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Application of design of experiments in accelerated degradation testing of new energy low voltage electrical appliances

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ABSTRACT

With the continuous development of the new energy industry, the lifespan requirements for low-voltage electrical appliances are increasing, and the time cycle for verifying lifespan is getting longer. Traditional testing methods no longer meet these requirements. Therefore, it is necessary to introduce accelerated degradation testing technology to shorten the testing cycle. The currently commonly used accelerated degradation method considers only a single stress factor. However, an electrical appliance is subjected to various stresses simultaneously during actual usage. These stresses affect the rate of degradation to varying degrees. A single stress factor cannot reflect the actual degradation effect of the appliance. The Six Sigma design and one of its tools, the Design of Experiments (DOEs) method, are presented here. Experiments show that the DOE method can identify key stress combinations in multiple stress sources. It can improve the efficiency of acceleration factor combination selection, derive the maximum degradation range of key accelerated stress factors, and then generate a DOE test scheme. Through the analysis of the experimental results, it is further verified that the degradation of the key stress factors combination can effectively improve the efficiency of product testing. Meanwhile, the value of key stress factors obtained by DOE has a great influence on the degradation effect.

I. INTRODUCTION

With the full support of the national dual-carbon target, the new energy industry has entered a stage of rapid development. The new energy industry mainly refers to wind energy, PV energy, energy storage, new energy vehicles, and other industries that are gradually emerging in the 21st century. The development of the new energy industry has also provided opportunities for the low-voltage electrical appliance industry, and this field has become crucial within the electrical appliance industry. However, at the same time, the new energy industry also puts forward higher requirements for the high reliability, high voltage, strong weather resistance, and long life of low-voltage appliances.

With the extension of the product service cycle, the lifetime target is getting higher and higher. Traditional life prediction is mainly obtained by accurate fault data analysis. Having sufficient and accurate breakdown data is essential to estimate the life expectancy. However, for many manufacturers of low-voltage electrical appliances at present, it is difficult or impossible to obtain sufficient fault data of their products in an economical and efficient manner prior to product launch. They even cannot be able to test whether their design has failed under normal operating conditions in the lab because their products have a long lifespan, the time between product development and launch is too short, or due to various other reasons.

This requires tracking and analyzing the degradation data of key factors during usage to obtain necessary information to make effective business decisions regarding the warranty period and/or demonstrate that the product meets customer reliability specifications. To use degradation data to estimate failure time, measured degradation factors must be directly related to the failure mechanism of the product, and there must be a clear degradation level at which failure occurs. For instance, if tire tread wear is directly related to tire failure and the degree of wear that causes tire failure can be defined, degradation analysis can be used to estimate the failure time of the product.

The degradation test is typically used to monitor the data change of product performance degradation under normal usage stress, to predict the degradation trend of performance characteristics in the time domain, and to extend the product life distribution curve, which can help to predict the lifespan of the product.

The degradation rate of high-reliability and long-life products under normal stress is too slow to collect sufficient useful degradation data in a short time, making accurate predictions of the degradation curve throughout the product life cycle impossible. Accelerated degradation testing can obtain more useful degradation data, greatly improving the efficiency and prediction accuracy of life testing.[1]

Currently, the Wiener degradation model is the most widely used among degradation models, capable of modeling both strictly monotonic and non-monotonic performance degradation processes.[2] The Wiener procedure has good computational properties and is the preferred choice for degradation test modeling.[3,4]

Bayesian theory can be utilized to predict the remaining lifetime of products. A considerable amount of literature employs performance degradation data of products under normal stress as prior information.[5] However, obtaining such prior data is subject to advancements in signal processing and sensing technology, as well as the selection of degradation factors and cooperation with on-site customers. Effectively integrating an increasing volume of high-quality data for statistical analysis has become a focus of our research.

ADT is a method that applies stress greater than normal usages to accelerate sample degradation within a short period, aiming to predict reliability under normal operating or storage conditions. ADT is a mature testing method based on statistical theory. It is an experimental method that uses statistical models related to physical degradation failure patterns to transform reliability information obtained in accelerated environments beyond normal stress levels, based on reasonable engineering statistical assumptions, to obtain reproducible numerical estimates of reliability characteristics of samples under normal usage conditions. The prerequisite for ADT is to ensure that the product failure mechanism remains unchanged.[6]

Many scholars have conducted extensive research on the accelerated degradation of electronic products. Some focus on modeling and data ADT analysis: Kai Liu's team established a product performance degradation model, extracted the drift performance data in ADT, and optimized the model by quasi-merging and merging into observation data.[7] Sachintha De Vas Gunawardena's team proposed a lifespan testing method and a model for predicting the failure time of an electrolytic capacitor LED driver during the output phase under cyclic power and heat conditions. The accelerated lifespan testing showed that the service life of the LED driver has an inverse exponential relationship with the operating temperature of the output capacitor.[8] Other scholars have studied the impact of operating conditions on reliability: Padmasali and Anjan's team conducted in-depth research on the continuous operation of the system over time and the reliability affected by the switching cycle, using the operating cycle to quantify the reliability of the system.[9] Yao Bo's team delved into degradation testing and failure analysis of metallized film capacitors used in megawatt (MW) power converters for AC filtering purposes, showing that electrochemical corrosion is the main aging factor, among others.[10,11]

However, these existing studies have not accounted for the complexity of the actual test process for accelerated degradation of electronic products. Due to the close relationship between the degradation acceleration stress coefficient and the actual working conditions of the product, the dominance of the acceleration stress factors varies under different working conditions. This variation results in relatively blind selection of acceleration stress factors and a significant increase in the number of experiments in the acceleration test combination scheme. In this article, an innovative approach is proposed to use Six Sigma tools—design of experiments to accelerate degradation testing, which can greatly reduce the blindness of testing and greatly improve the success rate of testing. This method can not only save a lot of testing resources but also improve the efficiency of the degradation testing.

II. DEGRADATION MODEL BASED ON WIENER PROCESS

Produce degradation exhibits a certain level of randomness, making it suitable to model accelerated degradation testing using a Wiener model. The Wiener degradation model is expressed as

$$Y(t) = Y_0 + \mu t + \sigma B(t), \tag{1}$$

where $Y(t)$ is the value of the characteristic parameter observed at time t, Y_0 is the initial characteristic parameter, μ is the degradation rate, σ is the diffusion coefficient, and $B(t)$ is the standard Brownian motion.

