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Prediction of the lifetime of a power transformer using an optimized SVR

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ABSTRACT

Predicting the lifetime of the transformer avoids a sudden cessation of its operation along with all technical, economic, and social consequences. The degree of polymerization of the cellulose which constitutes the transformer paper is a good indicator of aging. Since direct measurement of DP is not easy, DP can be determined from other transformer's quality parameters. One of the parameters used to determine indirectly the DP is the concentration of 2-furfuraldehyde. 2-furfuraldehyde is a product of cellulose degradation. In this article, we propose a support vector regression optimized by a Gold Sine Algorithm (Gold-SA) to predict the transformer's loss of life based on the 2-FAL concentration of its oil. The parameters of the model are calculated by the optimization algorithm operated by the model itself. As a result, the model automatically adjusts based on the data used for the designing of the model. The model was tested on nine transformers to assess performance. For DP prediction, the average error is 0.83%, the maximum error is 4.53% and the minimum error is 0.01%. For the transformer loss of life prediction, the average error is 0.90%, the maximum error is 4.46% and the minimum error is 0.01%.

1. INTRODUCTION

To avoid a sudden shutdown of the power transformer with all the associated consequences, it is necessary to predict the end of its life cycle with good accuracy [1]. This is possible through the design of a predictive model that determines the lifetime of the transformer. In the literature, there are several modeling approaches to predict the end of the transformer life cycle. [2]

Thermal models [3], for the most part, inspired by the IEEE model [4], determine the loss of transformer life using the hot spot temperature. They offer the possibility to follow the evolution of the transformer's life in real time but do not have good precision. Despite the addition of learning algorithms such as fuzzy logic [5], neural networks [6], and neurofuzzy [7], the accuracy of thermal models remains a weak point of this modeling approach.

Unlike thermal models, statistical models offer better accuracy but cannot be implemented in a real-time transformer life-tracking device. Statistical models generally look for the correlation between the different transformer's quality parameters. The degree of polymerization (DP) indicates very well the state of the insulation paper whose life is directly related to that of the transformer [8], [9]. The degree of polymerization (DP) is the number of glucose rings in a molecule of cellulose [10]. The transformer DP decreases with age according to equation (1) [11].

$$\frac{1}{DP(t)} - \frac{1}{DP(0)} = Ae^{-\frac{E_a}{RT}t} \tag{1}$$

Here, t is the time in hrs, R is the gas constant (8.314J.mol-1K-1), T is the Hot spot temperature in K, E_a the activation energy in J.mol-1, and A is an empirical constant in hr-1.
Manoj Kumar Pradhan and T. S. Ramu [12] explicitly linked the value of the Degree of Polymerization to the transformer's loss of life.

$$Con\_life = 20.5ln\left(\frac{1100}{DP}\right) \tag{2}$$

Direct measurement of DP is difficult because it requires complete disconnection of the transformer from the power grid [13]. The DP of a transformer will therefore be determined from other data such as the concentration of certain gases dissolved in its oil. The 2-furfuraldehyde (2-FAL) is one of the gases that has a good correlation with DP [14].

Statistical models are empirical models when a mathematical relationship is sought between the different quality parameters of the transformer. Several studies have proposed empirical models to determine the correlation between the 2-FAL concentration and the transformer DP. The most common models found in the literature are given in Table 1.

Table 1: Empirical models

Models	**Equations**	
Chendong model [15]	$DP = \frac{1{,}51 - log(FA)}{0.0035}$	(1)
Depablo model [16]	$DP = \frac{800}{0.186FA + 1}$	(4)
Burton model [17]	$DP = \frac{2.5 - \log(FA)}{0.005}$	(5)
Vuarchex model [17]	$DP = \frac{2.6 - log\, FA}{0.0049}$	(6)
Ghoeneim model [18]	$DP = 122.6\, ln(FA) + 1294.4$	(7)

Here, FA is the 2-FAL concentration given in ppm except in the Ghoeneim model where FA is given in ppb. These models have the advantage that they are simple and easy to operate. However, the disadvantage is that they do not guarantee suitable and stable accuracy for all 2-FAL oil concentration values.

