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Data-Driven Life Modeling of Electrochemical Migration on Printed Circuit Boards Under Soluble Salt Contamination

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ABSTRACT Under the air pollution environment, the dust enters the electronic products and deposits on the printed circuit boards (PCB) during the service life. Soluble salts in the airborne dust can reduce the critical humidity and increase the ion concentrations on condensed water film on PCB, which has been proven to aggravate the insulation failure of the high-density PCB caused by electrochemical migration (ECM). It is practical application significance for how to establish a life model to evaluate the ECM of PCB under the interaction of soluble salt with temperature, relative humidity, and electric field strength. In this article, through the temperature humidity bias acceleration experiment, the ECM failure of PCB under the contamination of the different concentrations of NaCl solution is simulated, and the ECM characteristics and failure mechanism are studied through the change of surface insulation resistance (SIR) and the morphology and element compositions of migration products. The time to the insulation failure of PCB under different conditions are obtained by the analysis of SIR curves. Based on the data-driven method, the life modeling of ECM failure of PCB under soluble salt contamination is studied by multivariate non-linear regression and machine learning methods, such as support vector regression, gradient boost regression tree, and random forest regression. It is proved that it is valid to use machine learning to establish the ECM failure life model of PCB in complex environments with limited life data.

INDEX TERMS Electrochemical migration, life model, NaCl solution, printed circuit board, data-driven.

I. INTRODUCTION

Electrochemical migration was first found on the silver-plated terminals of telephone switching connectors in 1955 [1], which is a kind of insulation failure phenomenon between adjacent circuits that under certain temperature and relative humidity environment. The anodic metal of the circuit is oxidized, and the metal cations migrate to the adjacent cathode through the adsorption water film on the surface of the insulation material driven by the electric field, so that the metal atom is formed by the reduction of metal cations at the cathode. Then the subsequent metal cations continuously reduce at the reduced metal depositions on the cathode, forming the dendrite-like products which eventually leads to the degradation of the insulation performance even shorting between the two electrodes. In serious cases, the short circuit between the electrodes will lead to the heating of the circuit components and even the fire accident caused by the burnt electrical appliances [2].

The environmental humidity, temperature, and electric field strength are the important factors that lead to the ECM failure of PCB. Besides, dust deposited on the surface of the circuit board is another important physical and chemical inducement of ECM. China has suffered from the severe environmental pollution in recent years, with frequent outbreaks of haze and dust. The dust enters the electronics with the airflow and deposits on the PCB and components by the static electricity and the gravity. The compositions of dust particles collected from indoor of Beijing are about 70% inorganics, which is divided into the soluble and insoluble parts [3]. On one hand, the insoluble particles not only block the heat dissipation from the surface of PCB but also change the local electric field distribution of PCB due to its dielectric properties [4].

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Moreover, due to the capillary action of dust particles, the desorption of water film on the surface of the circuit board is delayed [5]. Therefore, the dust particles have impacts on the temperature, the relative humidity, and electric field on PCB, which are the direct influencing factors of ECM. On the other hand, although the soluble part accounts for only about 4% of the inorganic matter in the dust, it can reduce the critical humidity on the PCB assembly by absorbing the moisture in the atmosphere, and can increase the ion concentration in the condensed water film, which reduces the insulation resistance between the circuits and accelerates the corrosion of the electrode metal materials to aggravate the insulation failure based on ECM of the PCB [5]. Dust pollution markedly increases the complexity of ECM failure of PCB, so how to predict the time to the insulation failure of the circuit board based on ECM under dust pollution has become a problem to be solved.

The commonly used modeling methods of the life prediction for the electronic components can be divided into two types: the failure physics-based method and the data-driven method, which includes the statistical data regression method and machine learning method. Failure physics usually uses a series of equations to describe the physicochemical principles of failure modes. DiGiacomo Giulio summarized the relationship of the time to failure (TTF) of ECM, t, with the temperature T, the relative humidity H, and the electric field strength E [6], as shown in (1) - (3) respectively. Among them, $E\sigma$ is the activation energy (eV), R is the gas constant, k_T, k_H, k_E, a, and b are the constants, which are parameters that vary with the materials.

$$t_T = k_T \exp\left(E_\sigma / RT\right) \tag{1}$$

$$t_H = k_H H^{-a} \tag{2}$$

$$t_E = k_E E^{-b} \tag{3}$$

The life model of PCB based on ECM under NaCl contamination with different salt concentrations, C, was deduced by the method of failure physics based on Faraday's Laws as (4) [7].

$$t_c = \frac{61.76 \times [0.1253 \ln(C) + 0.362]}{1.7162 \times 10^{-6} \times C\left(190 - 30\sqrt{58.5C}\right)} \tag{4}$$

Shuang Yang established a model of the relationship between the TTF of ECM and the temperature, the relative humidity, and the bias voltage, as (5) [8], [9].

$$t = nF \times \frac{m_0}{M} \times \beta \times \frac{1}{U} \times \frac{(1-H)[1+(c-1)H]}{cH} \times \exp\left(\frac{E_\sigma}{RT}\right) \tag{5}$$

Among them, t, T, H, and $E\sigma$ are the same as those in (2)-(4). n is the valence of the migrating metal ions; F is the Faraday constant; m_0 is the mass of the metal precipitated out of the anode in case of insulation failure; M is the atomic weight of the migrating metal; U is the applied voltage; β is a parameter inversely proportional to the adsorbed water on the surface of the insulation material, which depends on the relationship between the tested surface conductivity and the relative humidity; c is a parameter related to the evaporation heat and condensation heat.