The Wiener process has the property that the degradation increment $\Delta Y(t) = Y(t+\Delta t) - Y(t)$ follows a normal distribution,

$$\Delta Y(t) \propto N(\mu \Delta t, \sigma^2 \Delta t). \tag{2}$$

By accumulating the independent increments, it can be derived that $Y(t) \propto \mathrm{N}(\mu t, \sigma^2 t)$ and the probability density function (PDF) of $Y(t)$ is

$$f(y) = \frac{1}{\sqrt{2\pi\sigma^2 t}} \exp\left[-\frac{(y-\mu t)^2}{2\sigma^2 t}\right]. \tag{3}$$

When the failure threshold E is set for monitoring the performance of a product, the lifetime ξ of the product can be defined as the time when $Y(t)$ first reaches E,

$$\xi = \inf(t \mid Y(t) \geq E). \tag{4}$$

The cumulative distribution function (CDF) of product life follows the inverse Gaussian distribution as follows:

$$F(t) = \phi\left(\frac{\mu t - E}{\sigma\sqrt{t}}\right) + \exp\left(\frac{2\mu D}{\sigma^2}\right)\phi\left(-\frac{\mu t + E}{\sigma\sqrt{t}}\right), \tag{5}$$

where $\Phi(^*)$ is a standard normal CDF.

Substitute the normal distribution into Eq. (3) to obtain the probability density function of $Y(t)$ as follows:

$$f(t) = \frac{E}{\sqrt{2\pi\sigma^2 t^3}} \exp\left[-\frac{(E-\mu t)^2}{2\sigma^2 t}\right]. \tag{6}$$

III. ACCELERATED DEGRADATION MODEL

At present, the widely used acceleration factor models are mainly environmental acceleration factor models,[12] among which the three common types of acceleration factor models are as follows.

A. Arrhenius acceleration model related to temperature

Arrhenius was a famous physical chemist in Sweden. After extensively studying the reaction rate of many experiments at different temperatures, he found that the reaction rate accelerated with temperature increase. Then he applied this discovery to other fields and discovered similar logical relationships. In the later stage, he summarized that in a certain environment, when temperature becomes the primary factor affecting product aging and service life, using a model derived solely by considering the temperature acceleration factor to describe testing will yield results closer to the true value. The Arrhenius model expression is

$$AF = e^{\frac{E_a}{k}\left(\frac{1}{T_u}-\frac{1}{T_t}\right)}, \tag{7}$$

where AF is the acceleration coefficient; E_a is the activation energy, and the activation energy of different devices is different. In general, the activation energy value is between 0.3 and 1.2 eV; k is the Boltzmann constant, with a value of $1.380\,650\,5 \times 10^{-23}$ J/K; T_u is the temperature value in the non-accelerated state; T_t is the temperature value under the accelerated state.

B. Hallberg–Peck model related to temperature and humidity

The Hallberg–Peck model comprehensively considers the influence of temperature and humidity. Compared to the Arrhenius model, the Hallberg–Peck model can more accurately describe aging and life testing under temperature and humidity conditions. The expression is as follows:

$$AF = \left(\frac{RHt}{RHu}\right)^3 e^{\frac{E_a}{k}\left(\frac{1}{T_u}-\frac{1}{T_t}\right)}, \tag{8}$$

where AF, E_a, k, T_u, and T_t have the same meanings as those in Eq. (7); RHu is the relative humidity value under the conditions of use without acceleration; RHt is the relative humidity value under the accelerated state under the test condition.

C. Coffin–Manson model related to temperature cycle

The Coffin–Manson model considers aging and life testing under different temperature change rates under a temperature cycle, with the following expression:

$$AF = \left(\frac{\Delta T_{\text{test}}}{\Delta T_{\text{field}}}\right)^C, \tag{9}$$

where AF is the acceleration coefficient, ΔT_{test} is the temperature difference of a test cycle, ΔT_{field} is the temperature difference of a working cycle, and C is the Coffin–Manson index, which refers to the acceleration rate constant of temperature change and has different values corresponding to different failure types.

Common accelerated degradation models are based on the acceleration generated by environmental stress, but most only have one acceleration factor. For example, changes in monitoring parameters over time are tested at different temperatures without considering their own working stress, and then degradation results are analyzed. However, in actual product use, multiple stress factors often act simultaneously, and working stress is one of the main failure stresses, so selecting only one acceleration factor may not accurately simulate the real situation of the product during use. Therefore, degradation under multiple accelerating stress factors is discussed using Six Sigma tools.

IV. NECESSITY OF DOE ANALYSIS

The stress factors encountered in the operation of low-voltage electrical appliances mainly include voltage, current, temperature, humidity, vibration, power factors, harmonics, etc. In the process of product degradation, which specific stress or stresses play a major role and how these stresses accelerate the degradation cannot be determined using existing accelerated degradation models.

The most challenging part of establishing an accelerated test scheme is determining the stress acceleration factors. Due to the uncertainty of which acceleration factor has the greatest impact on product life, it is generally determined through the experience and intuition of engineers, introducing great uncertainty into the results of accelerated degradation testing.

The DOE method aids in determining the optimal combination of acceleration factors, determining the degradation scheme, and facilitating the accurate prediction of product life. Given that the DOE method necessitates a certain number of tests, field data from the existing use and testing can be utilized for analysis prior to identifying major stress factors. This enables the initial determination of the primary factor combinations. The tools required for DOE-regression analysis in Six Sigma design are necessary.

V. DOE-REGRESSION ANALYSIS

DOE regression analysis is a powerful tool in Six Sigma design.[13] In the analysis phase of Six Sigma design, it is critical to analyze the causes of problems and is useful when there are multiple multivariate test results. In addition to linear regression as shown in Fig. 1, quadratic, cubic, and polynomial function regression are also used.

Regression analysis tools can be used to analyze a wide range of data to estimate the impact of stress factors on life expectancy outcomes. By utilizing the working condition data corresponding to failed products used by clients, impact coefficients are sorted to identify possible combinations of primary stress factors.