Rather than being empirical models, statistical models can be designed using artificial intelligence tools, optimization algorithms, and so on. This has significantly improved the accuracy of statistical models. Several authors have launched in this field of research among which [19] have proposed an Artificial

Neural Network (ANN) to predict the DP value of a transformer's paper. [20] propose a fuzzy logic model that predicts the DP of an operating transformer. They have quite close results to empirical models. These models have globally good accuracy but their results are related to the training data and for each new dataset, the model must again be repaired manually. The setup time depends on the experience of the one who has to program the learning. One of the main advantages of SVR is that its prediction accuracy is high and its computational complexity does not depend on the dimensionality of the input space. Gold-SA on its part has fewer algorithm-dependent parameters and operators than other metaheuristic methods and faster convergence [21].

Taking advantage of these two methods, we propose in this article a machine-learning model for the prediction of the transformer's lifetime. The model consists of a support vector regression optimized by the Golden Sine Algorithm (Gold-SA). The proposed model has as input the 2-FAL concentration of the transformer's oil. The model's parameters are calculated automatically. The model adapts itself to new training data and therefore it can easily and quickly be implemented by someone not too experienced in programming.

The remaining part of the paper is as follows: section two presents the Proposed methodology, section three presents the results obtained and discussion, and section four is the conclusion of the article.

2. Methodology

2.1 Data processing

2.1.1 Data organization and distribution

The organization of the data consists of storing in a spreadsheet the various information required to design a model. The data must be separated into two parts: one part will be used for training and the other part for testing [22]. The choice of proportions must allow that it has neither over-training nor under training which would considerably reduce the performance of the prediction [23].

2.1.2 Data standardization

The purpose of standardization is to put all quantitative variables on the same scale. Data standardization is a necessary step in supervised learning data science [24]. There are several techniques to normalize data. [25] have shown that the method of standardization impacts the precision of the model. In this study, we have used the robust scaler technique. This method allows that the median value is 0 zero and the technique is robust to outliers.

$$X_{scaled} = \frac{X - Q_1(X)}{Q_3(X) - Q_1(X)} \tag{8}$$

X_{scaled}, Q_1, and $Q_3(X)$ are respectively the scaled value, the first and third quartile of variable X.

2.2 Support vector regression (SVR)

The support vector machine is a supervised learning algorithm introduced in 1995 by Vapnik [26] to solve classification problems. The algorithm has been extended to solve regression problems.

Considering a set of training data $\{(x_i; y_i)\}_{i=1}^{N}$ with $x_i \in \mathbb{R}^d$ and $y_i \in \mathbb{R}$. SVR consists of finding a function $y = f(x)$ such as for $i = 1\ to\ N, |y_i - f(x_i)| \leq \varepsilon$.

A nonlinear support vector regression uses commonly the RBF kernel function [27]. The mathematical expression of the RBF kernel function is [28]:

$$k(x_i, x_j) = \text{Exp}\left(-\frac{\|x_i - x_j\|^2}{2\gamma^2}\right) \tag{9}$$

The performance of the SVR depends on the kernel [29]. SVR model can be designed using LIBSVM [30] and scikit-learn libraries with the help of Python 3.7 [31]. One of the difficulties of this type of regression is the appropriate choice of kernel parameters [32]. An optimization algorithm can therefore be used to ensure that the parameters of the model are correctly chosen.

2.3 Golden Sine Algorithm (Gold-SA)

The Golden Sine Algorithm is a metaheuristic optimization algorithm based on the variation of the sine function. This algorithm was developed in 2017 by Erkan TANYILDIZI and Gokhan DEMIR [21] to solve optimization problems. Sine function periodically varies between -1 and 1 amplitudes at a regular frequency interval of 2π. The operator used by the algorithm is defined as follows:

$$Z_{ij} = Z_{ij}|sin(q_1)| - q_2 sin(q_1)\left|x_1 Z_{best,j} - x_2 Z_{ij}\right| \tag{10}$$

x_1 and x_2 are obtained by the golden section method.[33]

$$x_1 = b + \tau(a - b) \tag{11}$$
$$x_2 = a + \tau(b - a) \tag{12}$$

$\tau = \frac{\sqrt{5}-1}{2}$ is called the golden ratio, a and b are initial values generally chosen as π and $-\pi$.

