without which high voltage (HV) stations cannot function properly. Their mean time to repair (MTTR) is significantly longer, and their maintenance costs are exorbitant. Having to completely shut down a power plant due to a faulty transformer would have devastating effects on the economy. Additionally, there is a chance that lives will be lost, substation equipment will be damaged, and there will be negative environmental effects [1].

Similar to the majority of HV materials, transformer oil ages with use [2, 3]. Insulation ageing is the gradual, irreversible deterioration of the physicochemical properties of an insulator in service due to electrical, thermal, and environmental stresses. During operation, transformer oil degrades based on the transformer's loading condition and thermal stress [4, 5]. The thermal stress originates from either the copper or iron core losses of the windings. This causes the formation of partial discharges and transformer oil ageing by-products (ABPs) such as moisture-dissolved gases (carbon dioxide, methane, ethane, ethylene, acetylene, propane, propylene, methanol, and ethanol), acids, and sludge [4, 6-9]. Partial discharges are precursors to insulation failure [10] with a cyclical cause-and-effect relationship [11]. Other partial discharge sources include pressboard voids, moving bubbles, and winding surface discharge [12]. In addition, ageing has a significant impact on the chemical and electrical properties of transformer oil, including dielectric strength (decrease), dielectric dissipation factor, DDF (increase), flashpoint (decrease), and colour (darkening) [4, 13, 14].

The methods for detecting transformer oil ageing is categorised as either intrusive or non-intrusive, destructive, or non-destructive, and offline or online. Contrary to non-intrusive methods, intrusive detection techniques involve direct contact with transformer oil. In contrast to non-destructive methods, destructive methods alter (in the short or long term) the measured transformer oil's properties. The online detection method involves live age detection of the transformer oil while it is operating, in contrast to offline age detection, which requires sample collection for laboratory analysis. Conventional methods for determining the level of transformer oil degradation involve offline chemical/optical analysis. These techniques are ideal for preventive maintenance strategies in which samples are collected at varying intervals to determine the extent of deterioration. Nonetheless, these procedures incur losses in person-hours, life, and the possibility of missing key incipient problems, which can have negative repercussions prior to the next inspection cycle. In addition, the collection and transportation processes may have an impact on the quality of the collected transformer oil.

II. CLASSIFICATION OF SERVICE-AGED INSULATING OIL

The Myers Index Number or Oil Quality Index (OQIN) provides a metric for transformer oil classification into seven (7) categories summarised in Table 1. Table 1 provides suitable bases for prescriptive maintenance assessment. The OQIN value is the quotient of the IFT value and the NN value. The OQIN index can be used for offline and online oil classification. Table 1 takes its reference from IEEE C57.637 [15], BS EN 62961:2018 [16], and BS EN 62021-2:2014 [17]. Some of the limits set by IEEE C57.637 [15], BS EN 62961:2018 [16], and BS EN 62021-2:2014 [17] for fresh mineral oil are summarised in Table 2.

Table 1: Modified Oil Quality Index [18, 19]

S/N	Class	Metric Range
1.	Good Oil/Class A	NN 0.00 to 0.03 IFT 45 to 30 OQIN 1500 to 1000
2.	Proposition A Oil/Class B	NN 0.05 to 0.10 IFT 29.9 to 27.1 OQIN 600 to 271
3.	Marginal Oil/Class C	NN 0.11 to 0.15 IFT 27 to 24 OQIN 245 to 160
4.	Bad Oil/Class D	NN 0.16 to 0.40 IFT 23.9 to 18 OQIN 150 to 45
5.	Very Bad Oil/Class E (suitable for reconditioning)	NN 0.41 to 0.65 IFT 17.9 to 14 OQIN 44 to 22
6.	Extremely Bad Oil/Class F (suitable for reclaiming)	NN 0.66 to 1.50 IFT 13.9 to 9 OQIN 21 to 6
7.	Oil in Disastrous Condition/Class G	NN 1.51 or more OQIN Below 6
IFT in mN/m; NN in mg KOH/g of oil		

