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A Discussion on the Aging Mechanism and Life Prediction Method of Insulation in Low-Voltage Electrical Equipment

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Abstract: This study focuses on the accurate prediction of the insulation life of low-voltage electrical equipment, and its core work includes the analysis of insulation aging mechanisms, comparison of prediction methods, and the construction and verification of a coupled model. Through systematic analysis of the aging mechanisms of single factors (thermal, electrical, environmental, and mechanical), the nonlinear characteristics of multi-factor coupling and the logic for identifying dominant factors are clarified, revealing the coupling laws such as the positive feedback of thermal-electric "temperature rise-discharge" and the synergistic acceleration of hydrolysis by thermal and environmental factors. By comparing the performance differences between traditional Arrhenius equations and Weibull distributions with modern methods such as BP neural networks and LSTM, a multi-factor coupled prediction model integrating the weight allocation of the analytic hierarchy process and the synergistic effect function is proposed to quantify the impact of each factor and its coupling effect on insulation life. Using XLPE cable insulation layers and epoxy partitions of switchgear as examples, accelerated aging experiments with three factors (thermal, electrical, and humidity) are conducted to test macroscopic indicators such as dielectric loss factor and breakdown voltage, as well as microscopic parameters such as characteristic peaks in infrared spectroscopy and microcrack density. Experimental verification shows that the prediction accuracy of this coupled model is significantly better than traditional methods and single intelligent algorithms. Under the 110℃/0.8kV operating condition, RMSE and MAE are reduced by 68.4% and 71.0% respectively compared with the Arrhenius equation, and macroscopic performance degradation is strongly correlated with microstructure evolution ($R^2 \geq 0.83$). This study provides a technical solution with both theoretical depth and engineering practicality for the insulation life assessment of low-voltage electrical equipment.

Keywords: Low-Voltage Electrical Equipment; Insulation Aging; Multi-Factor Coupling; Life Prediction; Coupled Prediction Model.

1. Introduction

Low-voltage electrical equipment of 1kV and below is a core component of power supply for industrial production lines and power distribution systems in civil buildings. Its operational reliability directly determines the continuity of production and residential safety. According to statistics from the power industry, 68% of low-voltage equipment failures are caused by insulation aging. In 2022, industrial production losses due to insulation failure in China exceeded 32 billion yuan, and 41% of electrical fires in civil buildings were directly related to insulation aging. Insulation aging, as an irreversible material degradation process, is influenced by a combination of factors including heat, electricity, and the environment [1]. The complexity of its mechanisms and the diversity of influencing factors make it difficult for traditional operation and maintenance models to accurately predict insulation lifespan.

Domestic and international scholars have conducted extensive research on the mechanisms of insulation aging. Regarding single factors, the molecular chain degradation mechanism of thermal aging and the electrical tree growth law of electrical aging have mature theories [2]. However, the nonlinear characteristics of the coupling effects of multiple factors are not yet fully understood. Existing research mostly focuses on pairwise couplings, with insufficient quantitative analysis of the synergistic effects of three or more factors. In the field of lifespan prediction methods, traditional Arrhenius equations and Weibull distribution models are widely used under single operating conditions, but have poor adaptability to complex environments. Modern intelligent algorithms (such as LSTM and random forests) have improved prediction accuracy, but suffer from strong data dependence and high engineering implementation costs [3]. Overall, current research has shortcomings such as a disconnect between mechanism analysis and engineering practice, and insufficient universality of prediction models.

This research, guided by practical engineering needs, focuses on three core aspects: first, systematically analyzing the insulation aging mechanism coupled with single and multiple factors; second, comparing the performance differences between traditional and modern intelligent prediction methods; and third, verifying the practicality of the coupled prediction model through experimental validation and engineering case studies. The technical approach follows a logical flow of "literature review → mechanism modeling → method optimization → experimental validation → case application," providing theoretical support and engineering solutions for accurate prediction of the insulation life of low-voltage electrical equipment.