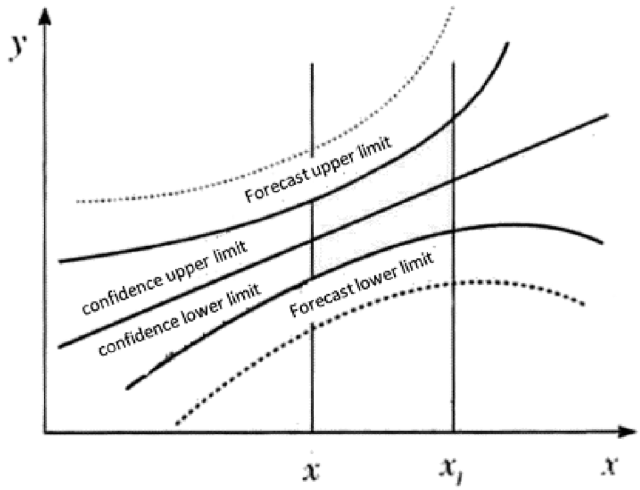

FIG. 1. Linear regression.

For example, suppose we want to establish an empirical model of contactor failure related to operating current, voltage, and temperature. A model that can describe this relationship is

$$y_1 = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_1 x_2 + \varepsilon, \tag{10}$$

where y_1 is the working life, x_1 is the current, x_2 is the operating temperature, $\beta_0, \beta_1, \beta_2$, and β_3 are the regression coefficients obtained by the least square method, and ε is the residual value.

As shown in Table I, the working voltage is not significant in the model ($P > 0.05$), so it is not included in Eq. (10).

In Table I, P refers to the probability that the difference between the calculated and measured values is caused by accidental factors. The smaller the P, the more reason to believe that there are real differences between the things being compared. $P > 0.05$ is referred to as "not significant." $P<=0.05$ refers to "significant," and $P<=0.01$ refers to "very significant." For example, $P < 0.05$ indicates that the probability of the difference shown in the results being caused by accidental factors is less than 5%, or that the probability of others repeating the same study under same conditions and reaching opposite conclusions is less than 5%. The characteristic of the T distribution is that the farther the value is from the origin, the less likely it is to obtain this value. In regression analysis, our hypothesis for testing is "the coefficient of X is equal to 0 (indicating that X and Y are independent)," so the larger the T value (taking an absolute value), the better. Because the larger the T value, the less likely the hypothesis for testing to occur. Therefore, the more significant the relationship between X and Y, the less likely the coefficient is to be 0. Generally, in univariate regression reports, a bilateral test is conducted, where the larger the absolute value of T, the smaller the P. If the P value is large, it indicates that the T value is very close to the origin; if the P value is very small, it indicates that the T value is far from the origin. It can be noted that these two values are actually one-to-one correspondences, and T or P values need to be compared.

It should be noted that the current relational model cannot be applied to accelerated degradation testing. This is because it is a model of product failure under normal working stress and normal ambient stress and cannot be extrapolated to obtain the functional relationship under accelerated stress. Therefore, through regression analysis, only the main possible stress factors that affect product failure can be obtained.

After selecting the potential major stress factors, the next step is to identify which of these stress factors have a significant acceleration effect (i.e., the key stress acceleration factors). Second, it is necessary to determine within what range these acceleration factors are, and the acceleration effect obtained from testing can yield the best results without affecting the failure mode of the product. This requires using DOE tools to design experiments for these stress factors and to determine the optimal combination of acceleration parameters for them.

VI. DOE-DESIGN OF EXPERIMENTS

Once the potential acceleration factor group is confirmed via regression analysis, an accelerated degradation testing scheme can be established based on the selected acceleration factor group. When defining the accelerated degradation program, we need to determine the monitoring parameters for accelerated degradation. Through analyzing prior data, the number of monitoring parameters and items can be obtained. Then the DOE tool can be used to establish the accelerated degradation program.

Six Sigma design has provided us a valuable tool for accelerating degradation testing, namely DOE.[14] DOE refers to a systematic series of experiments in which input factors are selectively changed to determine the causes of major changes in output responses. From the definition of DOE, it can be seen that the purpose of accelerated degradation testing is consistent with that of DOE.

In DOE, a 2^k design is particularly useful because it requires only a minimum number of experiments to study the k stress factors of a complete factorial design. Figure 2 is a 2^3-factor design, which shows that there are three stress factors, each with two levels (high

TABLE I. Result of linear regression.

Item	Coefficient	Coefficient standard error	T value	P value	Variance inflation factor
Constant	−2.390 00	0.398 00	−6.01	0.004	
Temp	0.007 60	0.001 36	5.57	0.005	1.20
Current	0.012 80	0.002 73	4.69	0.009	1.20
Voltage	0.003 60	0.002 23	1.62	0.181	1.40

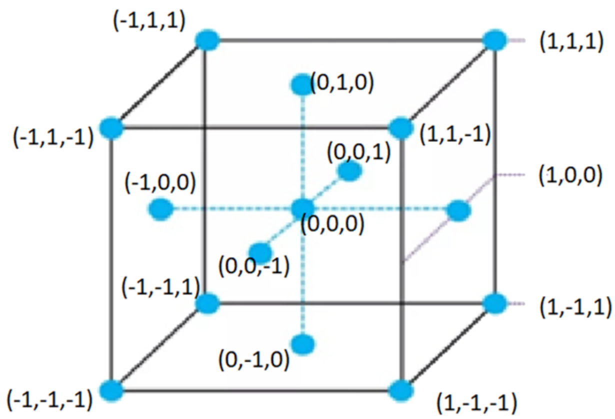

FIG. 2. 2^k DOE.

and low). 2^k designs contain k main effects, $\binom{k}{2}$ two-factor interactions, $\binom{k}{3}$ three-factor interactions, and a k-factor interaction. That is, for a 2^k design, the full model contains $2^k - 1$ effects. By estimating factor effects and examining their sign and value, it is determined which factors and interactions are important from the experiment and in which direction these factors should be adjusted to improve the response. Usually, the entire model, including all main and interactive effects, is chosen as the initial model for the experiment, as long as it is repeated once; then, the analysis of variance is used to test the significance of the main effect and the interaction effect, and the model is continuously improved. It usually involves removing non-significant items from the whole model and using residual analysis to test the suitability of the model. If the model is unsuitable or seriously deviates from the assumptions, sometimes it is necessary to re-improve the model after residual analysis. Finally, the response of the main effect or interaction is obtained through analysis. Therefore, the key stress factor combinations and their interactions that accelerate degradation can be obtained.