Table 2: Standard Specification for IFT and Acidity

S/N	Standard	Property	Specification
1.	BS EN 62021-3	Acidity	>0.014mgKOH/g
2.	BS EN 62961	Interfacial Tension	>20mN/m
3.	IEEE C57.637	Acidity	0.05mgKOH/g
4.	IEEE C57.637	Interfacial Tension	35mN/m

III. BOOTSTRAPPED OQIN, MODEL DATA SOURCES, AND PREDICTION FLOW

A. *Bootstrapped OQIN Datasets*

The statistical technique known as bootstrapping entails repeatedly sampling a data set with random replacements. It is an approach that works especially well when there are insufficient data to train machine learning models adequately.The modified OQIN datasets were bootstrapped to create 4200 × 4 multiclass datasets for OQIN classification machine learning model. The predictor variables include neutralization number (NN), interfacial tension (IFT), and the oil quality number (OQIN); the target variable was the class. The classes include all OQIN classifications (Class A, Class B, Class C, Class D, Class E, Class F, and Class G).

MATLAB was used to develop the machine learning model using five (5) fold cross validation to protect against overfitting. The test data is a 7 × 5 dataset from existing laboratory experiment [20] consisting of five (5) different age classes. K-Nearest Neighbour (KNN), Bagged-Tree Ensemble, Neural Network (NN), and Support Vector Machine (SVM) returned 100% result for all performance metrics, using training and test data.

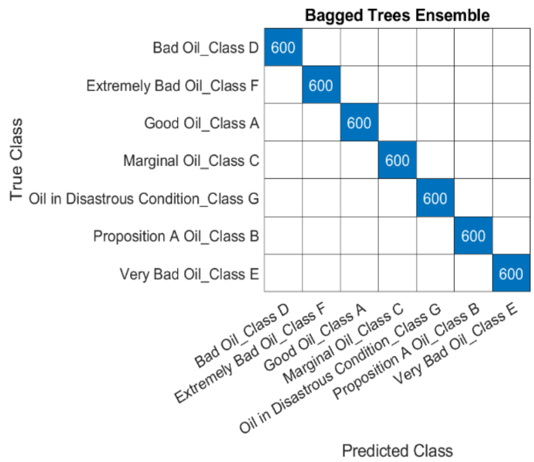

Figure 1: Confusion Matrix of Trained Dataset

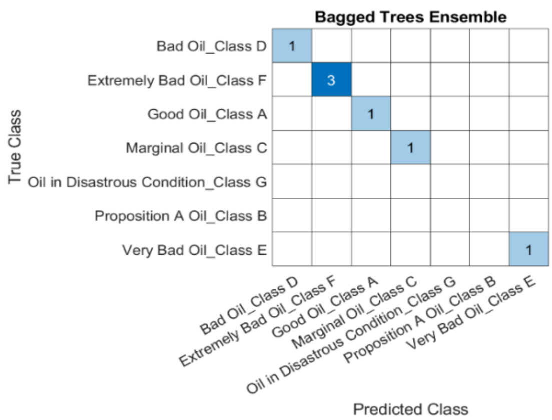

Figure 2: Confusion Matrix of Test Dataset

Table 3: Bagged Tree Ensemble Metric (Train)

S/N	Classes	Metric Score				
		Acc	Pre	Sn	Sp	F-Score
1.	Class A	1	1	1	1	1
2.	Class B	1	1	1	1	1
3.	Class C	1	1	1	1	1
4.	Class D	1	1	1	1	1
5.	Class E	1	1	1	1	1
6.	Class F	1	1	1	1	1
7.	Class G	1	1	1	1	1
Macro Average		1	1	1	1	1
Acc: Accuracy; Pre: Precision; Sn: Sensitivity; Sp: Specificity						