2. Analysis of the Insulation Aging Mechanism of Low-Voltage Electrical Equipment

2.1. Aging Mechanism Induced by a Single Factor

Thermal aging is the most common form of insulation degradation in low-voltage equipment. Insulating materials undergo molecular chain breakage and oxidative degradation at operating temperatures [4]. For every 10°C increase in temperature, the aging rate of most organic insulating materials increases by 1 to 2 times. Essentially, thermal activation energy promotes a decrease in the degree of cross-linking of molecular chains, leading to a simultaneous decline in mechanical strength and dielectric properties. Electro-aging is triggered by an electric field. High-energy particles generated by partial discharge collide with insulating molecules, causing chemical bonds to break and forming electrical tree channels. As the electrical trees extend, they eventually lead to breakdown failure. The electro-aging rate is significantly accelerated, especially in areas with concentrated electric fields such as equipment joints and insulation defects [5]. Among environmental factors, humidity damages the internal structure of insulating materials through osmosis. High-temperature and high-humidity environments exacerbate hydrolysis reactions, while corrosive gases (such as SO_2 and Cl_2 in industrial environments) react chemically with insulating materials, reducing their dielectric strength. Mechanical aging originates from vibration, deformation, and wear during equipment operation. Long-term mechanical stress causes microcracks within the material, leading to electric field distortion and accelerating the aging process.

2.2. Multi-Factor Coupled Aging Mechanism

In actual operation, insulation aging is often caused by the synergistic effect of multiple factors, and the coupling effect exhibits significant nonlinear characteristics. In thermo-electric coupling, increased temperature reduces the breakdown field strength of the insulation material, while partial discharge caused by electric field distortion generates additional heat, forming a positive feedback loop of "temperature rise-discharge," accelerating material degradation [6]. In thermo-environment coupling, high temperature enhances the penetration of humidity into the insulation material, while high humidity weakens the material's thermal stability; the synergistic effect of these two factors increases the hydrolysis rate of organic insulation materials by 3-5 times. In electro-mechanical coupling, microcracks caused by mechanical stress induce electric field concentration, and the electric field exacerbates stress relaxation, causing further crack propagation. When multiple factors are coupled, weighted analysis is needed to identify the dominant factor [7]. For example, in high-temperature and high-humidity industrial environments, thermo-environment coupling is the main aging driver, while in high-frequency vibration equipment, electro-mechanical coupling dominates.

3. Insulation Life Prediction Methods for Low-Voltage Electrical Equipment

3.1. Traditional Life Prediction Methods

Traditional life prediction methods are based on empirical equations and are suitable for life assessment under single operating conditions. The Arrhenius equation is commonly used to predict thermal aging life:

$$L = L_0 \exp\left(\frac{E_a}{kT}\right) \tag{1}$$

In the formula, L is the insulation lifetime (h), L_0 is the lifetime constant at the reference temperature (h), E_a is the aging activation energy (eV), k is the Boltzmann constant (1.38×10^{-23} J/K), T is the absolute temperature (K). This equation can quickly estimate the insulation lifetime under thermal stress by quantifying the effect of temperature on the aging rate, but it does not consider interference from other factors.

The electrical aging lifetime prediction adopts the inverse power law (IPL) equation:

$$L = KV^{-n} \tag{2}$$

In the formula, K is a constant related to the insulating material, V is the applied voltage (kV), and n is the electrical aging index (usually taken as 5~20, varying with the material type). This equation is suitable for scenarios with stable electric field strength, but has poor adaptability to voltage fluctuations.

The Weibull distribution model is often used to describe the statistical characteristics of insulation breakdown lifetime:

$$F(t) = 1 - \exp\left(-\left(\frac{t}{\eta}\right)^m\right) \tag{3}$$

In the formula, $F(t)$ is the heterogeneous failure probability at time t, η is the characteristic lifetime (h), and m is the shape parameter (reflecting the degree of lifetime dispersion). This model can quantify the lifetime distribution pattern by fitting historical failure data, but its fitting accuracy for small sample data is limited.