After determining the key stress factors and their interactions, their optimal values can be obtained through optimization to achieve the best acceleration of degradation.

Through the stress factor test, the model of key stress factors and the effect of each key stress factor can be obtained,

$$y_1 = \beta_0 + \beta_1 A - \beta_2 B + \beta_3 AB, \tag{11}$$

TABLE II. Contactor working time corresponding to working stress.

Working days	Max. temp. (K)	Medial humidity (RH%)	Vibration (Hz)	Voltage (V)	Current (A)	Power factor	Static electricity overload	Harmonic interference times
240	298	85	10	22	NA	0.25	NA	3
240	299	90	15	20	NA	0.25	NA	5
240	299	85	10	22	NA	0.25	NA	3
240	298	90	15	20	NA	0.25	NA	5
210	305	90	25	25	NA	0.25	NA	3
210	308	85	25	24	NA	0.25	NA	5
210	303	85	40	25	NA	0.25	NA	3
210	308	85	25	23	NA	0.25	NA	5
210	303	90	30	25	NA	0.25	NA	3
180	318	90	60	21	NA	0.35	NA	3
180	319	95	60	21	NA	0.35	NA	3
150	323	60	80	22	NA	0.50	NA	5
120	328	60	150	25	NA	0.55	NA	5
60	333	75	200	30	NA	0.60	NA	5
30	335	90	200	32	NA	0.65	NA	5

TABLE III. Potential stress factor analysis results.

Item	Coefficient	Coefficient standard error	T value	P value	Variance inflation factor
Constant	356.80	45.60	7.82	0.00	
Max. temp (k)	−1.61	0.45	−3.59	0.01	32.28
Medial humidity (RH%)	0.17	0.32	0.55	0.59	4.37
Vibration (Hz)	−0.43	0.16	−2.76	0.02	41.58
Voltage (V)	−2.09	1.04	−2.01	0.08	5.02
Power factor (cosΦ)	8.00	102.00	0.08	0.94	88.09
Harmonic interference (T)	0.46	1.85	0.25	0.81	1.43

TABLE IV. Screening DOE scheme.

C1 std order	C2 run order	C3 center point	C4 blocks	C5 temp	C6 voltage	C7 vibration
2	1	1	1	1	−1	−1
3	2	1	1	−1	1	−1
1	3	1	1	−1	−1	1
4	4	1	1	1	1	1

TABLE V. Factor high and low level value.

Factor	Temperature (K)	Voltage (V)	Vibrations (mm/s^2)
−1	298	20	10
+1	308	25	15

where y represents the degradation value of a certain key characteristic index of the product, A represents the key stress factor 1, B represents key stress factor 2, and β_0, β_1, β_2, and β_3 are the effects obtained through the least square method, in which $\beta_0 > \beta_1 > \beta_2 > \beta_3$.

A positive β_1 indicates that the effect of A is increasing, such that as A increases from low to high levels, it accelerates product degradation. A negative β_2 indicates that the effect of B is decreasing, such that as B decreases from low to high levels, it slows product degradation. Compared to the two main effects, the interaction effect is significantly smaller. By examining the magnitude and direction of key stress factors, the direction of acceleration of key stress factors can be determined.

In the early stages of experimental work, numerous stress factors may need to be studied, resulting in a rapid increase in the number of required tests to design a complete repetition. This can exceed available resources for most experiments. For example, a complete replication of a 2^6 design requires 64 experiments. Based on experience and environmental parameters, certain high-order interactions can be ignored if determined not significant. Information about main effects and low-level interaction effects can be obtained by partially completing a full factorial test. This type of DOE, also known as factor screening DOE, is mainly used to identify factors with significant effects from numerous factors. Factor screening DOE is one of the most widely used designs in product design, process design, and process improvement.

VII. APPLICATION OF DOE IN ACCELERATED DEGRADATION TESTING

In this section, an example will be given to illustrate how accelerated degradation testing utilizes DOE to establish the optimal testing plan.[15]

A certain model of contactor experienced failure where it could not engage during use. After analysis, it was found that a capacitor on the contactor control printed circuit board assembly (PCBA) failed. It is now necessary to determine the probability of capacitor failure and its reliability life.

The environmental stresses during product operation include temperature, humidity, and vibration. Electrical stresses include current, voltage, and frequency. Noise stresses include static and harmonic disturbances. Given that the capacitor's nominal failure rate is at the FIT level (10^{-9}), inducing failure through normal testing requires a substantial number of samples and an exceedingly long time, which is beyond the resources of most enterprises. After communication with suppliers and enterprises, it was agreed to conduct the test through accelerated degradation.[16]

To estimate the failure time of a product using degradation data, the measured degradation factor must be directly related to the failure mechanism of the product and must have a clear degradation level at which failure is deemed to have occurred. Preliminary research has revealed that the capacitance of this capacitor decreases over time with use, and failure occurs when it drops below a threshold value. Therefore, the degradation data of the capacitor's

TABLE VI. Screening test design results.

Run sequence	Temp. (K)	Voltage (V)	Vibration (mm/s^2)	Capacitance difference after 100 h (μF)
1	298	20	15	0.18
2	308	20	10	0.26
3	308	25	15	0.32
4	298	20	15	0.20
5	308	20	10	0.24
6	298	25	10	0.21
7	308	25	15	0.34
8	298	25	10	0.23

capacitance are taken as the output value for accelerated degradation. The next step is to determine the accelerated stress factors and their values.

There are a total of eight stress factors that could potentially influence the outcome. Analyzing all of them together or arbitrarily selecting a few for analysis would be unscientific and ineffective. In addition, since the extent of interaction among these eight stress factors is unclear, conducting experiments without proper consideration could likely yield incorrect results.

Now let us examine how to achieve accelerated degradation processes through DOEs.

First, the corresponding field stresses and operating stresses for the failed components were collected, corresponding to the operating time of the contactor as shown in Table II.