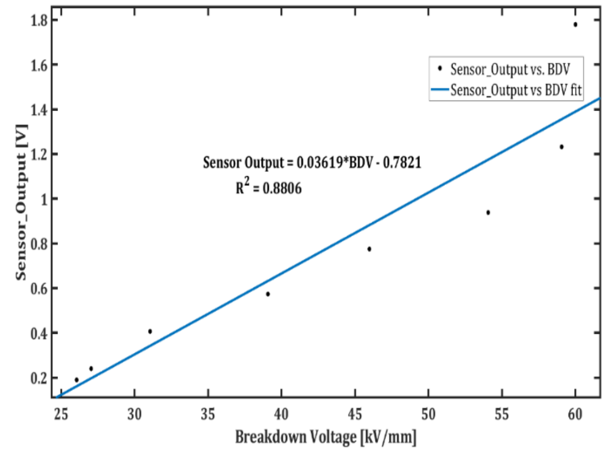

Figure 4: Plot of OFSTOV against BDV [20-22]

Table 4: Bagged Tree Ensemble Metric (Test)

S/N	Classes	Metric Score				
		Acc	Pre	Sn	Sp	F-Score
1.	Class A	1	1	1	1	1
2.	Class C	1	1	1	1	1
3.	Class D	1	1	1	1	1
4.	Class E	1	1	1	1	1
5.	Class F	1	1	1	1	1
Macro Average		1	1	1	1	1
Acc: Accuracy; Pre: Precision; Sn: Sensitivity; Sp: Specificity						

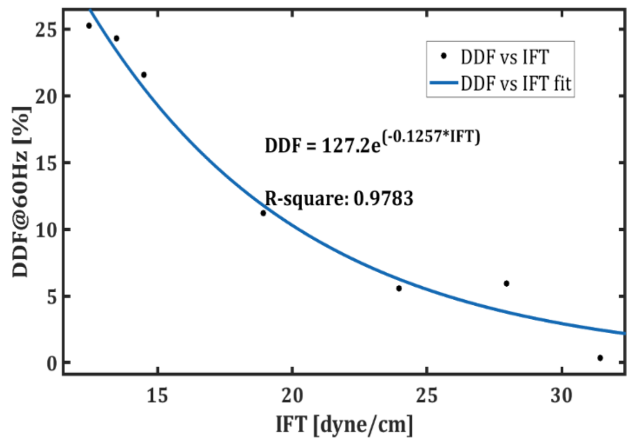

Figure 5: Plot of DDF against IFT [20-22]

B. Model Data Sources

To simulate an online ageing detection system, existing datasets [20-22] from offline characterisation techniques were extracted, plotted, and fitted using MATLAB. These results are summarised in Table 5. Figure 3 to Figure 9 show the data points and their respective fitted curves.

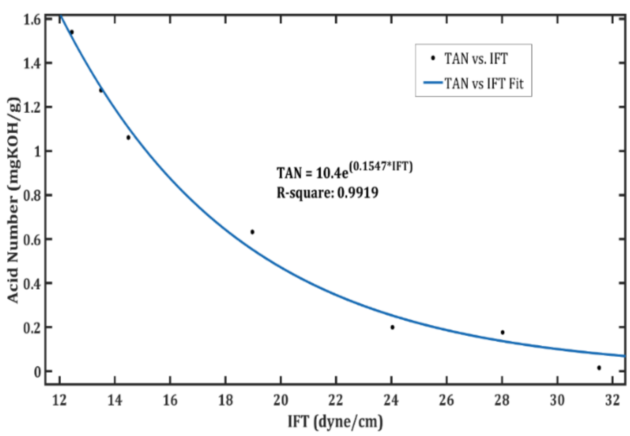

Figure 3: Plot of TAN against IFT [20-22]