It can be seen that when the influence parameters are increased to three, the model based on the failure physics of ECM has been very complex. Moreover, through the verification of experimental data, the standard mean square error (NMSE) of TTF calculated by (4) is 0.908, indicating a rather large prediction error [10]. However, if the soluble salt in dust contamination is further introduced, it is difficult to directly derive a theoretical model of ECM failure of PCB based on the chemical reaction on the electrode.

Data-driven modeling methods supply a solution for this situation when a model based on failure physics cannot be achieved. One data-driven method is the regression method of statistical data, which refers to using data statistics principle to establish a regression equation that describes the correlation between dependent variables and some independent variables and extrapolates to predict the change of dependent variables. Among them, the polynomial regression and the multivariate non-linear regression modeling methods are usually used for the case of non-linear function relationship between the independent variable and dependent variable. Loukopoulos *et al.* used several methods (multiple linear regression, polynomial regression, Self-Organising Map (SOM), K-Nearest Neighbors Regression (KNNR)) to predict the remaining useful life of reciprocating compressor valve based on the actual valve failure data obtained from the operation of a reciprocating compressor [11]. Saxena *et al.* chose four data-driven algorithms, Relevance Vector Machine (RVM), Gaussian Process Regression (GPR), Artificial Neural Network (ANN), and Polynomial Regression (PR), to predict the life of lithium battery based on the cycle-life test data of the second-generation lithium battery, and compared the effectiveness of nine metrics in evaluating their performance [12]. Zhang used a multivariate nonlinear regression analysis method based on a deformation equation of the Arrhenius equation to analyze the 520 sets of tensile test data of the crosslinked polyethylene cable, and then obtained the residual life prediction model [13]. Wang *et al.* predicted the residual capacity of tank battery based on the 34 groups of experimental data (the independent variable is electromotive force and internal resistance) using multivariate nonlinear regression theory. The simulation results show that the model has high accuracy, and the prediction results are better than those of the neural network and support vector machine [14]. In the modeling research of ECM under the combination of the temperature, the relative humidity, and bias voltage, Qi Xie considered three variables as independent influencing factors to get the combination relationship model of TTF of ECM by multiplying (1), (2), and (3), as shown in (6). Then by the logarithmic transformation, a multivariate non-linear function (7) was constructed and fitted to obtain the corresponding unknown coefficient. It is proved that the prediction ability of the ECM life model based on the combination of the multiple factors is better than that of the model based on the failure physics (5) [15].

$$TTF = k_T \exp\left(\frac{E_\sigma}{RT}\right) \times k_H H^{-a} \times k_E E^{-b} \tag{6}$$

$$\ln TTF = A + B \times \left(\frac{1}{T}\right) + C \times \ln\frac{1}{H} + D \times \ln\frac{1}{E} \tag{7}$$

where A is ln ($k_T \cdot k_H \cdot k_E$); B is E_σ/R; C is −a; D is −b.

The other data-driven method is the machine learning algorithm, such as the support vector machine regression (SVR), the random forest regression (RFR), the gradient boost regression tree (GBRT), the neural network and so on, which are widely used in the field of life prediction of component failure. These data-driven modeling methods effectively solve the problem that it is difficult to build the life model of failure physics due to the complexity of the failure mechanism. Moreover, RFR and GBRT, as the main methods of ensemble learning, have a better application effect in small sample sizes. Based on the 17 failure data of a rolling bearing obtained by PRONOSTIA experimental system, Wang applied SVR, RFR, and other machine learning algorithms to the life prediction of the rolling bearing, and proved that its life prediction performance is better than the traditional prediction method [16]. Based on 316 milling experimental data, Wu *et al.* used three common machine learning algorithms, artificial neural network, SVR, and RFR, to predict the tool wear in the milling process, and found that RFR can give more accurate prediction [17]. Wang *et al.* used the GBRT algorithm to predict the remaining life of electronic components, which were based on the relative entropy (KS divergence) data of 150 different time indexes of electronic components and proved that ensemble learning had a strong prediction ability on the remaining life of electronic components [18]. In the case of limited life data, Zhou *et al.* used SVR, RFR and GBRT algorithms to build a life prediction model of ECM of PCB with three parameters of the temperature, the relative humidity, and the bias voltage. The NMSE is 0.328, 0.247, and 0.271 respectively, which is significantly more accurate than the model based on failure physics (The NMSE is 0.908.). It has been preliminarily verified that it is valid for machine learning in the modeling of life prediction of circuit board based on ECM failure [10].

In this article, to study the interaction of soluble salt, the temperature, the relative humidity, and the bias voltage on the ECM failure of PCB, the acceleration experiments are designed by the temperature humidity bias (THB) with a pre-covering salt solution with different concentrations. Then the failure characteristics of ECM are studied by monitoring the surface insulation resistance (SIR), observing the morphology and detecting the element compositions of the ECM products. The time to the insulation failure of PCB is extracted by analyzing SIR curves. At last, based on the experimental life data of the ECM of PCB under four influencing factors, the modeling methods of the insulation failure life of the circuit board by both the statistical regression method and various machine learning algorithms are explored and compared.