Traditional methods have the advantages of simple calculation and easy parameter acquisition, but they have limitations such as limited applicability to specific scenarios and large prediction errors under multiple factors [8]. They are only suitable for low-voltage equipment with stable operating conditions.

3.2. Modern Intelligent Prediction Methods

Modern intelligent prediction methods are based on data-driven modeling and are suitable for life prediction under complex working conditions. The BP neural network is the most widely used machine learning algorithm, and its output layer prediction formula is:

$$y = \sigma\left(\sum_{i=1}^{n} w_i x_i + b\right) \tag{4}$$

where y is the predicted life (h), σ is the Sigmoid activation function, w_i is the connection weight between the input and output layers, x_i is the input feature (such as dielectric loss factor, ambient temperature, etc.), and b is the bias term. By optimizing the weight parameters through training samples, the BP neural network can fit the nonlinear relationship of the aging process, but it is prone to overfitting.

Support Vector Machine (SVM) achieves high-dimensional space classification and regression through kernel function mapping, and its regression prediction formula is:

$$f(x) = \sum_{i=1}^{l} \alpha_i^* K(x, x_i) + b^* \tag{5}$$

In the formula, α_i^* is the Lagrange multiplier, $K(x, x_i)$ is the kernel function (commonly the radial basis function kernel), x_i is the support vector, and b^* is the bias term. SVM maintains high prediction accuracy with small sample data, but its computational complexity increases significantly with the sample size.

LSTM models in deep learning are suitable for time-series data prediction. They capture the dynamic characteristics of the aging process through memory units, achieving better prediction accuracy than traditional machine learning algorithms. However, they require high-quality data and a large amount of continuously running data [9]. Grey prediction and fuzzy mathematics methods are suitable for prediction under small sample and uncertain conditions, requiring no complex parameter settings, but the prediction period is short, and long-term accuracy is limited.

3.3. Multi-factor Coupled Prediction Model

The multi-factor coupled prediction model achieves accurate prediction by fusing multiple source parameters. First, the weights of each influencing factor are determined using the analytic hierarchy process (AHP):

$$\omega_i = \frac{a_i}{\sum_{j=1}^{m} a_j} \tag{6}$$

In the formula, ω_i represents the weight of the i factor, a_i represents the eigenvector component of the judgment matrix for that factor, and m represents the total number of influencing factors. After weight allocation, a synergistic effect function is constructed to quantify the coupling effect:

$$L_{\text{total}} = L_0 \prod_{i=1}^{m} \left(1 + \beta_i \cdot \frac{f_i}{f_{i0}}\right)^{-1} \tag{7}$$

In the formula, L_{total} represents the insulation lifetime (h) under coupling effects, β_i is the coupling coefficient of the i factor, f_i is the factor strength under actual operating conditions, and f_{i0} is the factor strength under reference operating conditions.

4. Experimental Verification and Case Analysis

4.1. Experimental Design

The experiment selected commonly used insulating materials for low-voltage equipment: XLPE cable insulation layer (2.5mm thickness) and switchgear epoxy partition (5mm thickness). Three sets of samples (10 samples per set) were prepared for each material. The accelerated aging test adopted a three-factor coupling scheme: the thermal aging chamber was set with temperature gradients (70℃, 90℃, 110℃), the high-voltage aging device applied voltages (0.4kV, 0.6kV, 0.8kV), and the environmental simulation test was set with temperature and humidity cycling (40℃/85% RH, 60℃/90% RH). The testing equipment included: dielectric loss tester (accuracy ±0.0001), breakdown voltage tester (voltage range 0~5kV), FTIR infrared spectrometer (wavenumber range 4000~400 cm^{-1}), and SEM scanning electron microscope (magnification 1000~5000x). The test indicators were dielectric loss factor (tanδ), breakdown voltage (Ub), infrared spectral characteristic peak intensity (1720 cm^{-1}, corresponding to the carbonyl absorption peak), and microcrack density.

