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PREDICTING FURFURAL CHANGES IN POWER TRANSFORMERS DUE TO SHORT-CIRCUIT CURRENTS

Amir Reza Amini[1], Seyed Mahmoud Modaresi[2]*, Tahereh Daemi[1], Seyed Ziya Mazloom[3]

[1]Department of Electrical Engineering, Ya.C., Islamic Azad University, Yazd, Iran.
Amirreza.amini@iau.ac.ir
Ta.daemi@iau.ac.ir
[2]Department of Electrical Engineering, ST.C., Islamic Azad University, Tehran, Iran.
Modaresi@iau.ac.ir
[3]Department of Electrical Engineering, Mahr.C., Branch, Islamic Azad University, Mahriz, Iran.
Szmazloom@iau.ac.ir

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***ABSTRACT*:**

Power transformers are among the main equipment for transferring electrical energy from production fields to consumption fields. To ensure the health of the cellulose insulation of these equipment, oil sampling was performed and the amount of furfural in the oil was determined by liquid chromatography.In this study, the prediction of the amount of furfural changes in power transformer oil due to the passage of short-circuit currents and the age of the power transformers at the time of the fault has been addressed. For this purpose, 18 power transformers were investigated over a period of 11 years and the number and intensity of short-circuit currents, the age of the power transformer during the fault, and the changes in furfural in each power transformer oil sampling period were collected. By statistical analysis and comparison of machine learning models, the best model for predicting furfural changes was obtained based on the highest coefficient of determination and the lowest mean absolute error and root mean square error. The accuracy of this model was proven by examining two 230 kV and 160 MVA power transformers with different lifetimes, as well as applying a short circuit and measuring the amount of furfural in the oil of a 400 kV and 315 MVA power autotransformer in a high-voltage substation. In addition to creating a new framework for assessing the condition of transformers, this study allows analysts to predict the amount of furfural in power transformer oil without the need for sampling and testing.

***Keywords**: Power transformer, power transformer lifetime, furfural, machine learning.*

INTRODUCTION

Electrical, thermal and mechanical stresses applied to power transformers during their operation can lead to the gradual degradation of cellulose insulation[1]. Ensuring the integrity of cellulose insulation of power transformers is an important issue in the power system. Cellulose insulation consists of a chain of glucose bonds[2]. The number of glucose bonds in each cellulose molecule is called the polymerization number (DP)[3]. This number is a criterion for determining the integrity of cellulose insulation in power transformers. In transformers with new cellulose insulation, the DP value is approximately 1200, while a DP value of less than 200 indicates that the cellulose insulation no longer has any mechanical strength and the life of the power transformer has practically ended[4]. During the decomposition of cellulose and power transformer oil against thermal degradation, carbon monoxide, carbon dioxide, hydrocarbon by-products and water are produced[5]. However, furfural is produced only from the decomposition of cellulose[6]. Furfural is a substance from the class of aldehydes that are stable at high temperatures[7],[8]. In [9],[10],[11], the relationship between DP and furfural has been investigated and mathematical models have been presented to calculate it. Therefore, furfural can be used as a criterion to detect the extent of degradation of cellulose insulation and consequently the life of power transformers[12],[13].

In [14], the amount of furfural is predicted based on oil color, oil acidity, methane to hydrogen ratio, and operating time of power transformer using random forest regression model and support vector regression. In [15], furfural is predicted based on oil acidity, oil surface tension, water, and dissolved gases in oil using a generalized machine learning model.

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Short-circuit currents passing through power transformers, especially at high levels, exert severe electromechanical forces on the windings and insulation [6], [16]. It has been shown in [17] that cellulose insulation in older transformers is more sensitive to stresses caused by short-circuit currents. On the other hand, in younger transformers, although the insulation resistance is higher, repeated short-circuits with high currents can lead to an increased rate of cellulose degradation [18]. However, a detailed study showing the effect of short-circuit currents on the rate of furfural production and the breakdown of cellulose insulation of power transformers has not been conducted, and a quantitative model that accurately describes the relationship between furfural changes and short-circuit currents at different ages of power transformers has not been obtained.

In this study, using field data collected from 17 power transformers over a period of 11 years, machine learning was used to investigate the effect of short-circuit currents of different magnitudes on changes in furfural concentration. Given the large number of power transformers in a nationwide network, oil sampling and testing to obtain the amount of furfural in power transformer oil is difficult, time-consuming, and costly. This study provides an analytical framework for accurately predicting the amount of furfural dissolved in power transformer oil without conducting relevant tests.