Input the data into MINITAB for regression, and then the regression equation could be obtained,

$$\begin{aligned} \text{Workingdays} = {} & 356.8 - 1.615\,\text{Max.Temp.} + 0.175\,\text{Medial humidity} \\ & - 0.431\,\text{vibration} - 2.09\,\text{Voltage} + 8\,\text{power factor} \\ & + 0.46\,\text{harmonic interference}. \end{aligned} \tag{12}$$

The results of the latent stress factor analysis are shown in Table III. Through the analysis, it was found that the average humidity, power factor, and harmonic interference factors had P-values greater than 0.05, indicating that they were not significant in the regression model. Therefore, these factors can be excluded from subsequent analysis.

Upon field investigation, it was observed that all Printed Circuit Board Assembly (PCBA) units were covered with conformal coating, preventing moisture ingress; the main circuit was isolated from the control circuit, resulting in minimal impact on the power factor; harmonic suppression devices were installed in the field circuit, which had a negligible effect on the PCBA. The findings from the field analysis corroborated the results of the regression analysis.

Although the P-value for the voltage factor is also greater than 0.05, it is relatively close to 0.05. Furthermore, the object of regression analysis is the operating time of the contactor, not the failure time of the capacitor. Therefore, retaining the voltage factor would be beneficial for the subsequent DOE to screen out the key stress factors.

The next step involves determining which stress factors will be included in the accelerated degradation testing plan. DOE can be employed to identify the key stress factors. With three stress factors, a 2^3 design requires a total of eight experiments, which is considered excessive in terms of the number of trials and time-consuming. Using a screening DOE design, specifically a 2^{3-1} design, the 2^{3-1} design can effectively capture the main effects and interaction effects of each factor while mixing in third-order interaction effects. However, this does not affect the selection of main effects. The design of the screening DOE is shown in Table IV.[17]

Since the key characteristic of a capacitor is capacitance, the monitoring target is the degree of capacitance variation. Due to the unlikely linearity of the degradation process, small range values are used for the upper and lower limits during the DOE screening phase to ensure approximate linearity within a small range. The design scheme is shown in Table V.

Implement the screening DOE plan on the capacitor, and the test results are shown in Table VI.

TABLE VII. Screening DOE analysis results.

Item	Effect	Coef	SE coef	T value	P value	VIF
Constant		0.2475	0.005	49.5	0	
Temp (K)	0.0850	0.0425	0.005	8.5	0.001	1.00
Voltage (V)	0.0550	0.0275	0.005	5.5	0.005	1.00
Vibration	0.0250	0.0125	0.005	2.5	0.067	1.00
Model summary						
	S	R-sq	R-sq(adj)	R-sq(pred)		
Square residual error	0.014 14	0.9645	0.9379	0.8581		

TABLE VIII. Full factor design results.

Run sequence	Temp.	Voltage	Capacitance difference after 100 hours
1	308	25	0.38
2	318	25	0.46
3	308	28	0.52
4	308	28	0.53
5	318	25	0.44
6	308	25	0.41
7	318	28	0.58
8	318	28	0.56

TABLE IX. First full factor analysis results.

Item	Effect	Coef	SE coef	T value	P value	VIF
Constant		0.485	0.0053	91.45	0.000	
Temp (K)	0.0500	0.025	0.0053	4.71	0.009	1.00
Voltage (V)	0.1250	0.062	0.0053	11.79	0.000	1.00
Temp (K)* voltage (V)	−0.0050	−0.003	0.0053	−0.47	0.662	1.00

Input the results into MINITAB for analysis, and the results are shown as Table VII. Through Coded Coefficients analysis, it was found that the vibration had a P value greater than 0.05, indicating that the vibration factor was not significant in the model. Through the model summary analysis, we find that the square residual error of Model (R-sq) is 96.45%, and the adjusted square residual error of Model (R-sq(adj)) is 93.79%. These two data are similar and close to 1, which means the model is quite suitable. In addition, the predicted square residual error of Model (R-sq(pred)) is 85.81%. At the same time, in order to simplify the testing process, the vibration stress factor was removed in subsequent experiments.

Through DOE, two key stress factors for accelerating degradation were identified: temperature and voltage. Subsequently, combined tests would be conducted on these two stress factors to determine the optimal range of acceleration factor values.

Next, a full factorial testing DOE would be carried out. Since the working stress of the capacitor is 298 K and 25 V, based on the

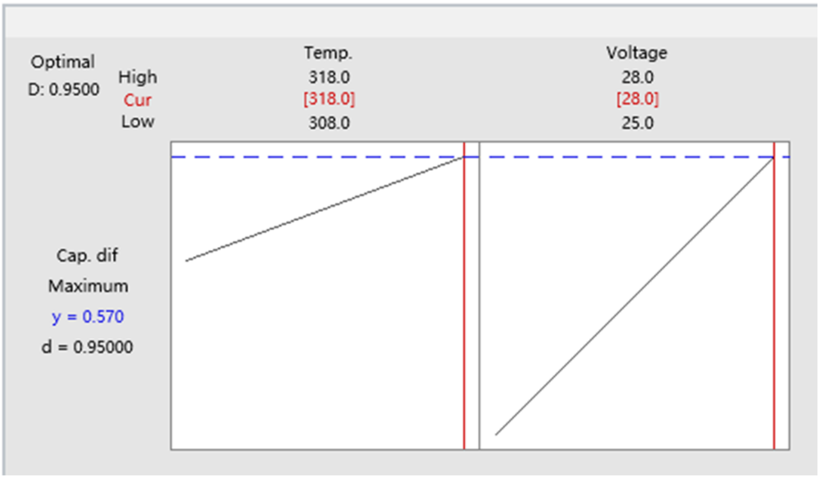

FIG. 3. Response optimization results of factors.

