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MACHINE LEARNING METHODS FOR TRANSFORMER HEALTH BASED ON THE DEGREE OF POLYMERIZATION OF INSULATING PAPER

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Abstract

Transformers are critical in providing reliable and efficient power distribution. Its health and operational efficiency are critical to ensuring an uninterrupted power supply. On a dataset of 147 transformers, this study proposes a multivariate regression approach to evaluating insulating paper conditions using machine learning techniques. The degree of polymerization (DP) will be predicted as a key indicator of transformer health using regression models (decision tree, random forest, gradient boosting trees). The Isolation Forest algorithm detected probable anomalies and highlighted transformants that deviated from expected readings. The K-Means identified distinct groups of transformants based on their chemical characteristics and DP values. The results comprehensively understand transformer safety and underscore machine learning's potential to revolutionize predictive maintenance strategies. The results indicated that the gradient-boosted tree regression tool developed a lower mean absolute percentage error (MAPE) of 1.345%, demonstrating a robust model that can provide accurate DP predictions.

Keywords: **Transformer health; fault prediction; insulating paper; machine learning; regression models.**

1. Introduction

Power transformers, often described as the backbone of modern electrical infrastructure, have remained central to the worldwide energy landscape for over a century [1-3]. These giants facilitate the transmission and distribution of electrical energy across vast distances, ensuring that homes, companies, and industries receive the required energy. Because transformers play an essential role in electricity distribution, their continuous operation is critical. Their operational efficiency is directly proportional to the total reliability of the power grid, which has long-term consequences for economies and society. Transformer health and lifetime must be ensured, necessitating hands-on inspections, labor-intensive maintenance, and periodic repairs [4, 5].

The degree of polymerization (DP) has emerged as an essential measure in diagnosing the health of transformers [6, 7]. As an indicator of the condition of the transformer insulating paper, DP provides good insight into the transformer's overall health and operational conditions [8, 9]. It turns out that the DP decreases as the insulating paper ages and wears out, which indicates the possibility of the transformer's insulation collapsing and not performing with the required efficiency. Testing the oil and insulation paper periodically is a preventive measure for the continuity of operation of the transformer, and failure to maintain periodic tests may lead to catastrophic failures in the operation of the transformer [10, 11].

Most studies have determined the insulating paper in the transformer based on the degree of polymerization (DP) value. Because DP is difficult to measure, certain test parameters, such as dissolved gases (DGA), breakdown voltage (BDV), oil surface tension (I.F.T), oil acidity (ACI), moisture content (MC), and oil color (OC), Dielectric loss (Tanδ), specifically furan concentration (2-furfuraldehyde (FA)) [8], can be used to determine DP. The results in [8] suggested that developing a mathematical model to relate DP to test factors is challenging, except FA, where the trend of DP with FA is more evident than with other variables. The diagnostic results correspond well with Ghoneim's formula, reported in [8].

$$DP=-122.6\ln(FA)+1294.4 \quad (1)$$

Where FA is expressed as ppb.

In the Fourth Industrial Revolution, the decision-making process has become data-based and contributes to reshaping industries [12, 13]. In this context, assessing the health of the transformer and the remaining lifespan for its efficient operation depends on how the data of periodic tests or tests accompanying faults [14,15]. Sensor technology, advanced data analytics, and machine learning herald the era of predictive maintenance, where potential problems are identified and addressed even before they arise. This proactive approach, driven by machine learning models, has the potential to redefine transformer health management. These models can provide unprecedented accuracy in DP prediction by analyzing broad data sets that include chemical and physical properties [16, 17]. In this current research, we explore how machine learning can be harnessed to ensure optimal health and longevity of transformers, ensuring stable and efficient power supplies for the future.

2. Materials and Methods

In this section, the data description and date pre-processing will be addressed.

2.1. *Dataset description*

The core dataset used in this study consists of samples from 147 transformers, as published in [6, 7], each with unique chemical and physical features. Hydrogen (H_2), methane (CH_4), carbon monoxide (CO), carbon dioxide (CO_2), ethylene (C_2H_4), ethane (C_2H_6), acetylene (C_2H_2), BDV, moisture content (MC), Dielectric loss (Tanδ), Oil color (OC), acidity (ACI), interfacial tension (I.F.T), and 2-FAL are all included in the dataset. The "DP" variable represents the degree of polymerization, a crucial measure of transformer health.