This study consists of 5 sections. The first section provides an introduction and review of the studies. The second section is dedicated to a discussion of the research methodology. The third section discusses the data and information studied. The fourth section presents the results and performance evaluation of the machine learning model in predicting furfural concentration and transformer life. Then, the last section presents the conclusions and implications of the research.

DATA AND METHODS

The data includes the age of use, short-circuit currents passed, and the amount of furfural dissolved in the oil of power transformers, and the method of use, machine learning models.

1-2- furfural

An organic compound produced by the degradation of cellulose insulation in power transformers[2]. The concentration of furfural was measured according to ASTM D5837 using high-performance liquid chromatography (HPLC), in which furfural was separated after a specified volume of sampled oil passed through a chromatography column containing silica adsorbent modified with alkyl chains (C18) and its amount was measured by ultraviolet light at a wavelength of 280 nm[19],[20].

2-2- Short circuit currents

The faults that occur, which cause the short circuit current to pass through the power transformer, are detected by the relevant protection relays and their characteristics are stored in the event log. As a result, by referring to the event log in the protection relays, the time, type and current of the short circuit that occurred can be observed and noted.

2-3- Data preprocessing

One of the important issues in using data for machine learning is the existence of data that contains noise or large errors. This data is called outliers. In machine learning models, in order to achieve more favorable results, outliers are first removed and the remaining data are normalized to ensure that all quantities have the same importance. Since the data in this study did not have a normal distribution, the interquartile range (IQR) method was used to identify and remove outliers [21].

In this method, first the first quartile (Q1) and the third quartile (Q3) and then the interquartile range are calculated according to equation (1). The lower and upper limits of data acceptance are defined as equation (2). Values outside this range are considered outliers and are eliminated. The Z-Score method is used to normalize the data according to equation (3). In this relationship, x is the data value, μ is the mean of the data, and σ is the standard deviation of the data. Data outside the range $-3<Z<3$ are considered outliers and are eliminated[22] and [23].

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$$\mathbf{IQR = Q_1 - Q_3} \quad (1)$$
$$\mathbf{LOWER\ BOUND = IQR * 1.5 - Q_1} \quad (2)$$
$$\mathrm{UPPER\ BOUND = IQR * 1.5 + Q_3}$$
$$\mathbf{Z = \frac{X - \mu}{\sigma}} \quad (3)$$

2-4- Examining correlation between variables

In order to examine the degree of dependence between the independent variables and the dependent variable, correlation analysis was performed on the data[24]. In order to evaluate the linear and nonlinear relationships between the variables, Pearson and Spearman correlation coefficients were used, respectively[25]. The value of the correlation coefficient in both cases is in the range of -1 to 1. So that values close to 1 or -1 indicate the existence of a strong direct or inverse relationship between the two variables, and values close to zero indicate the absence of a strong relationship[25] and [26]. Pearson and Spearman correlation coefficients were calculated according to equations (4) and (5), respectively. σ_X and σ_Y are the standard deviations of variables X and Y, cov(X.Y) is the covariance between variables X and Y, d_i is the rank difference between the i-th variable X and Y, n is the number of data related to each variable.[25].

$$\mathbf{corr = \frac{cov(X.Y)}{\sigma_X * \sigma_Y}} \quad (4)$$
$$\mathbf{\rho = 1 - \frac{6 * \sum_{i=1}^{n} {d_i}^2}{n * (n^2 - 1)}} \quad (5)$$

2-5- Variance inflation index (VIF[1])

In order to accurately assess the dependence between independent variables, VIF is calculated for each independent variable based on equation (6)[27]. The valueR_i^2 It indicates the degree of dependence of the i-th independent variable on other independent variables.

$$\mathbf{VIF_i = \frac{1}{1 - {R_i}^2}} \quad (6)$$

VIF It is only important in linear regression models. In nonlinear or tree-based methods, the dependence of independent variables does not significantly affect model performance[27],[28]. VIF values close to 1 indicate weak dependence, and values greater than 5 indicate strong dependence between independent variables[29]. Machine learning has been studied and compared to different learning models for furfural prediction.