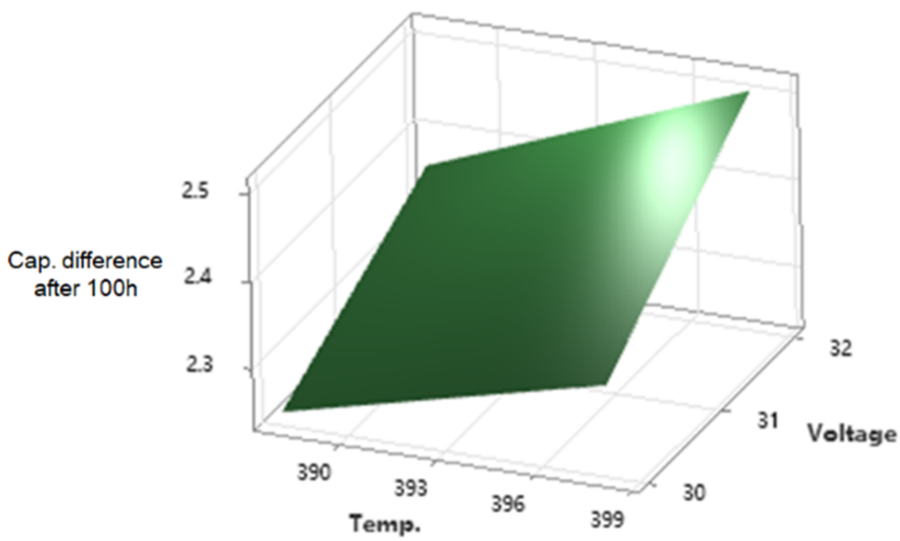

FIG. 4. Increasing effects of temperature and voltage factors.

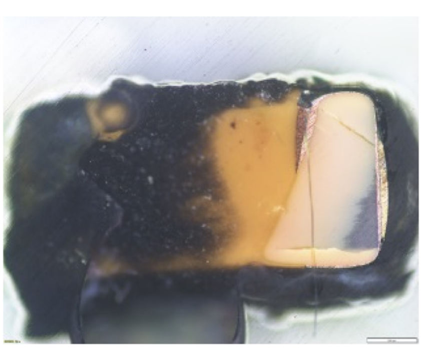

FIG. 5. Capacitor exploded picture.

TABLE X. Accelerated degradation testing program.

Temp. (K)	Voltage (V)	Degradation time (h)				
378	30	20	40	60	80	100
388	31	20	40	60	80	100
398	32	20	40	60	80	100
298	25	20	40	60	80	100

acceleration principle, the first acceleration point should be selected near the normal working stress so that there would be no sudden change between the accelerated degradation result and the normal working stress. The test started from the capacitor's operating

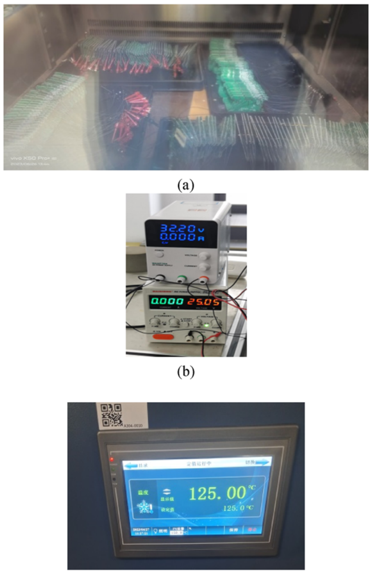

FIG. 6. Capacitance accelerated degradation testing: (a) samples testing status, (b) accelerated stress factor (current and voltage), and (c) accelerated stress factor (temperature).

temperature of 10° higher (298 K + 10 K) and the operating voltage of 25 V. The test results are shown in Table VIII.

Input the test results into Minitab software for analysis and obtain the acceleration direction of each factor to support subsequent test design. The initial analysis result of Minitab software is shown in Table IX. It is found that the P value of the interaction of Temp. with Voltage is greater than 0.05, indicating this interaction is not significant and can be removed in later analyses.

By analyzing the response optimization in Fig. 3, it was observed that the effects of temperature and voltage are increasing. Increasing temperature and voltage from low to high levels accelerated the degradation of capacitance. By examining the magnitude and direction of the key stress factors, it was determined that further increasing the values of these key stress factors could accelerate the rate of degradation, as illustrated in Fig. 4.

Through a series of DOE tests, it was discovered that when the temperature exceeds 408 K and the voltage exceeds 35 V, capacitor explosions or short-circuit phenomena occurred in the test. This confirmed that the failure mechanism of the capacitor had changed under these conditions, making them unsuitable as parameters for accelerated degradation, as shown in Fig. 5. The previous DOE results were therefore selected as the maximum parameters for capacitor accelerated degradation, with a temperature selection range of 378–398 K and a voltage selection range of 30–32 V.

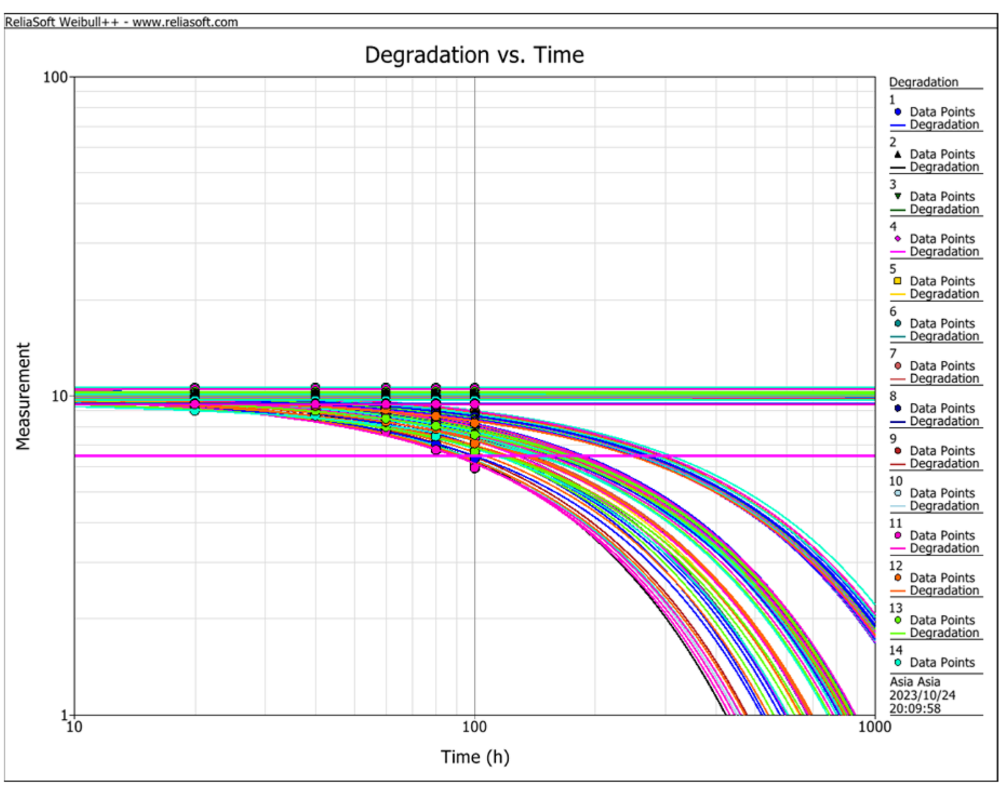

FIG. 7. Relationship between accelerated capacitor degradation and time.