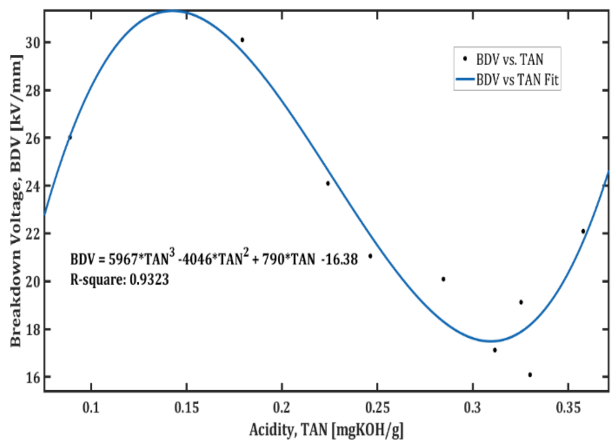

Figure 6: Plot of BDV against TAN [20-22]

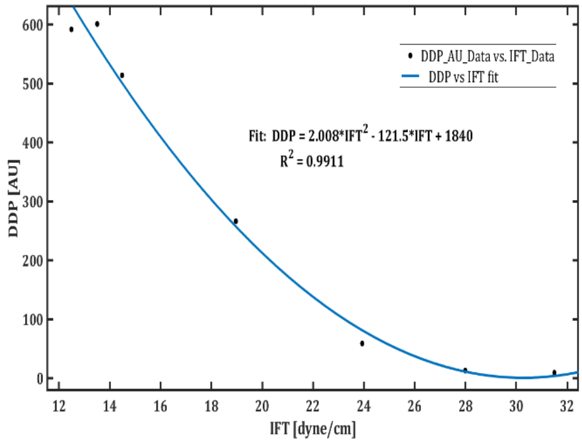

Figure 7: Plot of DDP against IFT [20-22]

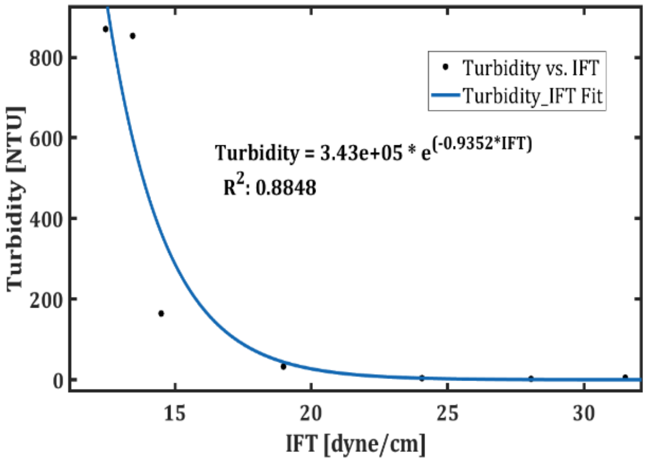

Figure 8: Plot of Turbidity against IFT [20-22]

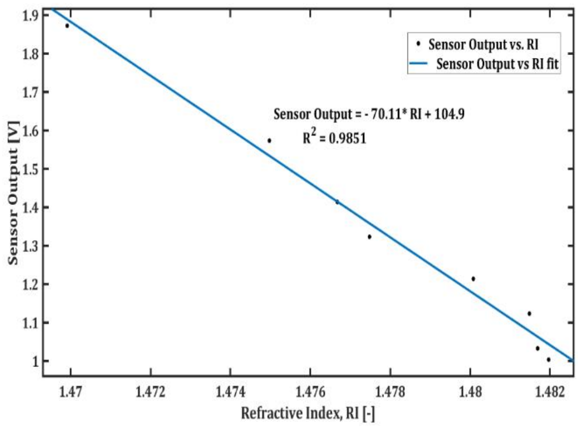

Figure 9: Plot of OFSTOV against RI [20-22]