Linear Regression : Due to its simplicity and high interpretability, it is used as a basic model to model the linear relationship between one or more independent variables and a dependent variable. The goal of linear regression is to find coefficients for the independent variables such that the mean square error between the predicted and actual values is minimized [30].

Polynomial degree(2) : This model has been shown to perform better than linear regression when the relationship between the independent and dependent variables is nonlinear. Quadratic polynomial regression has been used to improve prediction accuracy over simple linear models [31].

Ridge(alpha=1) : A regularized linear regression method developed to reduce overfitting and deal with multicollinearity between independent variables. This method reduces the model coefficients by adding a penalty, which makes the model more stable and generalizable to new data [32].

Decision Tree : A supervised learning model that uses a tree structure to divide data into homogeneous subsets to make predictions. This model is known for its simplicity and high interpretability, but it has a high probability of overfitting, which is corrected by techniques such as pruning[33],[34].

Random Forest : An ensemble learning algorithm that consists of multiple decision trees to make predictions. In this method, multiple trees are trained independently on random subsets of the data, and then the final output is

Variance Inflation Factor [1]

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obtained by combining the predictions of these trees. This approach makes the model more robust to noise and training data, and has better accuracy and generalizability than a single tree[35],[33].

Gradient Boosting : One of the most powerful ensemble learning methods that combines several weak models to create a strong model. In this method, trees are built sequentially, which increases the probability of overfitting, which is controlled by adjusting the learning rate and the depth of the trees. The main idea of this method is that the model gradually and step by step moves towards reducing the prediction error, and this is done using the gradient of the error function [33] and [15].

Neural Network : A machine learning model inspired by the human brain and capable of learning complex nonlinear relationships from data using a multilayer structure. Recent studies have shown that neural networks can perform very accurately in detecting the operational status and internal faults of power transformers [36].

Support Vector Machine : A powerful machine learning algorithm widely used for classification and regression problems. The main idea is to find an optimal hyperplane that can separate data belonging to different classes. This feature makes the model have higher generalizability and provides good performance against overfitting. In many electrical engineering systems, data is mapped to a higher-dimensional space using the concept of functions to allow for nonlinear separation[33],[37].

The goal of comparing these models is to find the model with the best performance in terms of prediction accuracy and interpretability. In order to evaluate the accuracy of machine learning models, the following criteria are defined.

Mean absolute magnitude of error)(MAE[2] : This quantity is the average absolute value of the difference between the actual values and the predicted values. This measure represents the average error of the model. The closer this value is to zero, the higher the accuracy of the model[15].

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \qquad 7)($$

Root mean square error This quantity is one of the most widely used criteria in the evaluation of **(RMSE):[3]** regression models. This quantity calculates the deviation of the predicted values from the actual values by considering the square of the errors. Its small value indicates a better performance of the model in predicting the data[38].

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \qquad 8)($$

Coefficient of determination([4] R^2): R^2 This quantity indicates how well the model was able to explain changes in the dependent variable using the independent variables. The value For data-fit models, it ranges between zero and one; the closer its value is to one, the more capable the model is in predicting the data [39].

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \qquad 9)($$

In these relations, y_i is the actual value of the ith data, yˆ_i is the predicted value of the ith data by the model, y¯_i is the average of the actual data values, and n is the number of data.

Time Series Split Cross-Validation : One of the most scientific methods for evaluating the performance of machine learning models on time-dependent data is the time series cross-validation method [40]. In this method, the temporal order of the data is preserved and the use of future data in training is prevented. To further ensure the performance of the models and reduce the possibility of overfitting, the data set is first divided into equal parts for training and then the algorithm is trained in Split iterations, so that at each time, Split-1 part is selected as the training set and the remaining part is selected as the test set. Finally, the average of the MAE, RMSE and R^2

Mean Absolute Error [2]
Root Mean Square Error [3]
Coefficient of Determination [4]

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criteria in all iterations is reported as the model performance [41.[This averaging has made the model performance evaluation more stable than the 80% training and 20% testing method [42]. The Split value is selected based on the value of K in the K-Fold Cross Validation method. In many authoritative studies, this value is set between 5 and 10, which provides a good balance between estimation accuracy and computational cost [43].