II. EXPERIMENTAL PREPARATIONS

To carry out proper the acceleration experiments for PCB under the effects of four factors, the soluble salt contamination, the temperature, the relative humidity, and the bias voltage, the selection of the PCB test samples was decided by the IPC standard. Then the composition and the concentration of the soluble salts in the dust were analyzed and chosen. The application method of salt contamination on the PCB samples was also discussed. The on-line monitoring system of SIR between wires on PCB was also designed so that the time to the insulation failure of PCB can be extracted corresponding to the first drop of SIR caused by dendrite formation of ECM.

A. PCB SAMPLES

According to the IPC-B-25A, a comb-type circuit is adopted as the test PCB samples, as shown in Fig. 1. Three comb-type circuits in a piece of circuit board can increase the experimental repeatability. The material of the circuits is immersion silver-finished copper. The thickness of the silver finish is about 0.15μm, the copper substrate is about 50μm thick. The distance between the parallel circuit traces is 0.32mm. The comb-type structure of the circuits is actually a pair of extended parallel circuit traces, which can increase the probability of ECM happened on PCB.

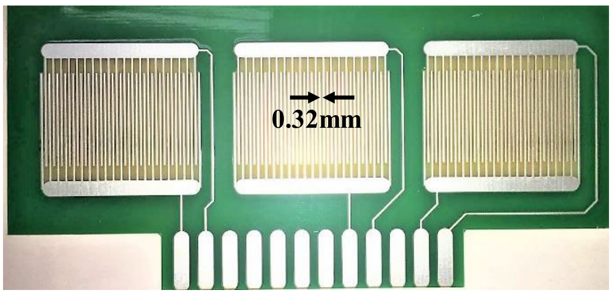


FIGURE 1. A comb-type test PCB sample.

B. SELECTION OF THE SOLUBLE SALT AND ITS CONCENTRATION

Reference [19] reported that the 70% natural dust indoor deposited in the west of Beijing were inorganic substances, and among them, 4% is soluble salts. The main cations and anions in the soluble salts are detected as K^+, Na^+, Ca^{2+}, Mg^{2+} and Cl^-, F^-, NO^{3-}, SO_4^{2-} respectively [19]. It was considered that NaCl has been widely used for corrosion acceleration tests for electronic products, so it is selected as the representative soluble salt in dust contamination in this research.

Then based on the equivalent conductivity of the natural dust solution, the concentration of NaCl solution for the accelerated corrosion tests was estimated. It was reported that the dust can accumulate the distribution density of 150μg/cm^2 indoor for about nine months [20] so that it is equal to about 981μg dust on a comb-type circuit with an area about 6.54cm^2. At the same time, it needs about 240μl solution to cover a comb-type circuit on the PCB sample, which is decided by the tentative trials. Therefore, the natural dust solution was prepared by dissolving 981μg natural dust in the deionized water of 240μl, and its conductivity of the dust solution was tested by a conductivity meter, about 231μS/cm. Then the corresponding concentration of NaCl solution was explored as 2.2mmol/l by repeatedly adjusting the concentration of NaCl solution and testing the conductivity. Since the accumulation of dust deposition appears almost linear increase, a series of concentrations of NaCl solution corresponding to the dust deposition density and time on PCB were estimated, as listed in Table 1 [21]. Since the natural dust particles have a kind of multi-layer wrapped structure, in which the soluble salts adhere to the insoluble particles, it is difficult for the soluble salts to fully dissolve in the thin water film condensed on PCB under a certain humidity. Therefore, 0.1~0.4mmol/l concentration of NaCl solution was adopted in this research.

TABLE 1. Correspondence between quartz particle coverage density and dust accumulation time.

No.	Deposition time of natural dust (month)	Distribution density of natural dust (μg/cm2)	Conductivity of dust solution (240μl) covering on a comb-type circuit (μS/cm)	Concentration of NaCl solution based on the same conductivity of dust solution (mmol/l)
1	0.3	5	10	0.1
2	0.9	15	21	0.2
3	1.5	25	30	0.3
4	2.1	35	42	0.4
5	2.7	45	54	0.5
6	3	50	61	0.6
7	6	100	143	1.4
8	9	150	231	2.2

There are two covering methods of soluble salt on the PCB mentioned in the literature. One is the salt particles are dispersed directly on the PCB [22], the other is the salt solution is dropped firstly and then the PCB samples are dried for further experiments [23]. The latter one shows a relatively even distribution of soluble salt on circuit traces on PCB. Therefore, the covering method of soluble salt on the PCB was adopted that the 240μl of NaCl solution was dropped firstly on PCB by a pipetting device and was smeared evenly on the comb circuit by a glass rod, and then the PCB samples were dried for two hours under 40 ± 2 °C condition.

C. CONDITIONS OF ECM EXPERIMENTS

Various combinations of the four factors were applied to the acceleration experiments to achieve life data of PCB based on ECM failure, as listed in Table 2. The temperature (T) is set at 65 °C, 70 °C, 75 °C, and 85 °C; the relative humidity (RH) is 75%, 80%, 85%, and 90%; the bias voltage (U) is 10V, 15V, 20V, and 25V; NaCl solution concentration (C) is 0.1 mmol/l, 0.2 mmol/l, 0.3 mmol/l, and 0.4 mmol/l respectively.