Table 5: Correlation Models from Existing Datasets

S/N	Ageing Relationship	Model/Coefficient of Determination	Transformer Oil
1.	Optical Fibre Sensor Output- Voltage (OFSTOV) vs Refractive Index (RI)	$\mathrm{RI} = -0.01405 \times \mathrm{OFSTOV} + 1.497$ $\mathbf{R^2 = 0.98}$	Mineral oil
2.	Optical Fibre Sensor Output- Voltage (OFSTOV) vs Breakdown Voltage (BDV)	$\mathrm{BDV} = 24.33 \times \mathrm{OFSTOV} + 24.14$ $\mathbf{R^2 = 0.88}$	Mineral Oil
3.	Breakdown Voltage (BDV) vs Total Acid Number (TAN)	$\mathrm{TAN} = 0.0004604 \times BDV^3 - 0.03169 \times BDV^2 + 0.6946 \times \mathrm{BDV} - 4.583$ $\mathbf{R^2 = 0.93}$	Mineral Oil
4.	Total Acid Number (TAN) vs Interfacial Tension (IFT)	$\mathrm{IFT} = 30.25 \times e^{-0.6544 \times \mathrm{TAN}}$ $\mathbf{R^2 = 0.99}$	Mineral Oil
5.	Turbidity [NTU] vs Interfacial Tension (IFT)	$\mathrm{NTU} = 3.43 \times 10^5 \times e^{(-0.9352 \times \mathrm{IFT})}$ $\mathbf{R^2 = 0.88}$	Mineral Oil
6.	Decayed Dissolved Products (DDP) vs Interfacial Tension (IFT)	$\mathrm{DDP} = 2.008 \times \mathrm{IFT}^2 - 121.5 \times \mathrm{IFT} + 1840$ $\mathbf{R^2 = 0.99}$	Mineral Oil
7.	Dielectric Dissipation Factor (DDF) vs Interfacial Tension (IFT)	$\mathrm{DDF} = 127.2 \times e^{(-0.1257 \times \mathrm{IFT})}$ $\mathbf{R^2 = 0.98}$	Mineral Oil

C. Prediction Flow

The prediction flow (Figure 10) is the framework for online ageing detection using an optical fibre sensor. There will be a correlation between the transduced output voltage of the optical fibre sensor and the desired ageing characteristics variables that are strong indicators of transformer ageing (example include IFT and TAN). The online instrument receives three (3) inputs: light (I1), power (I2), and transformer oil (I3). The light (I1) intensity is modulated based on the state-of-health of the transformer oil (I3) with the help of the uncladded section of the fibre-optic sensor. The light is powered by a constant voltage source (I2). The online instrument outputs a voltage (OFSTOV) that feeds into the high correlation model that has been developed. The verified and validated OQIN model receives predicted IFT and TAN values as input to classify the transformer oil state-of-health (SOH) in-situ.