2.4 Golden Sine Algorithm (Gold-SA) to calculate SVR parameters

SVR with RBF kernel function has three parameters, $C, \gamma,$ and ε. The Golden Sine algorithm can determine the best combination of the three parameters to give a predictive model good accuracy.
Optimization problem: find the combination $(C \quad \gamma \quad \varepsilon)^T_{best}$ that gives the smallest prediction error on an infinite number of possible combinations.

$$(C \quad \gamma \quad \varepsilon)^T_0 = r \times \left[(C \quad \gamma \quad \varepsilon)^T_{max} - (C \quad \gamma \quad \varepsilon)^T_{min}\right] + (C \quad \gamma \quad \varepsilon)^T_{min} \qquad (13)[21]$$

r is a random coefficient chosen between 0 and 1, $r_1 = 2\pi r$ and $r_2 = \pi r$.

2.5 Model flowchart

The model flowchart shown in Figure 1 allows us to predict the loss of life of a transformer based on 2-FAL concentration. Data processing consists first of all of collecting data on transformers. This data will be saved into an Excel database. Then, the recorded data will be classified in ascending order of 2-FAL concentration. Finally, the data will be randomly separated into training data and test data. The ratio between the training and the test data should be made according to the number of data available while ensuring that the model is not over-training or under-training. The parameters of the regression model C, γ, and ε are calculated by the optimization algorithm Gold-SA.

To prevent our optimization algorithm from infinitely searching for the optimal solution, we have set the maximum number of iterations to N. We have accelerated the convergence of the optimization algorithm by setting the boundary conditions and the initial parameter values. Boundary conditions indicate the maximum and minimum values that each parameter can have. The initial conditions are given by equation 13. We have, from the initial parameters and training data, trained, tested, evaluated the model, and recorded the performance of the model. We have changed N times the parameters according to equation 11. For each allowed parameter set, we have to train, test, evaluate, and record the model's performance.

The allowed parameter set is the parameter set for which $C, \gamma,$ and ε have values between the two boundary conditions. This additive constraint will prevent a program bug.