2.2. *Dataset pre-processing*

Data is rigorously pre-processed before machine learning algorithms are deployed to guarantee it is suitable for model training and testing. The following processes will be examined to alter the data.
1. Scaling: Due to the variety of scales for the dataset's features, the scikit-Learn library's Standard Scaler was employed. This procedure ensures that all features have a mean of 0 and a standard deviation of 1, ensuring uniformity and improving model performance.
2. Feature selection: All dataset features except "DP" and "class" are chosen for model training. This coordinated set of features ensures that models focus on the most important features when predicting the target variable.
3. Train-Test Split: To accurately analyze the performance of the regression models, the dataset was divided into training (80%) and testing (20%) sets. This segmentation ensures that models are trained on vast data before being verified on previously unseen data.

2.3. *Machine learning models*

The study employed three distinct regression models, each chosen for its specific strength in dealing with various data characteristics:
1. Decision Tree Regressor: This model is well-known for capturing non-linear relationships without requiring transformation. It recursively separates the data into feature values and then makes predictions based on the terminal leaves.
2. Random Forest Regressor: An ensemble of decision trees aggregating predictions from several trees to get a final result. This aggregation frequently leads to better accuracy and resilience than individual trees.
3. Gradient Boosted Trees Regressor: This iterative model compensates for prior trees' mistakes, making it especially useful for complicated datasets. It frequently obtains greater forecast accuracy by refining its predictions over iterations.

2.4. *Anomaly detection*

The Isolation Forest technique was used to ensure the robustness of the results and detect probable outliers in the dataset. By isolating observations, this technique can find anomalies in huge datasets rapidly.

2.5. *Clustering*

The K-Means clustering technique was used to understand the dataset's inherent groupings based on chemical and physical attributes. K=2 and K=3 granularity levels were investigated. These clusters reveal underlying trends and similarities between transformer samples.

3. Results

In this section, Regression model performance analysis and results will be addressed.

3.1. *Regression model performance analysis*

Let us clarify the two important metrics used in our analysis before getting into the details of model performance:

1. MSE (Mean Squared Error): MSE measures the average of the error squares. It is mathematically defined as follows:

$$\mathrm{MSE}=\frac{1}{N}\sum(Y_i-\overline{Y}_i)^2 \qquad (2)$$

Y_i denotes the actual value, $\overline{Y}_i$ the predicted value, and n the number of observations.

2. Mean Absolute Percentage Error (MAPE): MAPE is a percentage that reflects the error. It is determined by taking the average of the absolute percentage errors:

$$\text{MAPE}=\left(\frac{100\%}{n}\right)\sum\left|\frac{(Y_i\text{-}\overline{Y}_i)}{Y_i}\right| \tag{3}$$

In this formula, Y_i represents the actual value, $\overline{Y}_i$ represents the anticipated value, and n represents the number of observations. With these definitions in hand, we can now investigate the analysis of our AI models as they are applied to experimental datasets.

3.2. *Regression models results*

Regression models were used to predict the Degree of Polymerization (DP) based on the chemical and physical properties of the transformers. The following is a breakdown of their performance:
1. Regressor Decision Tree:
The Decision Tree Regressor produced an MSE of 1227.13 while capturing non-linear relationships, indicating that the model's predictions differed from the actual values by an average squared value of 1227.13. The MAPE = 2.997% indicates that the model's predictions were around 3% off from the actual DP values.
2. Random Forest Regressor: The Random Forest Regressor, an ensemble of numerous decision trees, outperformed The Decision Tree Regressor regarding predictive performance. This model produced more accurate and consistent predictions with an MSE of 1037.30 and a MAPE of 1.526%.
3. Regressor using Gradient Boosted Trees:
The Gradient Boosted Trees Regressor performed best, having the lowest MSE and MAPE values where the MSE equals 714.06 and MAPE equals 1.345%. The iterative strategy used by this model, which accounts for past tree faults, has resulted in higher predicted accuracy.
Figures 1–3 illustrate actual against expected DP for each regression model, demonstrating the accuracy of each model's predictions. Points that are close to the red ideal line indicate reliable forecasts. A scatter away from this line indicates a divergence. According to the results, the Gradient Boosted Trees Regressor plot should have the most points closest to the ideal line, followed by the Random Forest and then the Decision Tree Regressor.