TABLE 2. The experimental conditions.

T (℃)	RH (%)	U(V)	C (mmol/l)
65	75	10	0.1
	80	15	0.2
	85	25	0.1, 0.2, 0.3
		20	0.2, 0.3
	90	15	0.1, 0.3, 0.4
		20	0.1, 0.2, 0.3, 0.4
		25	0.1, 0.2, 0.4
70	75	20	0.2
	80	25	0.1
	85	10	0.4
	90	15	0.3
75	75	25	0.3
	80	10	0.2
		20	0.4
	85	10	0.3, 0.4
		15	0.1, 0.2, 0.3, 0.4
		20	0.1, 0.2, 0.3, 0.4
	90	10	0.1, 0.2
		15	0.1, 0.2, 0.4
		20	0.1, 0.2, 0.3, 0.4
85	75	15	0.4
	80	10	0.1, 0.2
		15	0.1, 0.2, 0.3
		20	0.1, 0.2
	85	10	0.1, 0.2, 0.3, 0.4
		15	0.1, 0.2, 0.3, 0.4
		20	0.1, 0.2, 0.3, 0.4
		25	0.2
	90	10	0.1, 0.2, 0.3
		15	0.1, 0.2
		20	0.1, 0.2

D. DEVICE OF ECM EXPERIMENTS

The temperature and the relative humidity are controlled by a temperature and humidity chamber, and an external voltage source provides the bias voltage between parallel wires on the circuit board. The PCB samples covered with salt contamination are put into the temperature and humidity chamber and are applied by bias voltage for THB tests.

The SIR of normal PCB is usually higher than $10^9\Omega$, but it will decrease the 1~2 order of magnitude when the PCB is exposed in a high humid environment. If the ECM happened between the parallel circuits on the PCB, the SIR between two electrodes will drop markedly, usually lower than $10^6\Omega$ caused by the formation of dendrites, so the SIR of PCB needs to be monitored to judge whether the ECM happen or not. Refer to IPC-TM-650 2.6.14.1 "Electrochemical migration resistance test" [24], the TTF of ECM failure can be obtained by monitoring the SIR. Therefore, a SIR measurement system for the multiple comb-type circuits of PCB samples is used during THB tests, as shown in Fig. 2. The system can take turns to measure the SIR of every comb-type circuits on multiple PCB samples every other 40s by a picoammeter.

III. CHARACTERISTICS OF ECM OF PCB UNDER SOLUBLE SALT CONTAMINATION AND THB CONDITIONS

The ECM characteristics and failure mechanism of PCB covered with soluble salt during THB tests can be studied

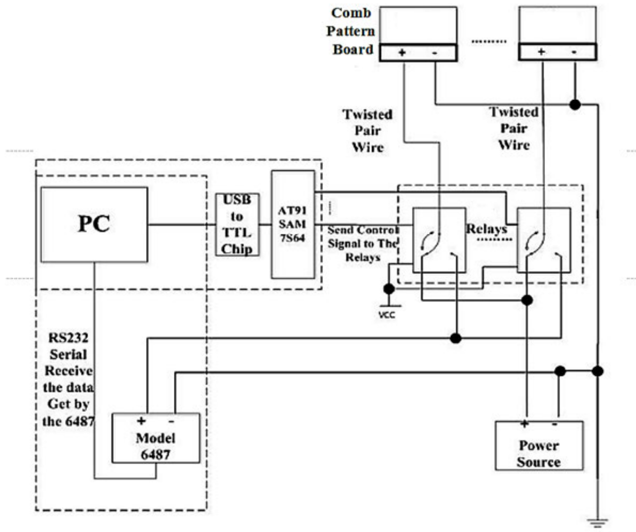


FIGURE 2. A multichannel measurement system for SIR of PCB samples.

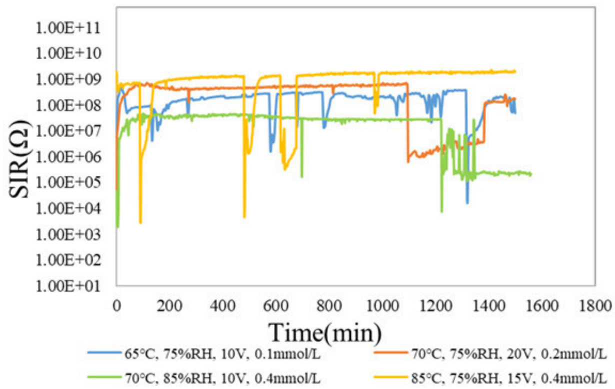


FIGURE 3. SIR performance curves of the comb-type PCB samples under four different THB and NaCl solution concentration conditions.

through the change of SIR, the morphology analysis, and element composition detection of electrochemical migration products. Four test examples are chosen to show the ECM characteristics of PCB.