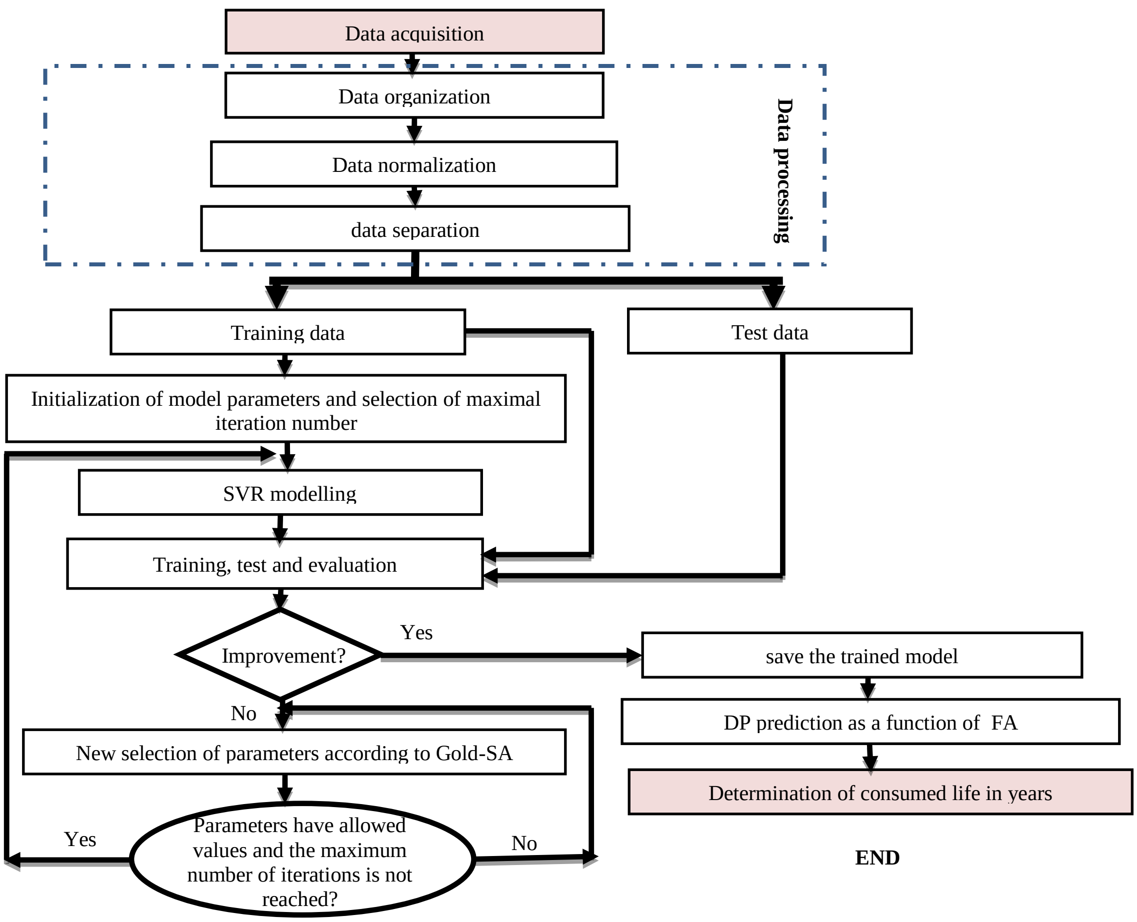

Figure 1: Model flowchart

3. Results and discussions

3.1 Implementation

The model flowchart presented in subsection 2.5 can be implemented into a Python program. We have simulated the Python program into a DELL computer, core i7, 8Go of RAM, and 500Go SSD.

The thirty data used for the training and the test of the model come from the literature [18], [34], [35]. These data were stored using the Excel spreadsheet as a CSV file. We randomly selected 85% of the data for training and 15% for testing. We have standardized the data using the standard scaler method [25].

3.2 Optimal parameters of the model, training, and testing

We have fixed the maximum iteration number N=10000. The optimal parameters of the model obtained are as follows: $C = 11019.40103607$, $\gamma = 3.67313368$ and $\varepsilon = 2.20787954 \times 10^{-6}$.

By setting the values of the three model parameters following the optimization algorithm calculations, we have trained and tested the model. The results are shown in Figure 2.

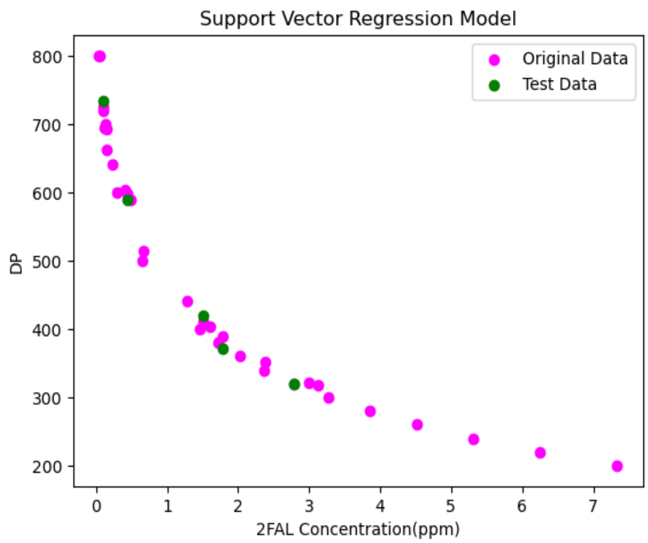

Figure 2: Training and testing result

The green curve of Figure 2 indicates the predicted DP during the test and the cyan curve is the original data. We find that the data predicted by the model during the test phase are very close to the original data. We can calculate the mean square error using Equation 14.

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(\widehat{y_i} - y_i) \tag{14}$$

The mean square error obtained is $MSE = 0.0031$. This error is very small, which shows that during the test phase, the model predicts values very close to the actual data. This observation is a performance indicator of the proposed model.

To assess the performance of the proposed model, we conducted a comparative study between the results of the proposed model and other results available in the literature. We have used the nine transformer data employed by Bonginkosi A. et al in their work [19] to exploit the proposed model and make a comparative study. Firstly, the results obtained by our model will be compared to six empirical models respectively, Chendong model [15], Depablo model [36], [34], Burton model [36], Vuarchex model [16] and Ghoeneim model [18]. Secondly, we will compare the result of our model to another machine learning model, namely the Feedforward Backpropagation Artificial Neural Network model provided by Bonginkosi A. Thango and Pitshou N. Bokoro [19]. We will compare the performance of models on DP prediction and transformer consumed life prediction.