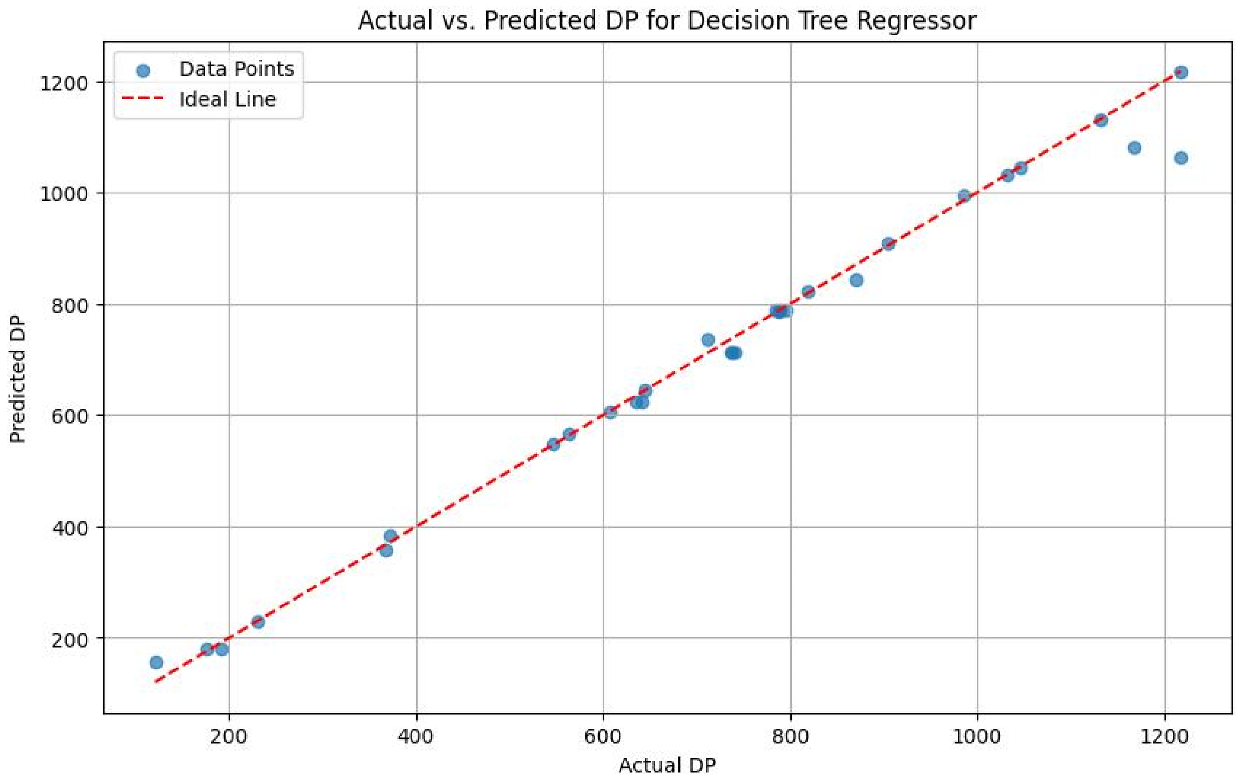

Fig. 1. Actual and predicted DP using Decision Tree Regressor

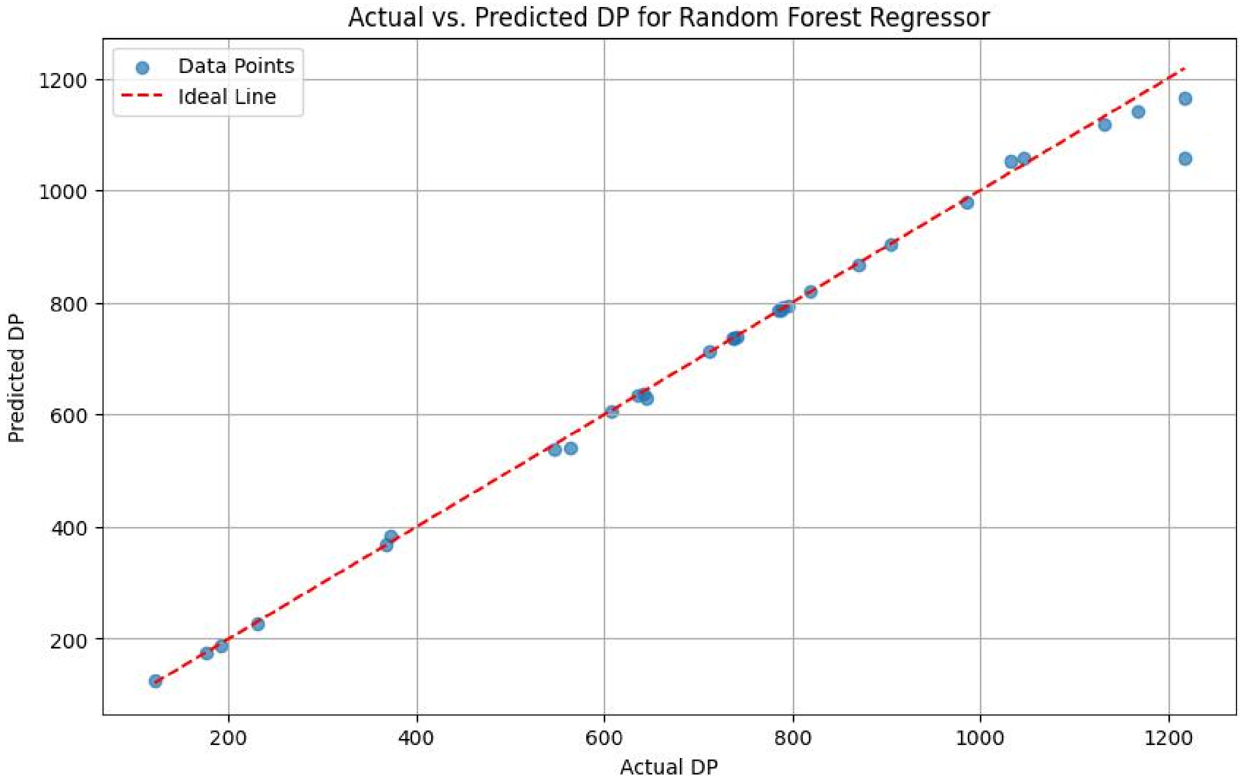

Fig. 2. Actual and predicted DP using Random Forest Regressor

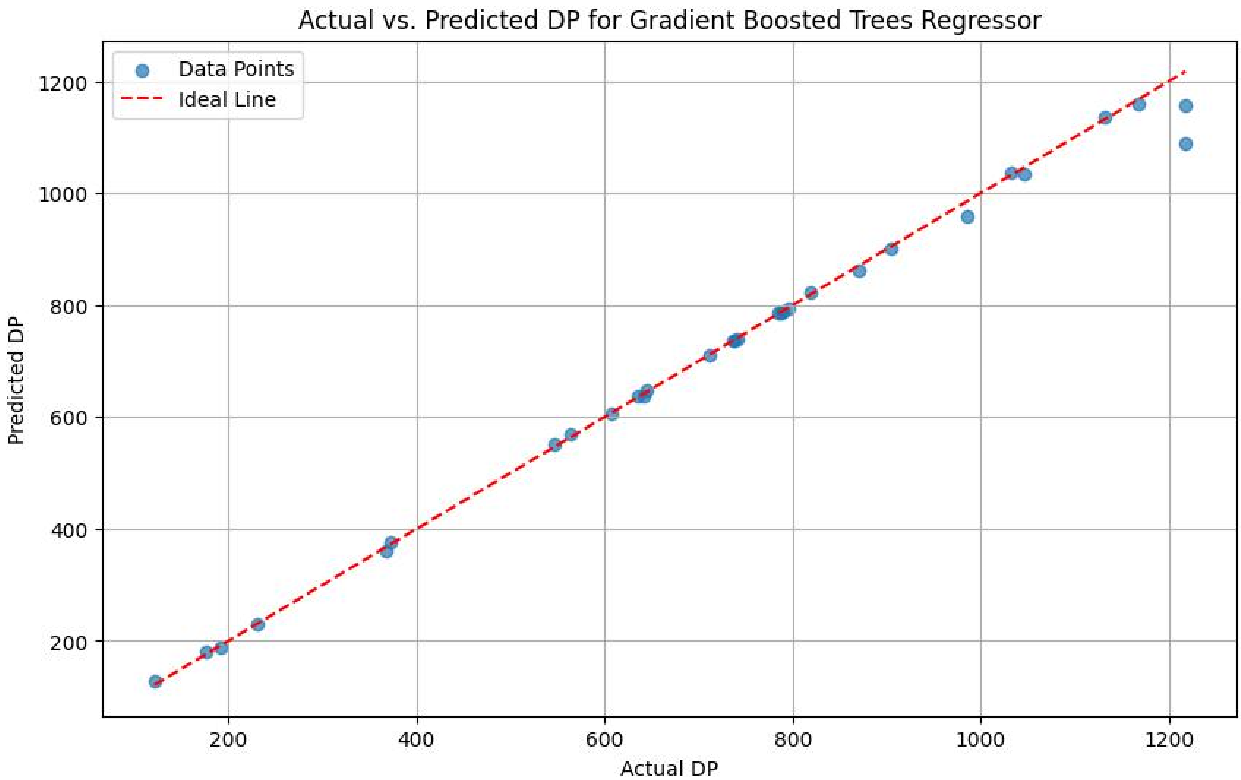

Fig. 3. Actual and predicted DP using Gradient Boosted trees Regressor

3.3. *High MSE and low MAPE*

Our models' Mean Squared Error (MSE) was high, indicating that the model's predictions deviated greatly from the actual data. On the other hand, the Mean Absolute Percentage Error (MAPE) was modest, showing that the model's predictions are, on average, quite close to the actual values in percentage terms. This paradox may develop due to outliers, which disproportionately impact MSE due to its squared-term nature. This difference is exacerbated by the error distribution and the model's sensitivity to error magnitude.

3.4. *Outlier removal: A Double-Edged sword*

Theoretically, deleting outliers could increase MSE but risk jeopardizing the dataset's integrity. Outliers that are true representations of observable phenomena, which were produced from real experimental measurements, are included in our dataset. Eliminating these data points would imply deleting true information, which could result in an inadequate understanding and reduced model robustness when dealing with real-world data complications. Our decision to keep the outliers in the dataset demonstrates our dedication to preserving the experimental data's integrity and authenticity. Compared to a low MAPE, the high MSE emphasizes the necessity for a nuanced interpretation of model performance indicators, particularly in datasets produced from experimental observations. It highlights the significance of picking measures that accurately reflect the difficulties inherent in real-world data processing.