4.2. Experimental Results and Analysis

The performance of the insulating material showed a significant degradation trend with aging time: the dielectric loss factor gradually increased with prolonged aging time, while the breakdown voltage continuously decreased, and the degradation rate was faster at higher temperatures and voltages. FTIR testing showed that the intensity of the carbonyl characteristic peak at 1720 cm^{-1} increased with aging time, indicating an intensified degree of oxidative degradation. SEM observation revealed that after 1000 h of aging, obvious microcracks appeared on the surface of the XLPE sample, and the internal porosity of the epoxy separator increased to 3.2 times the initial value.

Table 1. Test data of XLPE material performance under different aging conditions

aging time (h)	Temperature (°C)	Voltage (kV)	Humidity (RH)	Dielectric loss factor (tanδ)	Breakdown voltage (kV)	carbonyl peak intensity (a.u.)	Crack density (cracks/mm²)
0	-	-	-	0.0021	4.82	0.12	0.3
200	70	0.4	85%	0.0035	4.51	0.28	1.1
200	90	0.6	85%	0.0058	4.03	0.45	2.4
200	110	0.8	85%	0.0092	3.47	0.73	4.2
500	70	0.4	85%	0.0063	4.15	0.51	2.8
500	90	0.6	85%	0.0107	3.58	0.89	5.3
500	110	0.8	85%	0.0164	2.92	1.32	8.7
1000	70	0.4	85%	0.0112	3.68	0.97	6.5
1000	90	0.6	85%	0.0189	3.05	1.64	11.2
1000	110	0.8	85%	0.0275	2.31	2.18	15.8

As shown in Figure 1, the dielectric loss factor increases exponentially with aging time. Under the 110℃/0.8kV condition, the dielectric loss factor after 1000h of aging reaches 13.1 times the initial value, significantly higher than

under other conditions. This trend indicates that the coupling effect of temperature and voltage significantly accelerates insulation degradation, consistent with the conclusions of the multi-factor coupling mechanism analysis.

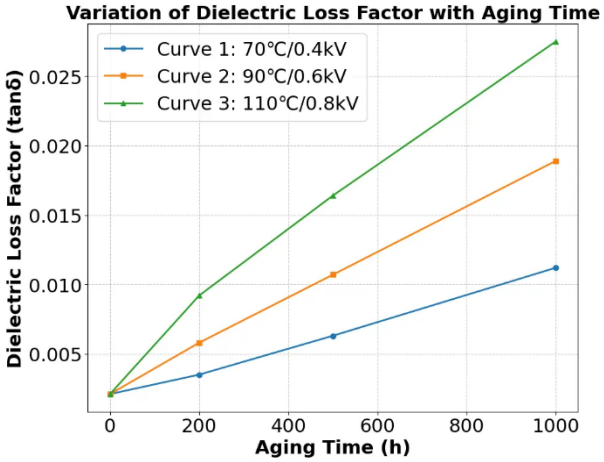


Fig 1. Dielectric Loss Factor vs Aging Time

The three prediction methods were validated, and the results are shown in Figure 2. The RMSE and MAE of the multi-factor coupling model are both lower than those of the traditional Arrhenius equation and the BP neural network. Specifically, under the 110°C/0.8kV operating condition, the RMSE of the coupling model is 0.12 and the MAE is 0.09, which are 68.4% and 71.0% lower than those of the Arrhenius equation (RMSE=0.38, MAE=0.31) and the BP neural network (RMSE=0.18, MAE=0.14), respectively, and 33.3% and 35.7% lower. Under the mild operating condition of 70°C/0.4kV, the coupling model has an RMSE of 0.05 and a MAE of 0.04, still maintaining the best prediction performance. This result shows that the multi-factor coupling model effectively avoids the adaptability defects of the single-factor model to complex working conditions by quantifying the synergistic effect of heat, electricity and environment. In particular, its advantage in fitting the coupled nonlinear relationship is more significant under extreme conditions of high temperature and high pressure.