DATA

In this study, 18 power transformers in 12 high-voltage substations, with different lifetimes, were investigated over a period of 11 years. These transformers were selected in such a way that their oil was not treated or replaced during the study period. Between 1390 and 1401, oil sampling was performed 11 times from each power transformer. Between two consecutive samplings of power transformer oil, changes in furfural, the number of short circuits with a current less than the rated current, the number of short circuits with a current between the rated current and one and a half times the rated current, the number of short circuits with a current between one and a half to two times the rated current, the number of short circuits with a current between two and three times the rated current, the number of short circuits with a current greater than three times the rated current, and the age of the power transformer were extracted. Power transformers in high-voltage substations have complete protection systems. These protection systems do not allow the transformer to increase in temperature and increase in load beyond a certain limit. For this reason, in this study, the effect of temperature and load increase for power transformers has not been considered separately, and their effect has been shown in the operating age of transformers. ppm is the unit of measurement of furfural content. The power transformers lifetime has been considered based on years.

RESULTS

In this study, considering the dependence of the age of the power transformer on time, in order to prevent information leakage from the future to the past, the data has been divided chronologically from old to new. Thus, the initial 80% of the data has been considered as the training set and the final 20% of the data as the test set. This approach has enabled a realistic assessment of the model's performance in predicting future values. From the training data set, 6 outliers have been identified and removed by the IQR method. The Pearson and Spearman correlation coefficients as well as VIF have been obtained according to Figures 1 and 2.