3.3 Prediction of transformer's degree of polymerization

The results of the prediction of the DP of the nine transformers chosen for the comparative study are recorded in Table 2. The first two columns of Table 2 provide the different experimental values of the

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2FAL concentrations of the nine transformers selected to evaluate the performance of the proposed model and the measured DP values of these transformers. Columns 3 and 4 of Table 2 give the DP prediction obtained from the proposed model and an artificial neural network model. From column 5 to column 9, we have the DP predicted by empirical models, respectively, the models of Chendong, De Pablo, Burton, Vuarchex, and Ghoeneim.

Table 2: DP prediction.

Experimental measured [19]		Machine Learning Model DP		Empirical models DP				
FA (ppm)	Measured DP	Proposed Model	ANN model	Chendong model	Depablo model	Burton model	Vuarchex model	Ghoeneim model
1.778	389.2	371.58	388.581	360.019	316.32055	450.013	479.605	376.954
2.377	352.2	352.24	353.234	323.991	262.79309	424.794	453.871	341.357
3.000	321.8	321.78	325.068	295.108	223.46368	404.575	433.240	312.819
1.601	403.5	402.17	401.054	373.031	336.57851	459.121	488.899	389.810
0.676	514.8	515.12	505.379	480.0152	505.89366	534.010	565.317	495.514
0.231	640.8	640.72	635.306	613.253	667.41194	627.277	660.487	627.159
0.143	693.5	689.4	676.561	672.761	712.39024	668.932	702.992	685.955
1.513	411.6	419.0	407.895	380.0460	347.64772	464.032	493.910	396.741
1.563	410.6	410.2	403.961	376.0117	341.27072	461.208	491.028	392.755

For a better comparison, we will calculate the absolute relative error e_{DP}

$$e_{DP} = \frac{\left|DP_{measured} - DP_{predicted}\right|}{DP_{measured}} \tag{15}$$

Table 3: DP prediction error comparison.

FA (ppm)	Proposed Model	ANN model	Chendong model	Depablo model	Burton model	Vuarchex model	Ghoeneim model
1.778	4.53%	0.16%	7.50%	18.73%	15.63%	23.23%	3.15%
2.377	0.01%	0.29%	8.01%	25.39%	20.61%	28.87%	3.08%
3.000	0.01%	1.02%	8.29%	30.56%	25.72%	34.63%	2.79%
1.601	0.33%	0.61%	7.55%	16.59%	13.78%	21.16%	3.39%
0.676	0.06%	1.83%	6.76%	1.73%	3.73%	9.81%	3.75%
0.231	0.01%	0.86%	4.30%	4.15%	2.11%	3.07%	2.13%
0.143	0.59%	2.44%	2.99%	2.72%	3.54%	1.37%	1.09%
1.513	1.80%	0.90%	7.67%	15.54%	12.74%	20.00%	3.61%
1.778	4.53%	0.16%	7.50%	16.88%	12.33%	19.59%	4.35%
Mean	**0.83%**	1.08%	6.83%	14.70%	12.24%	17.97%	3.04%
Maximum	4.53%	**2.44%**	8.42%	30.56%	25.72%	34.63%	4.35%
Minimum	**0.01%**	0.16%	2.99%	1.73%	2.11%	1.37%	1.09%

The maximum error value of the proposed model is recorded for the concentration of 1.778 ppm. This may come from the learning data in the vicinity of this concentration value that appears slightly noisy. An improved database of around 1.778 ppm concentration should improve the proposed model.

3.4 Prediction of the consumed life of the transformer

We will determine the life consumption in years of the transformer from the degree of polymerization using equation 2. The results of the prediction are recorded in Table 4.

Table 4: Life consumption in years

FA (ppm)	Measured Values	Proposed Model	ANN model	Chendong model	Depablo model	Burton model	Vuarchex model	Ghoeneim model
1.778	21.299	22.249	21.332	22.897	25.549	18.323	17.017	21.954
2.377	23.347	23.344	23.287	25.058	29.350	19.505	18.148	23.988
3.000	25.197	25.199	24.990	26.972	32.673	20.505	19.101	25.778
1.601	20.559	20.627	20.684	22.169	24.277	17.912	16.624	21.267
0.676	15.565	15.553	15.944	17.000	15.923	14.814	13.646	16.348
0.231	11.077	11.080	11.254	11.978	10.243	11.514	10.457	11.518
0.143	9.457	9.578	9.964	10.079	8.906	10.196	9.178	9.681
1.513	20.152	19.786	20.337	21.787	23.613	17.694	16.415	20.906
1.563	20.202	20.222	20.536	22.006	23.993	17.819	16.535	21.113

Table 5: Life consumption error.