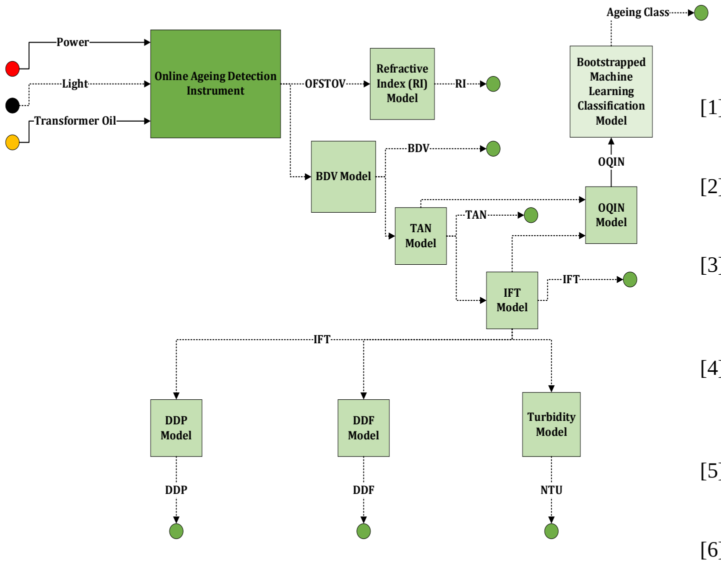

Figure 10: Prediction Flow

IV. ONLINE AGEING SOLUTION

To demonstrate online ageing capability, Figure 11 depicts a control room dashboard that features the following live ageing characteristics variables of in-situ transformer oil (based on the high correlation models developed) from OFSTOV: refractive index (RI), breakdown voltage (BDV), total acid number (TAN), Dielectric Dissipation Factor (DDF), Decayed Dissolved Products (DDP), turbidity, OQIN, and interfacial tension (IFT). The dashboard includes alarm/indicators based on the OQIN classification model for monitoring the ageing process. The dashboard also includes a live-ageing plot with threshold markers for good oil (class A), marginal oil (Class C) and bad oil (Class D). The dashboard solution is adaptable to IoT devices for remote monitoring and analytics.

V. CONCLUSION

This paper demonstrates the viability of switching from offline age detection methods (scheduled maintenance) to intelligent online age detection (condition-based monitoring) using an optical fibre sensor from existing datasets. Different oil types (and methods of ageing) may yield distinct correlation models, but the methodology is essentially identical. To have an instrument that accurately predicts the field transformer's ageing, the oil type and method of ageing should closely align with the transformer. This will enable accurate real-time monitoring of oil degradation and overcome the limitations of offline ageing detection methods already mentioned. Online detection of ageing will revolutionise ageing detection by enabling predictive maintenance and digital twinning, thereby enhancing reliability.

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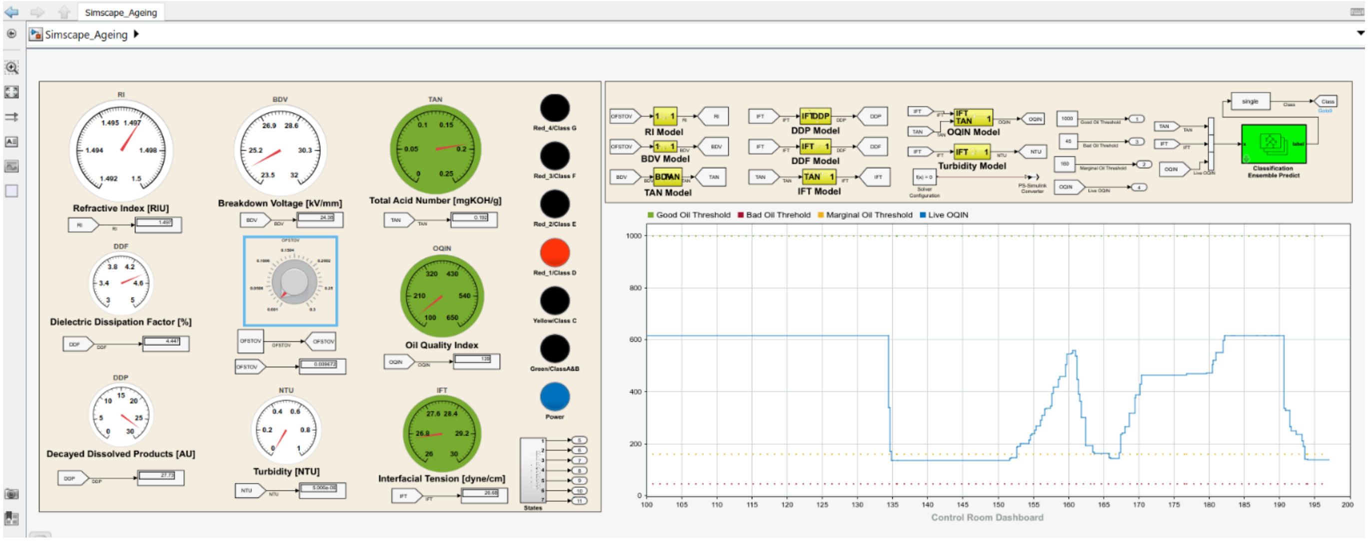

Figure 11: Control Room Dashboard