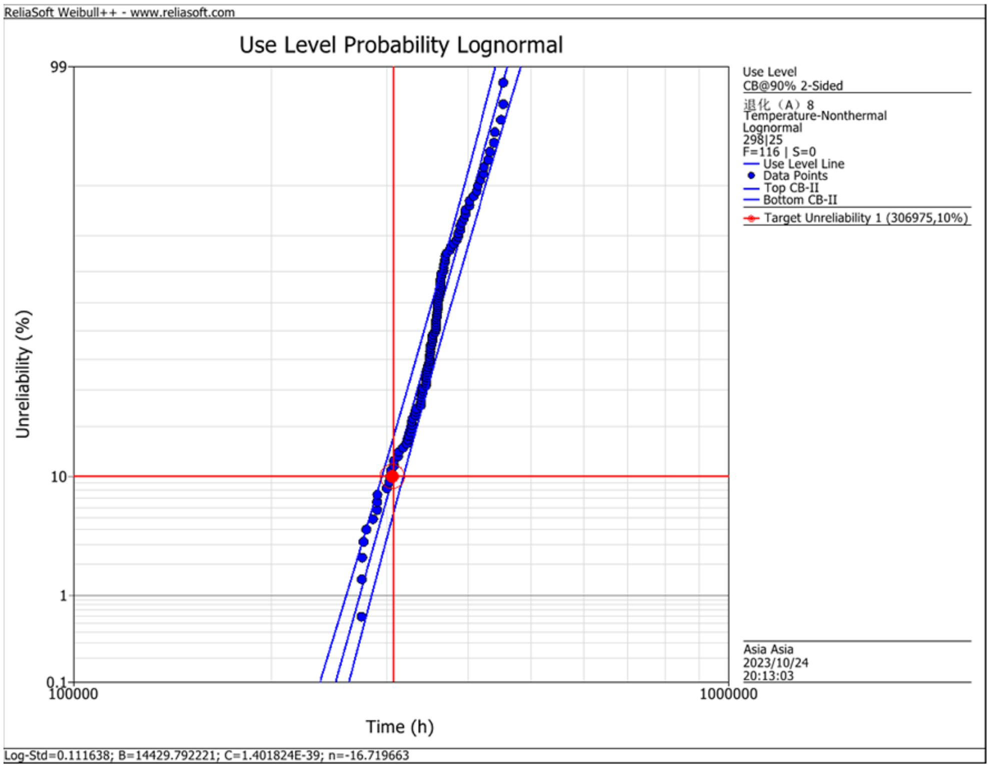

FIG. 8. Degradation curve of capacitance under service stress.

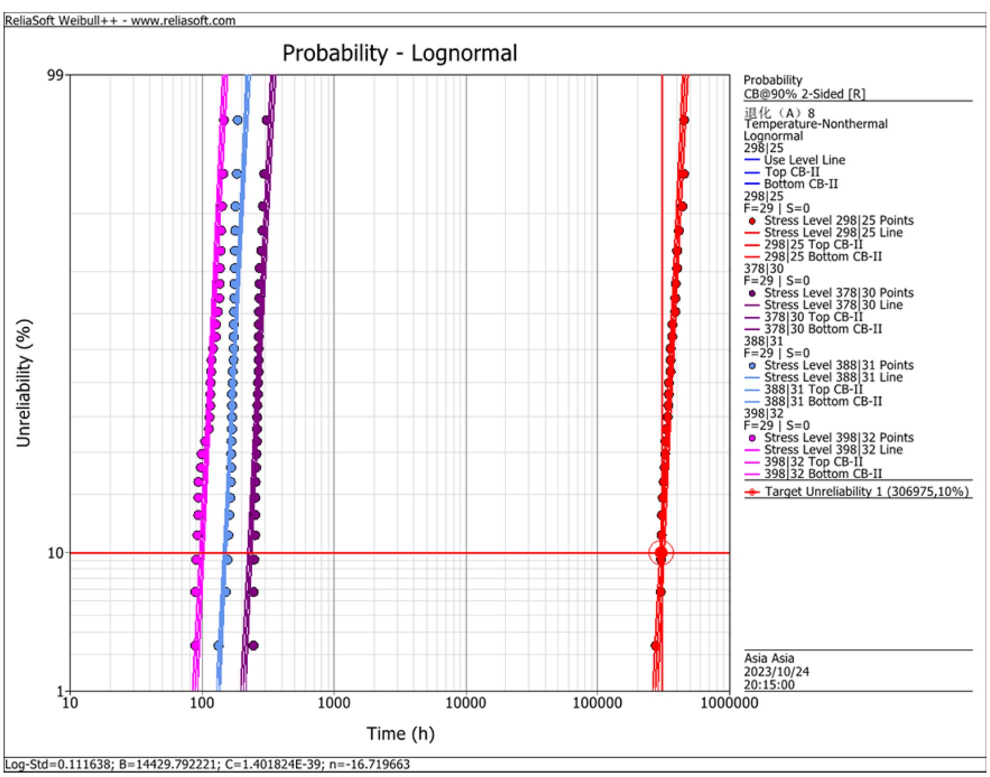

FIG. 9. Capacitance failure probability curve under different stress accelerations.