FA (ppm)	Proposed Model	ANN model	Chendong model	Depablo model	Burton model	Vuarchex model	Ghoeneim model
1.778	4.46%	0.15%	7.50%	19.96%	13.97%	20.10%	3.08%
2.377	0.01%	0.26%	7.33%	25.71%	16.46%	22.27%	2.75%
3.000	0.01%	0.82%	7.04%	29.67%	18.62%	24.19%	2.30%
1.601	0.33%	0.61%	7.83%	18.08%	12.88%	19.14%	3.44%
0.676	0.08%	2.43%	9.21%	2.30%	4.83%	12.33%	5.03%
0.231	0.02%	1.59%	8.13%	7.53%	3.95%	5.60%	3.98%
0.143	1.29%	5.36%	6.58%	5.83%	7.82%	2.95%	2.37%
1.513	1.81%	0.92%	8.11%	17.18%	12.20%	18.55%	3.74%
1.563	0.10%	1.65%	8.93%	18.77%	11.79%	18.15%	4.51%
Mean	**0.90%**	1.53%	7.85%	16.11%	11.39%	15.92%	3.47%
Maximum	**4.46%**	5.36%	9.21%	29.67%	18.62%	24.19%	5.03%
Minimum	**0.01%**	0.15%	6.58%	2.30%	3.95%	2.95%	2.30%

The first column of Table 4 provides the different experimental values of the 2FAL concentrations of the nine transformers selected to evaluate the performance of the proposed model. The second column of Table 4 give the life consumption of the transformer obtained from the DP-measured values. The others columns give the consumed life predictions obtained by different models consider in this work.

The absolute relative error between the consumed life predicted by the following models and the consumed life calculated from experimental DP values are given in table 5. The model proposed has the smallest minimum error value (0.01%), the lowest mean error value (0.90%), and the smallest maximum error value (4.46%).

The proposed model has more precise results than the different empirical models and most models exploit artificial intelligence. It auto-configures itself, allowing it to be used without any other calculations or configurations when the database is updated.

However, the proposed model cannot be implemented like all other statistical models in a real-time transformer life monitoring tool. The model is only usable when we can measure with good precision the 2-FAL concentration, however, it is possible to exploit other gases such as methanol or ethanol to indirectly determine the DP of a transformer. Like all learning machine models, the performance of the model is closely linked to data. Thus, the intrusion of noise in the database will very quickly decrease the model's performance.

4. Conclusion

This article proposes a machine-learning model to predict the lifetime of a transformer based on the 2-FAL concentration of its oil. The model is based on support vector regression optimized by the golden sine algorithm. The model does not require a lot of data, which allows not a lot of memory to be occupied and a relatively low learning time. The model was tested on nine transformers to assess performance. For DP prediction, the average error is 0.83%, the maximum error is 4.53% and the minimum error is 0.01%. For the transformer loss of life prediction, the average error is 0.90%, the maximum error is 4.46% and the minimum error is 0.01%. The comparative study between the results of the proposed model and other models predicting a loss of life based on the 2 FAL concentration shows that the model we propose is largely mesh than all the models stack and even the artificial neural network model proposed by Bonginkosi A. Thango and Pitshou N. Bokoro. The model's performance comes firstly from the performance of the support vector regression with the kernel. Secondly, the performance of the model results from the correct choice of ratio between the training data and the test data. In the end, the optimization algorithm used allowed us to efficiently configure our kernel regression with a relatively low computation time.

However, the model can only be used when the 2FAL concentration of the transformer's oil can be accurately determined. Also, apart from the 2FAL concentration, other parameters provide information about the aging of the transformer. The proposed model does not take into account these other parameters which also provide enough information about the life of the transformer.

The model can be improved by providing more reliable information to the database. DP can also be correlated with other gases that are more easily traceable and measurable in transformer oil. It is possible to increase the number of quality parameters taken as input to the model to take into account other aging actions that do not necessarily induce gas production.

Conflicts of Interest: The authors declare no conflict of interest

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