A. ECM FAILURE CHARACTERISTICS OF PCB UNDER THE SOLUBLE SALT CONTAMINATION AND THB CONDITIONS

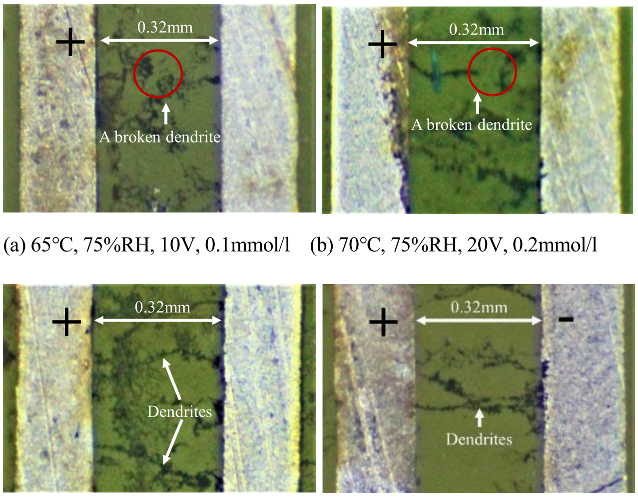
1) SIR CHARACTERISTICS OF PCB

Fig. 3 shows the SIR curves of the comb-type circuit board samples under four different conditions of THB and NaCl solution concentrations for 24 hours. For a PCB sample under the condition of 65 °C, 75% RH, 10V, and 0.1mmol/l NaCl solution, the initial SIR is stable at about $9.18 \times 10^7\Omega$ in high temperature and humidity environment for 35 mins, and then there are several fluctuations of the SIR, but none of them is lower than $10^6\Omega$. Until 1320 mins, the SIR suddenly drops to $1.71 \times 10^4\Omega$, and then immediately recovers to $4.95 \times 10^6\Omega$. After 1420 mins, the SIR of PCB restores to about $1.90 \times 10^8\Omega$. For a PCB sample under the condition of 70 °C, 75% RH, 20V, and 0.2mmol/l NaCl solution, the initial SIR is stable at about $4.25 \times 10^8\Omega$ in high temperature and humidity environment for 50 mins, and suddenly drops to about $6.61 \times 10^5\Omega$ in 1097 mins, and recovers to $1.03 \times 10^8\Omega$ after 300 mins. For a PCB sample under the condition of 70 °C, 85% RH, 10V, and 0.4mmol/l NaCl solution, the SIR is stable at about $1.85 \times 10^7\Omega$ after the initial 50 mins. At 698 mins, the SIR suddenly drops to $1.65 \times 10^5\Omega$ and recovers immediately. After 1360 mins, the SIR is stable at $2.25 \times 10^5\Omega$. For a PCB sample under the condition of 85 °C, 75% RH, 15V, and 0.4mmol/l NaCl solution, the SIR is stable at about $6.3 \times 10^8\Omega$ at the beginning. After 92 mins, the SIR suddenly drops to $2.7 \times 10^3\Omega$ and recovers immediately. After that, the SIR fluctuates many times.

It is seen that the initial SIR of a prepared PCB sample, covered by salt but dried, is usually higher than $10^9\Omega$, which is the SIR of PCB samples at room temperature and low humidity. Once the PCB samples are put into the high temperature and high humidity chamber, the SIR immediately decreases several orders of magnitude due to the condensation of moisture on the PCB surface and the ion conductivity caused by salt dissolution, but SIR will recover to $10^7\Omega$ at a balance after the water desorption. It is deduced that when the short circuit between parallel wires on PCB occurs due to the presence of dendrites formed by ECM, the SIR curve appears a sharp drop. However, if the cross-section of the dendrites is too thin to endure the current passing through, they will be broken down, so that the insulation resistance will return to a high value until new dendrites growth. That is why the SIR curves are characterized by many fluctuations.

2) MORPHOLOGY CHARACTERISTICS OF PCB

The four PCB samples after THB tests were observed by an optical microscope. As shown in Fig. 4, the obvious dendrite-like ECM products are formed on the PCB, which is the root reason for the insulation failure between the parallel wires of the PCB, that is, the anode metal is ionized to dissolve into the water film condensed on the PCB, then the metal cations migrate toward the cathode driven by the electric field and reduce to the metal atoms at the cathode. The metal cations continuously migrate to reduce on the deposited metal atoms so that the dendrites gradually grow from the cathode to the anode. The steep drop in the SIR curve means the short circuit caused by the dendrites formed between the two electrodes on the PCB. At this point, it is easy for the thin dendrite to be broken down by the current, so there are many discontinuous thin dendrites remained of the PCB, as shown in Fig. 4a and 4b. Then the SIR immediately recovers to a high resistance value. After that, ECM continues to occur, and the SIR drops and recovers to high-value many times in a period, appearing an intermittent failure. When the dendrites reach a sufficiently thick and strong state, as shown in Fig. 4c, the SIR of the PCB fails and cannot be recovered, as shown in the SIR curve of



(a) 65°C, 75%RH, 10V, 0.1mmol/l (b) 70°C, 75%RH, 20V, 0.2mmol/l

(c) 70°C, 85%RH,10V, 0.4mmol/l (d) 85°C, 75%RH, 15V, 0.4mmol/l

FIGURE 4. **Morphology of dendrites formed on PCB samples covered by NaCl after THB tests taken by optical microscope.**

the PCB sample after 1360 mins under the condition of 70 °C, 85% RH, 10V and 0.4mmol/l NaCl solution in Fig. 3.