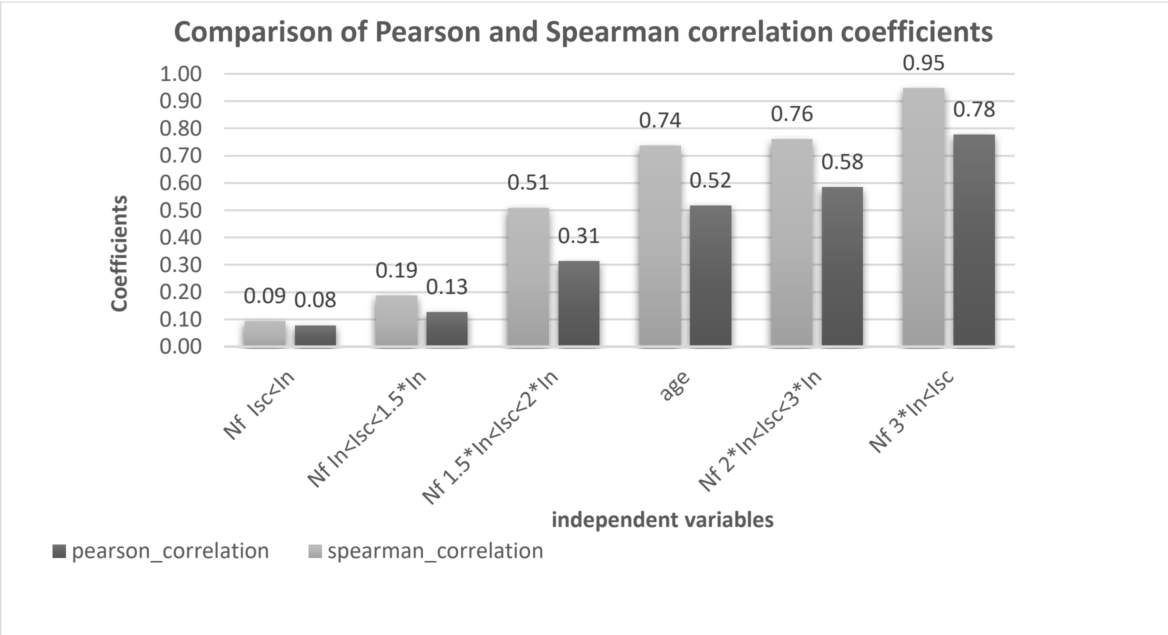

Chart 1: Comparison of Pearson and Spearman correlation coefficients

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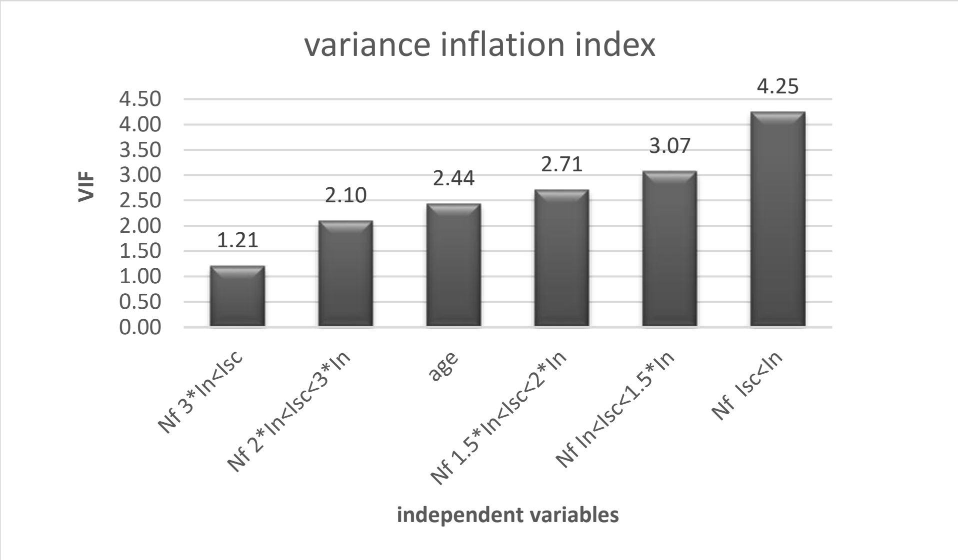

Chart 2: Variance inflation index for independent variables

Comparing Pearson and Spearman coefficients has shown that a linear relationship cannot robustly define the dependent variable based on the independent variables. VIF coefficients have shown that the independent variables have very little dependence on each other and there is no need to eliminate any of them.

Time Series Split Cross-Validation with a Split value of 5 based on the default Scikit-Learn library was used to calculate MAE, RMSE, and R^2 metrics for 80% of the training data and the generalizability of the models was measured. Then, the metrics obtained from validation were compared with the results from the final test set based on Table 1 and the best Gradient Boosting prediction model was selected.

Table 1: Comparison of quantitiesR^2 ‹MAE ‹RMSE ‹For training and testing data in machine learning models

Model	R^2 Training	R^2 Test	MAE Training	MAE Test	RMSE Training	RMSE Test
Linear Regression	0.736	0.643	0.1828	0.2485	0.2719	0.3653
Neural Network MLP	0.883	0.814	0.0264	0.0505	0.0533	0.0942
Random Forest	0.939	0.896	0.0078	0.0085	0.0093	0.0102
Polynomial_deg2	0.834	0.798	0.1710	0.2211	0.2454	0.3549
Gradient Boosting	0.989	0.968	0.0003	0.0008	0.0006	0.0019
Decision Tree	0.929	0.909	0.0008	0.0013	0.0009	0.0013
Ridge_alpha1	0.735	0.712	0.1976	0.2886	0.3226	0.4683
SVM_SVR	0.815	0.782	0.0135	0.0202	0.0279	0.0469

4-1- Evaluation of the selected model

To ensure the accuracy of the model obtained for predicting furfural based on the short circuits that occurred with different intensities and the age of the power transformers at the moment of the short circuit, in addition to allocating 20% of the data for testing and experimentation according to Table 1, three power transformers with the specifications of Table 2 were tested in a high-voltage substation with the single-line map of Figure 1.

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Table 2: Specifications of the tested power transformers

rated current)LV(	rated current)HV(	Rated voltage)LV(	Rated voltage)HV(	Impedance percentage	rated power)MVA(	grouping	Year of operation	Manufacturing factory	Transformer number
879/1173/1466	TAP1)349/279/209(	63	TAP1)264.5(	TAP1)16.54(	96/128/160	Ynd11	Aprill 2023	Iran Transfo	T1
	TAP10)401/321/241 (		TAP10)230(	TAP10)15.34(					
	TAP19)472/378/283 (		TAP19)200(	TAP19)14.34(					
879/1173/1466	TAP1)349/279/209(	63	TAP1 264.)(5	TAP1)16.59(	96/128/160	Ynd11	October 1992	ABB	T2
	TAP10)401/321/241(		TAP10)230(	TAP10)15.31(					
	TAP19)472/378/283(		TAP19)200(	TAP19)14.42(					
477/628/791	TAP1)238/314/395(	230	TAP1)347.8(	TAP1)17.55(	190/250/315	Yna0d11	March 2013	Iran Transfo	T3
	TAP10)274/361/455(		TAP10)400(	TAP10)15.43(					
	TAP19)322/434/534(		TAP19)470.5(	TAP19)15.72(					

