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Investigation on the Aging State Assessment of Transformer Insulation Paper Based on Multi-Feature Comprehensive Assessment Method

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Abstract. The aging state of transformer insulation papers was not assessed accurately. In this paper, multi-feature comprehensive assessment method was proposed to convert the nonlinear problem into a linear problem fitting for assessing the aging state of insulation papers. The whole aging process was divided into two stages with the degree of polymerization of 500 as the dividing point. The backward multiple linear regression analysis model was established and the error of the fitting results was analyzed. Most of the relative assessment errors were within ± 5 %. It compensated for the deficiency of aging assessment of transformer insulation paper based on single feature, and the accuracy of assessment results was improved.

Keywords. Transformer, paper insulation, aging state estimation, linear regression

1. Introduction

In the operation of power equipment, the oil-paper insulation aging system is an essential component [1-3]. However, as equipment service time increases and the external environment takes its influence, the oil-paper insulation aging system may encounter various issues, including decreased insulation performance and partial discharge. Therefore, assessing the aging state of the oil-paper insulation system is crucial for ensuring reliable equipment operation and improving system safety [4-8].

The current chemical assessment of aging state of insulating paper primarily focuses on carbon oxides (CO, CO₂) [9-10], furfural (2-Furaldehyde, 2-FAL) [11-15], and methanol. The CO, CO₂, and 2-FAL are relatively mature indicators that can provide insight into the aging state of insulating paper. In practical application, it has been found that the assessment accuracy of CO, CO₂, 2-FAL, and methanol is limited due to several reasons. Firstly, CO and CO₂ in oil come from both insulating paper and the oxidation of insulating oil or air [16,17]. Secondly, there are issues with 2-FAL in oil, including limited detection in the early stages of aging and difficulty in detecting it in transformer

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oil with thermal modified paper [18-20]. The methanol content in oil-paper insulation varies with aging time at the ending stage of insulation life of the transformers, which would lead to inaccurate assessment results [21-27]. The investigation on sugar content in insulation oil is seldomly, the relationship between sugar content in insulation oil and DP of insulation paper has not been established well.

The traditional assessment methods for assessing aging state of transformer rely on only one feature or indicator, which could not comprehensively and accurately assess the DP of insulation paper. Various multi-feature assessment methods have emerged to address this problem. This method utilizes simultaneous monitoring and analysis of multiple characteristic quantities, along with advanced detection methods and data processing technology. It enables more accurate assessment of the performance and lifespan of oil-paper insulation aging systems.

Presently, the comprehensive assessment methods include Hierarchical analysis, Superior-inferior solution distance method, Variable weighting, Improved hierarchical analysis-approximation of ideal solution method, Principal component analysis, Deep learning, et. al.. However, these methods are only applied for hierarchical assessing the aging state of oil-paper transformer, and can't establish the mathematical relationship between multi-feature quantities and the DP.

In this study, a multivariate linear regression model was used to assess aging state of insulation paper. Different characteristic quantities were selected for different periods, and a reliable prediction model was obtained after conducting a goodness of fit test. The aging period was divided into two stages using backward multiple linear regression analysis. Most of the assessment relative errors were within ± 5 %. This research provides theoretical support for ensuring the reliable operation of power equipment.

2. Analysis of Assessment Methods

2.1. Linear Regression Analysis

a. Mathematical Model for Unary Linear Regression

Unary regression is used to solve the relationship between the two variables. If there is a set of data structures as follows:

$$y_t = \beta_0 + \beta_1 x_1, \quad t = 1, 2, \cdots, N$$
 (1)

where β_0 is the intercept, β_1 is the slope, x_1 is the independent variable, and y_t is the dependent variable. Assuming that b_0 and b_1 are the least squares estimates of the parameters a and s, the regression equation for one-way linear regression is obtained:

$$\hat{y} = b_0 + b_1 x \tag{2}$$

 b_0 and b_1 are called regression coefficients, and for any one, a regression value can be determined by the equation.

The difference between the actual measured data and the regression value is called the error ε_i .

$$\varepsilon_i = y_i - \hat{y}_i = y_i - b_0 - b_1 x_i, \quad i = 1, 2, \dots, N$$
(3)

The regression coefficient can be obtained by using the least square method, that is:

$$b_{1} = \frac{N \sum_{i=1}^{N} x_{i} y_{i} - (\sum_{i=1}^{N} x_{i}) (\sum_{i=1}^{N} y_{i})}{N \sum_{i=1}^{N} x_{i}^{2} - (\sum_{i=1}^{N} x_{i})}$$
(4)

$$b_{0} = \frac{\left(\sum_{i=1}^{N} x_{i}^{2}\right)\left(\sum_{i=1}^{N} y_{i}\right) - \left(\sum_{i=1}^{N} x_{i}\right)\left(\sum_{i=1}^{N} x_{i}y_{i}\right)}{N\sum_{i=1}^{N} x_{i}^{2} - \left(\sum_{i=1}^{N} x_{i}\right)^{2}}$$
(5)

b. Multiple linear regression model

Multivariate linear regression allows for the introduction of multiple independent variables while still assuming a linear relationship between the independent variables and the dependent variable. This extends the mathematical model of univariate linear regression to the mathematical model of multivariate linear regression. In practical problems, the relationship between multiple variables is often expressed using mathematical methods, specifically through multiple linear regression analysis. If the dependent variable Y and N independent variables satisfy a linear relationship, and the data are measured through experiments.