3) MAIN COMPOSITIONS OF THE DENDRITES OF THE ECM

The morphology of the ECM products on the PCB after THB test under the condition of 85 °C, 85% RH, 10V, and 0.3mmol/l NaCl solution were observed by a scanning electronic microscope (SEM), shown in Fig. 5, and the main element compositions were detected on the two electrodes, the edge of the electrodes, and the dendrite products in the red rectangular areas A-G in Fig. 5 by an X-ray energy dispersive spectrum (XEDS), as shown in Fig. 6.

It is seen that the main compositions on the dendrites are Cu and a little Ag. The content of Cu on area B and F, where are the edges of the electrodes, is higher than that on the electrodes, which means the silver plating on the edges of electrodes is thin and cannot fully cover the substrate Cu. Therefore, the exposed copper in the intrinsic defects of the plating forms cations. The surface silver dissolves in the water film and migrates firstly, then more substrate copper is exposed to migrate, so the content of Ag on the dendrites close to the cathode is higher than that of Cu, but the content of Cu on the dendrites close to the anode is higher than that of Ag.

B. TTF OF ECM OF PCB UNDER THE SOLUBLE SALT CONTAMINATION AND THB CONDITIONS

In engineering applications, the TTF of PCB is usually defined as the time required for the SIR to drop to $10^6\Omega$ for the first time considering the safety of the equipment. Therefore, TTF for the PCB under the four conditions, 65 °C, 75% RH, 10V and 0.1mmol/l, 70 °C, 75% RH, 20V and 0.2mmol/l, 70 °C, 85% RH, 10V, 0.4mmol/l, and 85 °C, 75% RH, 15V, 0.4mmol/l, is obtained by analyzing the SIR curves

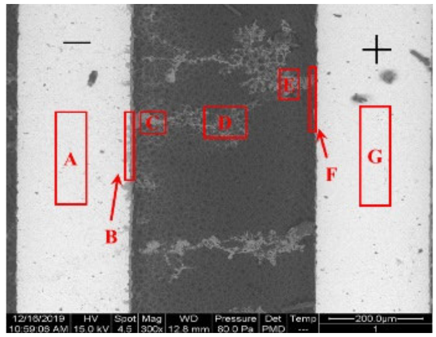


FIGURE 5. **Morphology of the ECM products on the PCB under 85 °C, 85% RH, 10V and 0.3mmol/l NaCl solution after tests.**

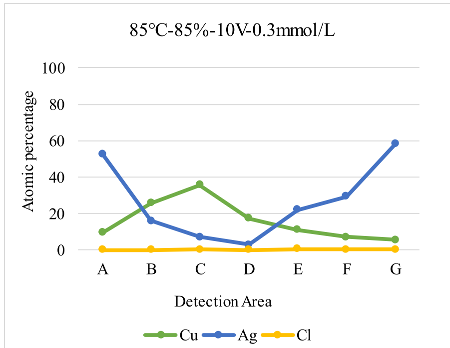


FIGURE 6. **Element compositions of the electrodes and ECM products in Fig. 5.**

in Fig. 3, as 1320mins, 1097mins, 698mins and 92mins respectively.

To study the modeling methods driven by data, 71 groups of different experimental conditions were selected in this research, including four independent variables, namely the temperature, the relative humidity, the bias voltage, and the NaCl solution concentration, as shown in Table 2. Part of the experimental conditions comes from orthogonal experiment design, and the other part comes from the research of the effect of salt concentration on the ECM failure of PCB, so the experimental conditions are not evenly covered on various influencing factors. In each experimental condition, the tests were repeated for three times so that there are 213 accelerated failure life data were obtained. The average TTF and its deviation under 71 groups of test conditions are shown in Fig. 7. It can be seen that the TTF under same salt contamination and THB condition has a certain discreteness since the ECM is an electrochemical process, which involves complex factors, such as the materials on the anode, circuit conditions, environmental conditions, and plating quality.

In the study of life modeling, two out of three TTF data of each experimental condition were selected as the training set and the other one of each condition was selected as the test set. The test set covers all of the experimental conditions of the combinations of the influencing factors and the change range, to improve the effectiveness of evaluation.

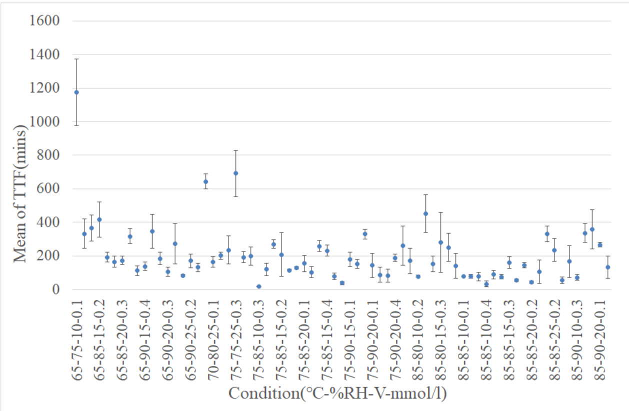


FIGURE 7. The TTF of ECM under 71 groups of test conditions.

IV. MODELING METHOD ANALYSIS

As mentioned in (5), the model of the relationship between the TTF of ECM and the THB factors has shown the complexity of the ECM failure model under multi-factor conditions. When the effect of the concentration of the salt solution is superimposed on the THB factors, it is difficult to establish a model based on failure physics. Therefore, the data-driven modeling methods, such as the multivariate non-linear statistical regression method and the machine learning methods of SVR, RFR, and GBRT, are considered.