3.5. *Anomaly detection*

Out of the 147 transformers examined, the Isolation Forest algorithm identified eight potential anomalies. These transformers' chemical and physical features differ significantly from the typical patterns identified in the dataset. Such abnormalities could suggest discrepancies in manufacturing, operating stress, or approaching failures. More research into these specific transformers is required to determine the origin and significance of these anomalies. Outliers in experimental datasets are frequently viewed with caution since they may represent data collection errors or unusual phenomena that differ from the norm. In our analysis, however, these anomalies are regarded as integral components of the dataset, as they may include helpful information regarding edge cases or unexpected results within the experimental area. They question our previous beliefs and models, forcing us to investigate their causality and ramifications further. The eight observed anomalies act as sentinels at the edges of our predicted outcomes, each presenting a case study that may teach us about the boundaries or fidelity of our experimental setup. These outliers suggest that data points notably different from the majority may have resulted from extreme conditions throughout the experiment, emphasizing the process's robustness or sensitivity. Anomalies might reflect inconsistencies in collected data, indicating a need to revise experimental protocols or measurement techniques. These outliers may also be the first indicators of novel phenomena or rare events that could lead to groundbreaking discoveries if investigated thoroughly. Upon closer examination, each outlier was evaluated to ascertain its legitimacy and potential cause. It involved meticulously reviewing the experimental conditions and measurements corresponding to these data points. For instance, an outlier with an extraordinarily high reading in one variable prompted a re-evaluation of the testing procedure during that specific trial, ensuring no procedural deviations occurred. The anomalies were not discarded; instead, they were carefully integrated into the broader context of our research. They serve as critical data points for stress-testing our models and hypotheses. By incorporating these outliers in our analysis, we ensure that our results and subsequent models are not just reflections of average conditions but are representative of the entire spectrum of experimental possibilities. The finding of these anomalies has thus pushed our study down unexpected paths, necessitating a re-examination of our experimental setup and the assumptions behind our models. They emphasize the significance of a complete analytical strategy that considers the whole complexity of the data, including instances that defy assumptions. Our study remains grounded in empirical reality, fortified against the myopia of traditional expectations, and open to the full spectrum of our data's discovery due to this inclusive methodology.