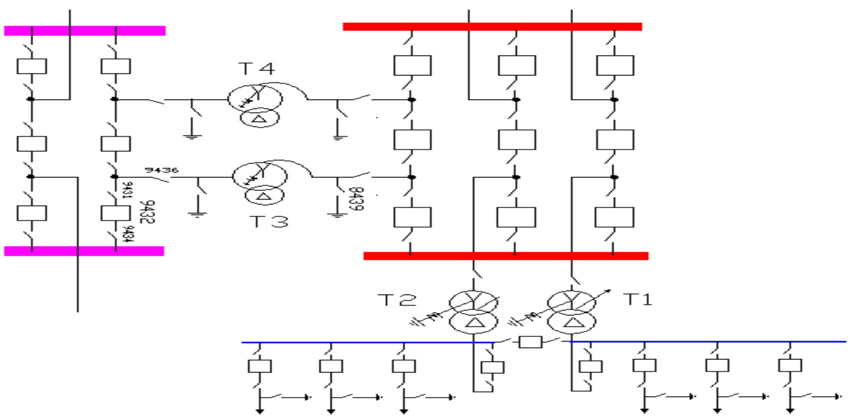

Figure 1: Location of the studied transformers on a single-line map

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For transformers T1 and T2, oil sampling was done twice from May 2023 to October 2025 and the amount of furfural in the oil was measured by HPLC method. The number of short circuit currents passing with different intensities during this period was extracted. An experiment was performed on the power autotransformer T3. The transformer was removed from the circuit, and a short circuit was applied by closing the earthing sectioner 8439 according to Figure 2 (a). By energizing T3 from the high voltage side, the short circuit current passing through the transformer was measured by the protective relay as shown in Figure 2(b). This was repeated 4 times at a certain time interval. Before and after the test, oil sampling was performed as shown in Figure 3(a) and furfural in the oil was measured by HPLC in the laboratory as shown in Figure 3(b). Based on the age and intensity of the short circuit currents passing through the power transformers, the changes in furfural dissolved in the oil were calculated by the model obtained in this paper and compared with the values obtained by HPLC method and the results are presented in Table 3.

(a) (b)

Figure 2: (a) Applying a short circuit by closing the earthing switch at the T3 output. (b) Measuring the contact current by the protective relay

(a) (b)

Figure 3: (a) Oil sampling from T3. (b) HPLC for measurement of oil-soluble furfural.

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Table 3: Comparison of the obtained model and the HPLC method in calculating the furfural changes of the tested transformers due to the passage of short-circuit currents.

Power transformer number	Calculation method	Furfural in the first stage	Furfural In the second stage	Nf 3*In<Isc	Nf 2*In<Isc<3*In	Nf 1.5*In<Isc<2*In	Nf In<Isc<1.5*In	Nf Isc<In	age	Delta furfural
T1	HPLC	0.001	0.004	*	*	*	*	*	*	0.003
	Gradient Boosting	*	*	_	1	2	5	12	2.5	0.004
T2	HPLC	0.151	0.184	*	*	*	*	*	*	0.054
	Gradient Boosting	*	*	_	_	2	5	12	33	0.056
T3	HPLC	0.151	0.184	*	*	*	*	*	*	0.028
	Gradient Boosting	*	*	4	0	0	0	0	11.5	0.027

Based on the comparison of the HPLC method and the Gradient Boosting prediction model presented in this article, it was observed that the presented model has high accuracy in predicting changes in furfural dissolved in power transformer oil, and it can be used as an alternative to costly laboratory methods.

CONCLUSION

Predicting the furfural content in power transformer oil is a cost-effective approach to assess the insulation condition of power transformers. This study presents the best machine learning model that can accurately predict the changes in furfural concentration in power transformer oil based on the life span and the number of short circuit currents passing through the power transformer with different intensities. In this way, given the initial furfural content and the life span and number of short circuits with different currents at any given moment, the furfural content for the power transformer can be calculated. The reliability assessment of the presented model was carried out by field survey of three power transformers in a 400 kV substation, in addition to allocating 20% of the data for testing. This data-based method is particularly valuable in cases where testing facilities are limited, and it saves time and money in obtaining the amount of furfural dissolved in power transformer oil.

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