A. EVALUATION OF THE MODELING METHODS

The ECM failure model of PCB under the influence of four factors of soluble salt concentration and THB can be established by the training set which has been obtained by the simulation tests, and then the validity of the modeling methods can be evaluated by using the test set. The accuracy of different life models is assessed by normalized mean square error (NMSE). NMSE is the ratio of the model prediction performance to benchmark model prediction performance as (8). Set $\bar{y}$ as the mean dependent variable, $\hat{y}$ as the projections for the dependent variable.

$$NMSE = \frac{\sum (y-\hat{y})^2}{\sum (y-\bar{y})^2} \tag{8}$$

The prediction performance of the model is inversely proportional to the NMSE value. The smaller the NMSE value is, the better the prediction performance of the model is. If the NMSE value is greater than 1, the performance of the model is not as good as that of the mean model, so the model makes no practical sense [25].

B. MULTIVARIATE NON-LINEAR REGRESSION MODELING

The multivariate non-linear regression has good applicability for the modeling of nonlinear data. When the multivariate non-linear regression is adopted, it needs to establish a non-linear function between the independent variable and dependent variable and to be fitted by the data to gain the unknown coefficient. For the ECM failure of PCB, the empirical models have been established for the independent variables respectively, such as the temperature, the relative humidity, and the bias voltage, as shown in (1) ∼ (3). The relationship between the concentration of soluble salt and the TTF has been deduced by failure physics, as shown in (4). Therefore, it can make use of the existing empirical models and the failure physical model, which have a function with a single independent variable, to establish the multivariate non-linear regression model with four independent variables to improve the life prediction accuracy of the statistical model.

Firstly, the relationship between TTF and the salt solution concentration C is simplified from (4), as (9).

$$y = e^{c+\frac{d}{C}} \tag{9}$$

Then, the effects of the temperature T, the relative humidity H, the bias voltage U and the soluble salt concentration C on the ECM failure of the circuit board are considered as the effect of the four independent factors to multiply corresponding to (1) ∼ (3) and (9), as (10).

$$TTF = k_T e^{\frac{E_\sigma}{RT}} \times k_H H^{-a} \times k_E U^{-b} \times e^{\left(c+\frac{d}{C}\right)} \tag{10}$$

After taking the logarithm of (10), (11) shows the multivariate non-linear regression model with four independent variables,

$$\begin{aligned} \ln TTF &= A' + B' \times \left(\frac{1}{T}\right) + C' \times \ln\frac{1}{H} + D' \times \ln\frac{1}{U} \\ &\quad + E' \times \frac{1}{C} \end{aligned} \tag{11}$$

All the unknown parameters in (11) are estimated by the least square method based on the training set data. The optimal regression equation of the TTF of the four independent variables was obtained as (12).

$$\begin{aligned} y &= 283065.022 e^{\frac{200.874}{T}} \times 3088420.563 H^{-8.22} \\ &\quad \times 39.493 U^{-0.045} \times e^{7.754+\frac{0.048}{C}} \end{aligned} \tag{12}$$

Then, the NMSE of life prediction model of ECM based on multivariate non-linear was obtained by the test set data, as 0.531.

C. MACHINE LEARNING MODELING

1) SVR ALGORITHM TO PREDICT ECM LIFE OF PCB

Support vector machines (SVM) learning method can build models from a simple one to a complex one, whose basic model is used to define a linear classifier with the largest interval in the feature space. SVM is a supervised learning algorithm that is good at processing data with a small sample size. SVM solves the problem of classification and regression by seeking the optimal hyperplane and has a better adaptability and higher discrimination rate to the data. The simple model is the case where the training data is linearly separable, as shown in Fig. 8. It is not only the basis of the complex model but also the special case of the complex model. As the support-vector, the points on the boundary play

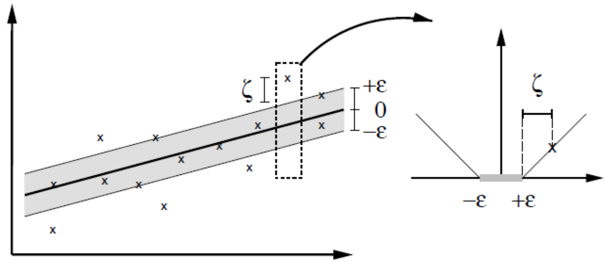


FIGURE 8. SVR loss function [26].

an important role in the prediction. Support vector regression (SVR) uses a strip to fit the data. The point in the strip means the zero error. Only the point beyond the boundary can calculate the error [26]. Therefore, the task of SVR is to find a hyperplane, $y = w^T \cdot x_i + b$, for the training set data. The optimal hyperplane to be sought is to maximize the band width $\rho = 2/\|w\|$ so that the strip can cover as many sample points as possible to minimize the total error. To build the complex model for the training data of linear inseparability, a hyperplane is finally found in the high-dimensional space by using kernel technique, which is equivalent to learning the linear SVM implicitly in the high-dimensional feature space. In other words, the regression problem can be realized by the algorithm of classification.

The algorithm flow of SVR for predicting the ECM life of PCB is shown in Fig. 9, which can be divided into two steps. The first step is to build a prediction model and adjust the parameters of the model through the training set. The second step is to predict the TTF of ECM of PCB and to compare it with the actual life by inputting the test set of data into the model. The NMSE of the life prediction model of ECM of PCB by SVR is 0.371.