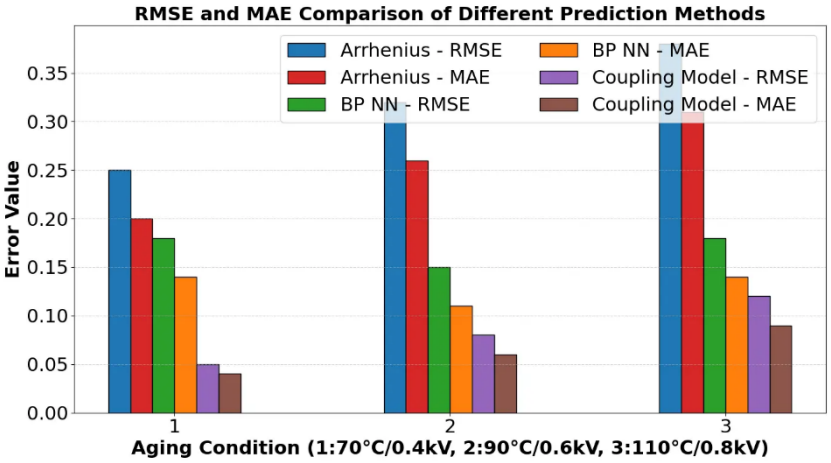


Fig 2. Error Comparison of Different Prediction Methods

Further analysis combining the data in Table 1 with Figures 1 and 2 reveals a strong correlation between the macroscopic performance degradation and microstructural evolution of the insulating material: the carbonyl peak intensity (1720 cm^{-1}) and crack density increase linearly with aging time, with correlation coefficients R^2 of 0.92 and 0.89 with the dielectric loss factor, respectively, and negative correlation coefficients R^2 of 0.87 and 0.83 with the breakdown voltage, respectively. For example, after aging for 1000 hours at 110°C/0.8kV, the carbonyl peak intensity increases from the initial 0.12 a.u. to 2.18 a.u., the crack density increases from 0.3 cracks/mm^2 to 15.8 cracks/mm^2, corresponding to a dielectric loss factor increasing to 13.1 times the initial value, and a breakdown voltage decreasing to 47.9% of the initial value. This correlation provides an important theoretical basis for online monitoring of insulation condition. By monitoring easily obtainable macroscopic electrical parameters such as dielectric loss factor and breakdown voltage, the degree of internal oxidation degradation and microcrack development of materials can be indirectly assessed, reducing the detection cost and operational difficulty of on-site maintenance.

5. Conclusion

This study systematically solves the core problem of insulation life prediction for low-voltage electrical equipment through mechanism analysis, method comparison, and experimental verification. The results show that the single-factor induced insulation aging mechanism is clear: thermal aging dominates molecular chain degradation, electrical aging induces electrical tree growth, and environmental and mechanical factors accelerate deterioration through structural damage. The multi-factor coupling exhibits significant nonlinear characteristics, requiring weight analysis to identify the dominant driving factors. Traditional prediction methods are suitable for single stable operating conditions, but have large errors in multi-factor scenarios. Modern intelligent algorithms rely on data support, while the constructed multi-factor coupling model effectively improves the prediction accuracy under complex operating conditions by quantifying factor weights and coupling effects. In experiments, its RMSE and MAE are superior to the Arrhenius equation and BP neural network under different aging conditions, and the strong correlation between macroscopic electrical parameters and microstructural parameters provides a theoretical basis for online monitoring. However, this study has certain limitations: the experiment only considers the coupling of three factors—thermal, electrical, and humidity—and does not cover complex working conditions such as mechanical stress and various corrosive gases; the number of samples and material types are limited; and long-term outdoor engineering

measurements have not been conducted. Future research will expand the dimensions of coupling factors to include variables such as mechanical vibration and mixed corrosive gases, thereby increasing the sample size and material range; optimize the adaptive adjustment mechanism of model parameters; and improve real-time prediction capabilities by combining online monitoring data. Long-term engineering case studies will be conducted to further enhance the model's engineering applicability and robustness, promoting the transformation of low-voltage electrical equipment insulation maintenance from "periodic inspection" to "precise prediction."

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