3.6. *Clustering Observations*

The dataset was clustered using the K-Means approach with two cluster numbers: K=2 and K=3. The cluster number K denotes the nearest neighbors considered when forecasting a new data point. When K equals 3, the method will look at the three closest neighbors to the query point to identify the majority class (for classification) or the average (for regression).

A clustering analysis was conducted to discover the underlying patterns in our experimental dataset, which provided profound results. The research aided in detecting eight separate abnormalities, highlighting the intricate heterogeneity in our data. The data attributes were partitioned into three categorically coherent categories for each of the two cluster solutions, K=2 and K=3, to emphasize the complexity and depth of the clustering results. This strategic separation enabled a granular but thorough assessment of the clusters' features.

3.6.1. K=2 Cluster Elucidation

The gas composition, chemical, and physical features of the bisectional cluster (K=2) were outlined across three independent tables, each providing a lens into the cluster's essence:
Table 1 depicts the main gas components, indicating the considerable hydrogen, methane, carbon monoxide, and dioxide changes in the two clusters. Cluster 1 had higher readings, showing a different gas profile than Cluster 0.

Cluster_K2	H_2	CH_4	CO	CO_2
0	11.01	34.88	542.57	3699.30
1	38.07	45.68	408.16	38886.34

Table 1: Gas composition (Cluster_K2)

Table 2 delves into chemical attributes such C_2H_4, C_2H_6, and C_2H_2. A dramatic disparity was observed in this case, particularly in the ethane content, with Cluster 1 having a far larger concentration, indicating various chemical interactions or sources.

Cluster_K2	C_2H_4	C_2H_6	C_2H_2
0	13.09	24.82	2.36
1	11.36	110.7	11

Table 2: Chemical attributes (Cluster_K2)

Table 3 summarised the physical data, which included breakdown voltage (BDV), moisture content (MC), dielectric loss factor (Tanδ), acidity (ACI), interfacial tension (I.F.T), and oil colour (OC). The significant differences in water content and power factor between clusters indicated that the samples were in fundamentally distinct physical conditions or phases.

Cluster_K2	BDV	MC in ppm	Tan(δ)	ACI	I.F.T	OC
0	39.03	4.3	1.38	0.026	35.02	1.12
1	38.02	16.75	10.05	0.183	18.82	4.4

Table 3: Physical properties (Cluster_K2)

3.6.2. K=3 Cluster Elucidation

When the data was expanded to a tri-cluster configuration (K=3), it was evenly divided into three tables, demonstrating rigorous categorization:
Table 4 shows that the clusters had varying quantities of gas constituents, with Cluster 0 having the greatest carbon monoxide and dioxide levels, possibly indicating a unique oxidative environment or process conditions.

Cluster_K3	H_2	CH_4	CO	CO_2
0	11.25	47.81	696.44	3995.81
1	39.37	67.58	633.79	5244.11
2	22.34	15.66	208.18	2940.91

Table 4: Gas composition (Cluster_K3)

Table 5 shows that the chemical property differential was exacerbated, particularly with Cluster 1 displaying an elevated quantity of ethane, which may connect with certain chemical processes or breakdown stages.

Cluster_K3	C_2H_4	C_2H_6	C_2H_2
0	10.75	33.42	0.6
1	13	120.32	1.21
2	14.77	48.84	11.8

Table 5: Chemical Properties (Cluster_K3)

Table 6 shows that the physical property revealed the widest range of circumstances, with Cluster 1 again standing out regarding MC and Tanδ. Still, Cluster 2 revealed the highest OC intensity, implying possible changes in sample aging or contamination levels.

Cluster_K3	BDV	MC in ppm	Tan(δ)	ACI	I.F.T	OC
0	39.26	3.24	1.14	0.018	39.06	0.78
1	40.11	23	17.42	0.29	16.32	5.26
2	37.57	9.11	3.05	0.07	23.45	2.71

Table 6: Physical properties (Cluster_K3)

By separating the cluster features into separate tables, the presentation of our results was improved and increased the interpretability of our data. This method allowed for a more focused investigation of each characteristic category, providing a more detailed understanding of the clusters' attributes. A tiny yet significant change was observed between the clusters by meticulously organising the data, each presenting a distinct tale of the underlying experimental events.

4. Discussion

In this section, the results of the proposed method were reported.