$$(x_{i1}, x_{i2}, \cdots, x_{iN}; y) \quad i = 1, 2, \cdots, M$$
 (6)

The multivariate linear regression model is:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_N x_N + \varepsilon, \varepsilon \sim N(0, \sigma^2)$$
(7)

The regression equation is:

$$\hat{y} = b_0 + b_1 x_1 + b_2 x_2 + \dots + b_N x_N \tag{8}$$

This paper utilizes backward multiple linear regression analysis, a commonly employed method for modeling multiple linear regression. The main concept is to systematically eliminate independent variables with weak explanatory power in order to identify the ones that have a significant impact on the dependent variables. The specific steps are as follows:

- 1) All independent variables are included in the initial regression model.
- 2) Use statistical methods, such as the F test or t test, to assess the significance of each independent variable and identify the variables with weak explanatory power for the model.
- 3) Remove the selected independent variables from the regression model and refit it.

85

- Continuously repeat steps 2 and 3, eliminating insignificant independent variables and re-fitting the model, until all remaining independent variables are significant.
- 5) The final regression model includes independent variables that significantly impact the dependent variable, allowing for explanation and prediction of changes in the dependent variable.

The flowchart is shown in Figure 1.

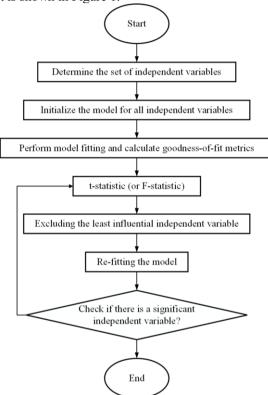


Figure 1. Flow chart of Backward linear regression.

The importance of the same characteristic quantity varies in different periods, and multiple linear regression is conducted for each period. Backward regression analysis offers the advantage of efficiently identifying the independent variables that significantly impact the dependent variables from a large set of variables. This simplifies the model, reduces redundant variables, and decreases complexity. When performing backward regression analysis, it is important to consider the model's explanatory power, adaptability, and the assessment results of relevant statistical indicators.

The basic mathematical model is :

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_\alpha x_\alpha + \varepsilon$$
⁽⁹⁾

y is the dependent variable, β_0 represents the constant, $\beta_1, \beta_2, \beta_3, ..., \beta_\alpha$ is the constant term in the partial regression coefficient.

2.2. Phased Fitting

The influence of furfural concentration in oil on DP varies before and after reaching a DP of 500. Before reaching a DP of 500, there is minimal influence. Therefore, this paper uses 500 as the boundary point for piecewise fitting. The data can be divided into two groups: data with DP less than or equal to 500, and data with DP greater than 500. For each group of data, the feature with the highest correlation can be selected to fit with DP. Piecewise fitting can better reflect the characteristics of each group of data, especially when the characteristics of the two groups are different.

3. Results and Analysis

In order to verify the accuracy of the model, this paper cited the experimental data of literature [28], as shown in table 1.

Aging time (h)	Degree of polymerization of insulating paper	Methanol content in oil(µg/L)	Furfural content in oil(mg/L)	Total sugar content in oil (mg/L)
0	915.00	0.00	0.00	9.86
24	777.00	26.90	0.08	21.80
48	712.00	48.00	0.16	27.60
72	643.00	57.20	0.47	29.80
96	608.00	66.50	0.70	30.50
120	572.00	70.70	1.25	31.70
168	513.00	72.40	1.17	29.60
216	454.00	76.60	1.88	26.10
264	440.00	93.40	2.27	24.90
312	399.00	97.60	5.39	30.90
384	387.00	106.00	4.22	34.40
456	352.00	148.00	6.72	36.90
528	324.00	160.00	12.00	30.10
600	304.00	176.00	7.66	30.30
684	295.00	183.00	12.70	35.60
756	281.00	191.00	15.30	39.20
828	242.00	199.00	23.10	43.10

Table 1. Experimental data of aging products of oil-paper insulation changing with time [28].

The comparison of the true value and the predicted value of the DP of the two-stage insulating paper is shown in Fig. 2 and Fig. 3.

The DP of insulating paper was fitted in stages with the content of methanol, furfural, and total sugar in oil. The goodness of fit (R^2) was then tested. When R^2 is used to verify the fitting results, a higher R^2 value closer to 1 indicates a better fitting effect. The paper sets the DP as the dependent variable (y) and the concentrations of methanol, furfural, and total sugar as x_1 , x_2 , and x_3 , respectively.

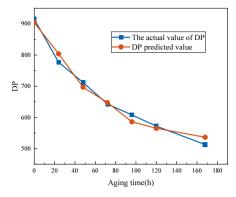


Figure 2. Comparison of the actual value and the predicted value in the first stage.