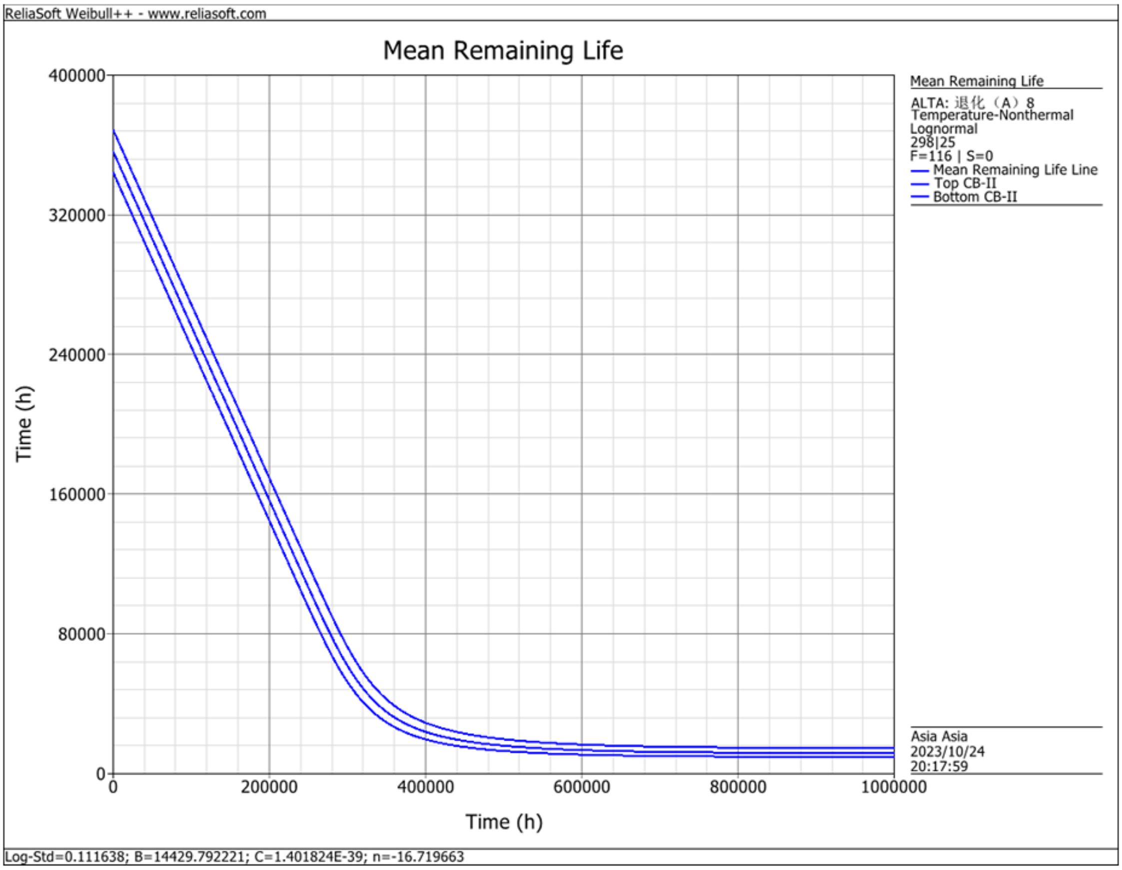

FIG. 10. Average remaining life curve of capacitance.

Therefore, the designed accelerated degradation test scheme is as follows.

Based on the prior data, the temperature stress obeys the Arrhenius relation model, and the accelerated degradation test stress is 378, 388, and 398 K. The voltage stress follows the power function relationship model, and the accelerated degradation test stress is 30, 31, and 32 V. The total number of samples is 120. The capacitance change value is recorded every 20 h, and the expected test time is 100 hours. At the same time, data under stress (298 K, 25 V) will be used as on-site monitoring data, and the testing scheme is shown in Table X.

After initial preparation, the samples were put into a high and low temperature environment chamber for testing, as shown in Fig. 6. Among them, figure (a) and figure (c) were taken through glass outside the environmental chamber.

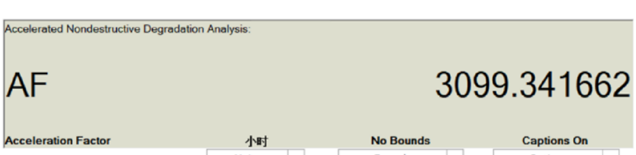

FIG. 11. Average acceleration coefficient of capacitance.

Analyze the collected accelerated degradation data[18] and obtain the relationship between accelerated degradation data and time, as shown in Fig. 7. The higher the stress, the faster the rate of performance degradation.

The degradation curve under a use stress environment is obtained as shown in Fig. 8, and it can be seen that the B10 lifespan of this component is ~300 000 hours.

By comparing the failure probability distribution curves under accelerated stress and use stress, as shown in Fig. 9, it can be found that the slopes of these curves are almost the same, indicating that the activation energy of these accelerating degradation factors remains basically unchanged, that is, the failure mechanism of acceleration remains basically unchanged, and the selection of accelerated stress factors is correct.

By analyzing the remaining life distribution of the product as shown in Fig. 10, the acceleration coefficient under accelerated tests is about 3099.34, as illustrated in Fig. 11. In other words, under this accelerated stress condition, the accelerated testing of the product achieved the optimal effect with the minimum testing expended. Simultaneously, this approach ensured that the failure mode remained largely unchanged, significantly reducing the time for degradation testing. Since the degradation testing approaches the failure interval, the degradation effect is more pronounced.

VIII. CONCLUSION

The demand for longer service life of new energy products has made it increasingly difficult to test products until failure under normal conditions, complicating the study of product life distribution. By investigating the degradation of key performance parameters, it is possible to effectively study the distribution of product life. This paper presents a case study that illustrates how to identify critical stress factors in a multi-factor degradation process using Design of Experiments (DOEs) methodology. In addition, through the use of DOE tools, the maximum stress range that can be applied to these critical stress factors is determined. The experimental design is then validated, and the reliability software Weibull++ is employed to analyze the degradation under the simultaneous influence of two stress factors. The findings reveal that the degradation under dual stress factors more closely matches the actual stress conditions experienced by the product, significantly outperforming single-factor degradation. This approach not only saves substantial testing resources but also enhances the efficiency of degradation testing. The application of DOE in accelerated degradation testing significantly expanded its utility range.

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AUTHOR DECLARATIONS

Conflict of Interest

The authors have no conflicts to disclose.

Author Contributions

Yinfang Huang: Data curation (equal); Formal analysis (equal); Validation (equal); Writing – original draft (equal). **Yunhong Zhou**: Funding acquisition (equal); Writing – review & editing (equal).

DATA AVAILABILITY

The data that support the findings of this study are included within the article.

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