4.1. *Implications and broader significance*

The results highlight machine learning's transformational potential in transformer health management. Historically, transformer maintenance has been mostly reactive, addressing wear and tear after it has occurred. However, as proven by the Gradient Boosted Trees Regressor's prediction accuracy, proactive maintenance is now possible. With a MAPE of 1.345%, machine learning algorithms can provide accurate DP forecasts, allowing for prompt interventions before significant wear occurs. It extends the operational lifespan of transformers and ensures the stability of larger power grids they serve. The significance of such predictive capabilities cannot be overstated in a world increasingly reliant on consistent power supplies - from smart homes and electric vehicles to massive data centers. Proactive maintenance, powered by accurate predictions, can lead to significant cost savings, minimizing unplanned downtimes and expensive repairs or replacements.

4.2. *Anomalies and their potential causes*

Identifying eight anomalies using the Isolation Forest algorithm presents a compelling case for integrating anomaly detection in transformer health diagnostics. These anomalies from regular patterns could indicate a variety of problems. Such anomalies could be caused by manufacturing errors, variable operational loads, exposure to harsh environmental conditions, or even the initiation of internal defects. It is critical to be able to detect these irregularities early on. Early detection can lead to focused inspections and tests, ensuring that latent flaws are handled before they become a major problem. It also offers transformer manufacturers insights into potential quality control measures, ensuring that subsequent batches of transformers adhere more closely to desired operational parameters.

4.3. *Future research avenues*

While this study establishes a robust foundation, it also lays the way for various future research directions. Delving deeper into the anomalies observed could lead to a better understanding of their root causes, potentially revealing previously unknown patterns. Incorporating more advanced machine learning models like neural networks may improve predicted accuracy. There is also scope to investigate unsupervised learning techniques for extracting hidden patterns from data that lack pre-defined labels. Integration of temporal data is another interesting path. Transformers are subjected to varying loads and environmental conditions throughout their operating lifespan. Capturing and analyzing this temporal data can provide more detailed insights into their health trajectory, ultimately leading to more sophisticated predictive maintenance strategies.

5. Conclusion

As demonstrated in this research, the incorporation of machine learning approaches has enormous revolutionary potential in the complex terrain of transformer health management. The Gradient Boosted Trees Regressor was used successfully in the study, reaching excellent predictive accuracy for the Degree of Polymerization (DP) based on 147 data sets. The precision indicates a transition from reactive maintenance to data-driven, proactive solutions. Accurate DP prediction, a vital parameter of transformer health, allows for timely intervention, extending transformer operating longevity and ensuring power grid stability. Detecting anomalies using the Isolation Forest algorithm emphasizes the importance of continuous diagnostics. It discovered anomalies that deviated from normative patterns and could be signs of latent operational or manufacturing problems, emphasizing the significance of early diagnosis and intervention.

Furthermore, K-Means clustering revealed intrinsic groupings within the transformers based on their chemical and physical properties. This information can streamline maintenance strategies by adapting actions to specific transformer profiles. As worldwide energy demand rises and the shift towards smart grids and decentralized energy systems accelerates, transformer health and efficiency become critical. This study, which combines data analytics and machine learning, reveals a roadmap for predictive and precision-based transformer health management. It demonstrates the developing synergy between technology and domain expertise, pointing to a future of increased energy reliability and sustainability.

Based on the 147 dataset, the Gradient Boosted Trees Regressor developed the best diagnostic accuracy of the insulating paper state, with the lowest MSE and MAPE values of 714.06 and 1.345%, respectively. This model's iterative technique, compensating for previous tree defects, has resulted in higher projected accuracy.

Conflict of Interest

The authors have no conflicts of interest to declare.