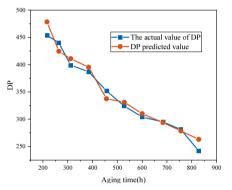


Figure 3. Comparison of the actual value and the predicted value in the second stage.

3.1. First-Stage Fitting

We can attempt to create a linear regression model prior to conducting piecewise fitting. In this paper, the initial step is to extract the relevant data samples for regression analysis. Subsequently, multiple linear regression analysis is used to fit the two groups of experimental data.

The fitting results are as follows:

$$y = 826.958 - 7.22x_1 + 7.843x_3 \tag{10}$$

The results of the backward multiple linear regression analysis indicated that furfural was excluded as an independent variable in the first stage. Therefore, the analysis only included two independent variables: methanol and total sugar. The equation above represents the model fitting, with a goodness of fit $R^2 = 0.981$. This indicates a strong relationship between the first stage of the fitting model DP and the levels of methanol and total sugar in the oil.

3.2. The Second Stage Fitting

Establish a backward multiple linear regression model following the steps outlined in section 3.1. Begin by extracting the data samples for the second stage of regression analysis, and then proceed with the regression operations.

The fitting results are as follows:

$$y = 574.418 - 1.157x_1 - 1.872x_2 - 1.327x_3 \tag{11}$$

The results of the backward multiple linear regression analysis revealed that methanol, furfural, and total sugar in oil were selected as independent variables in the second stage. The goodness of fit ($R^2 = 0.983$) indicated a strong relationship between the fitting model DP and these variables.

4. Error Test Analysis of the Model

The two-stage model error is shown in Table 2 and Table 3.

Table 2. Calculation of polymerization degree and relative error in the first stage.

Measured DP	Model predictions	Evaluate relative error
915.00	904.29	-1.17%
777.00	803.72	3.44%
712.00	696.86	-2.13%
643.00	647.70	0.73%
608.00	586.04	-3.61%
572.00	565.13	-1.20%
513.00	536.38	4.56%
Table 3. Calculation o	f polymerization degree and relative	error in the second stage.
Table 3. Calculation oMeasured DP454.00	f polymerization degree and relative Model predictions 478.61	
Measured DP	Model predictions	Evaluate relative error
Measured DP 454.00	Model predictions 478.61	Evaluate relative error 5.42%
Measured DP 454.00 440.00	Model predictions 478.61 424.58	Evaluate relative error 5.42% -3.51%
Measured DP 454.00 440.00 399.00	Model predictions 478.61 424.58 411.01	Evaluate relative error 5.42% -3.51% 3.01%
Measured DP 454.00 440.00 399.00 387.00	Model predictions 478.61 424.58 411.01 395.38	Evaluate relative error 5.42% -3.51% 3.01% 2.17%
Measured DP 454.00 440.00 399.00 387.00 352.00	Model predictions 478.61 424.58 411.01 395.38 337.52	Evaluate relative error 5.42% -3.51% 3.01% 2.17% -4.11%
Measured DP 454.00 440.00 399.00 387.00 352.00 324.00	Model predictions 478.61 424.58 411.01 395.38 337.52 331.16	Evaluate relative error 5.42% -3.51% 3.01% 2.17% -4.11% 2.21%
Measured DP 454.00 440.00 399.00 387.00 352.00 324.00 304.00	Model predictions 478.61 424.58 411.01 395.38 337.52 331.16 310.14	Evaluate relative error 5.42% -3.51% 3.01% 2.17% -4.11% 2.21% 2.02%

The paper's comprehensive assessment has a very low relative error, with most of the errors being within 5%. Meet the specific inspection requirements. However, when DP is 513 and 454, the relative error between the actual and predicted values is relatively large. This is because these values are closer to the demarcation point of DP = 500, and there are too few data points in the 500 region. As a result, there is a large fitting error in the two regions before and after this point. When DP = 242, the relative error of the assessment reached 8.67%. This is because when DP is close to 200, the transformer insulation paper is at the end of its aging process, and the small data point selection leads to a significant error.

Linear regression assumes a linear relationship between the independent variables and dependent variables. In practice, the aging state of insulation paper may be affected by a variety of factors which result in the variables do not always follow a linear relationship, and further more result in the linear regression model may not fit the data.

5. Conclusion

In this paper, the DP, methanol, furfural, and total sugar were fitted. The aging period was divided into two stages using backward multiple linear regression analysis. It was discovered that there is a strong correlation between the DP and the presence of methanol and furfural, but only when the DP is greater than 500. When DP is less than 500, it shows a positive correlation with methanol, furfural, and total sugar. This relationship can be expressed in two stages. Most of the assessment relative errors were within ± 5 %. The relative errors reached 5.42% and 8.67% when the DP was near 500 as well as 200, and the assessment errors were larger than 5%. It may be caused by the fact that the linear relationship between the selected feature quantity and DP is no longer satisfied at this time.

The DP is used to assess the aging state of transformer insulation paper. A method for assessing the degree of insulation aging state is established based on the fitting results of the DP and three characteristic indexes: methanol, furfural, and total sugar. Each characteristic index can be monitored online.

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