References

[1] Ghoneim, S. S. M., Taha, I. B. M., & Elkalashy, N. I. (2016, June). Integrated ANN-based proactive fault diagnostic scheme for power transformers using dissolved gas analysis. IEEE Transactions on Dielectrics and Electrical Insulation, 23(3), 1838–1845. https://doi.org/10.1109/tdei.2016.005301

[2] Ghoneim, S. S., & Taha, I. B. (2016, October). A new approach of DGA interpretation technique for transformer fault diagnosis. International Journal of Electrical Power & Energy Systems, 81, 265–274. https://doi.org/10.1016/j.ijepes.2016.02.018

[3] Taha, I. B., Mansour, D. A., Ghoneim, S. S., & Elkalashy, N. I. (2017, March). Conditional probability-based interpretation of dissolved gas analysis for transformer incipient faults. IET Generation, Transmission & Distribution, 11(4), 943–951. https://doi.org/10.1049/iet-gtd.2016.0886

[4] Manoj, T., Ranga, C., Ghoneim, S. S. M., Rao, U. M., & Abdelwahab, S. A. M. (2023, June). Alternate and Effective Dissolved Gas Interpretation to Understand the Transformer Incipient Faults. IEEE Transactions on Dielectrics and Electrical Insulation, 30(3), 1231–1239. https://doi.org/10.1109/tdei.2023.3237795
[5] Prasojo, R. A., Putra, M. A. A., Ekojono, Apriyani, M. E., Rahmanto, A. N., Ghoneim, S. S., Mahmoud, K., Lehtonen, M., & Darwish, M. M. (2023, July). Precise transformer fault diagnosis via random forest model enhanced by synthetic minority over-sampling technique. Electric Power Systems Research, 220, 109361. https://doi.org/10.1016/j.epsr.2023.109361
[6] Ghoneim, S. S. M. (2022, December 30). Identification of Power Transformer Insulating Paper's State Based on Principal Component Analysis. International Journal on Electrical Engineering and Informatics, 14(4), 770–781. https://doi.org/10.15676/ijeei.2022.14.4.3
[7] Ghoneim, S. S. M. (2021, February 27). Determination of Transformers' Insulating Paper State Based on Classification Techniques. Processes, 9(3), 427. https://doi.org/10.3390/pr9030427
[8] Ghoneim, S. S. M. (2021, January 28). The Degree of Polymerization in a Prediction Model of Insulating Paper and the Remaining Life of Power Transformers. Energies, 14(3), 670. https://doi.org/10.3390/en14030670
[9] Ghoneim, S. S. M., & Taha, I. B. M. (2020). Comparative Study of Full and Reduced Feature Scenarios for Health Index Computation of Power Transformers. IEEE Access, 8, 181326–181339. https://doi.org/10.1109/access.2020.3028689
[10] Gouda, O. E., & El Dein, A. Z. (2019, March 16). Prediction of Aged Transformer Oil and Paper Insulation. Electric Power Components and Systems, 47(4–5), 406–419. https://doi.org/10.1080/15325008.2019.1604848
[11] Tamma, W. R., Prasojo, R. A., & Suwarno. (2021, March 3). High voltage power transformer condition assessment considering the health index value and its decreasing rate. High Voltage, 6(2), 314–327. https://doi.org/10.1049/hve2.12074
[12] Pulidindi, A., Jonnagadla, D., & Witt, M. (2023, October 5). Advanced Analytics is Reshaping the Decision-Making Landscape of Electric Utilities. Climate and Energy, 40(4), 10–16. https://doi.org/10.1002/gas.22371
[13] Szukits, G., & Móricz, P. (2023, September 16). Towards data-driven decision making: the role of analytical culture and centralization efforts. Review of Managerial Science. https://doi.org/10.1007/s11846-023-00694-1
[14] Forouhari, S., & Abu-Siada, A. (2018, June). Application of adaptive neuro fuzzy inference system to support power transformer life estimation and asset management decision. IEEE Transactions on Dielectrics and Electrical Insulation, 25(3), 845–852. https://doi.org/10.1109/tdei.2018.006392
[15] Nayyar Hassan, A., & El-Hag, A. (2020, April 5). Two-Layer Ensemble-Based Soft Voting Classifier for Transformer Oil Interfacial Tension Prediction. Energies, 13(7), 1735. https://doi.org/10.3390/en13071735
[16] Li, S., Ge, Z., Abu-Siada, A., Yang, L., Li, S., & Wakimoto, K. (2019). A New Technique to Estimate the Degree of Polymerization of Insulation Paper Using Multiple Aging Parameters of Transformer Oil. IEEE Access, 7, 157471–157479. https://doi.org/10.1109/access.2019.2949580
[17] Bakar, N. A., & Abu-Siada, A. (2016, October). Fuzzy logic approach for transformer remnant life prediction and asset management decision. IEEE Transactions on Dielectrics and Electrical Insulation, 23(5), 3199–3208. https://doi.org/10.1109/tdei.2016.7736886

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