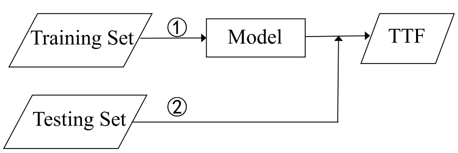


FIGURE 9. The structure diagram of the SVR algorithm.

2) GBRT ALGORITHM TO PREDICT ECM LIFE OF PCB

Both gradient boosted decision tree (GBDT) and random forest (RF) in machine learning belong to ensemble learning, which is, integrating multiple weak classifiers into one strong classifier. Bagging and Boosting are two main algorithms of ensemble learning, the difference between them is that Bagging adopts uniform sampling with a fallback, while Boosting takes samples according to the error rate. GBRT is an improvement of the Boosting algorithm, which integrates multiple models for calculation. These models are not independent of each other. The lifting method is a decision-making method based on the additive model (the linear combination of the primary functions) and the forward classification algorithm.

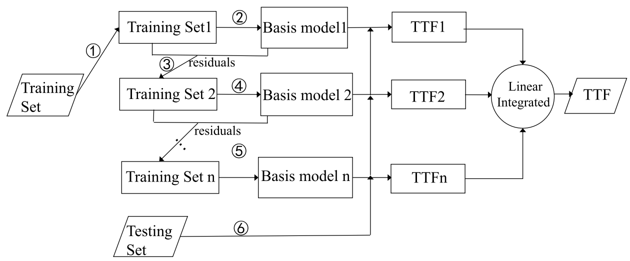


FIGURE 10. The structure diagram of the GBRT algorithm.

As shown in Fig.10, the modeling method by GBRT consists of six steps to build a TTF model of ECM of PCB. The first step is to give all the data of training set to the training set 1; the second step is to establish a decision tree as the base model 1 in the negative gradient direction of the loss function based on the training set 1; the third step is to take the residual of the base model 1 relative to the training set 1 as the training set 2; the fourth step is to continue to establish a new base model 2 in the negative gradient direction of the loss function; step 5 repeats the step 3 to the step 4 until independent base model n is established; in the last step 6, the sample characteristics of the test set to be predicted are input into each weak learner decision tree. According to the judgment criteria of each node in the decision tree, the corresponding leaf node is reached. Finally, the values of all decision tree leaf nodes are linearly integrated into the final prediction dependent variable. The base models are not independent of each other, which means the next base model compensates for the residual of the previous base model. The NMSE of the life prediction model of ECM of PCB by GBRT is 0.091.

The core of GBRT is that every calculation step can reduce the last residual, which is used to build a new model in the gradient direction of residual reduction to minimize the residual according to the gradient descent method. GBRT can adjust its structure according to the characteristics of data, so it can fit the function well. As an ensemble algorithm, GBRT not only inherits the advantages of the decision tree algorithm, it can also effectively avoid the overfitting problem comparing with the single decision tree algorithm. GBRT is regarded as one of the best methods in statistical learning [18].

3) RFR ALGORITHM TO PREDICT ECM LIFE OF PCB

RF is an algorithm of the base classifier based on the decision tree proposed by Leo Breiman, which is a representative of the Bagging algorithm. Bagging is closely related to "Bootstrap", which is a sampling method with a fallback. "Bootstrap" technique extracts a certain number of samples from the original samples to calculate the statistics to be estimated. This process allows repeated sampling to estimate the real distribution of data. It is a popular statistical method

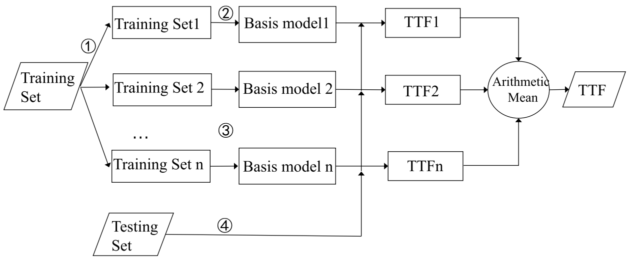


FIGURE 11. The structure diagram of the RFR algorithm.

in modern statistics, and it works well in a small sample size, which is suited to the ECM failure data of PCB with a limited sample size.

RFR algorithm is used to solve the regression problem, which consists of four steps, as shown in Fig.11. The first step is to randomly select n samples to form the training set 1. The second step is to randomly select P features ($P \leq 4$, the total number of features is 4) from the n samples to establish the decision tree as the base model 1. The third step is to repeat the first and second steps until the base model n is set up independently. In the last step, the test set is input into the base model for prediction, and integrate the n prediction results to get the final prediction value. The NMSE of the life prediction model of ECM of PCB predicted by RFR is 0.111.

RF can be used to deal with regression, classification, clustering, and survival analysis. When it is used for classification or regression, the main idea is to generate many tree regressors or classifiers by bootstrap. When there are too many noise or split attributes in the data, the RF algorithm can solve the problem of imbalance of trees and overfitting of the training set. This method is also considered as one of the best statistical learning performance methods.

V. DISCUSSION

A. ECM OF PCB UNDER THE COMBINATION OF SALT CONTAMINATION AND THB

The critical humidity on the surface of the PCB is decreased due to the absorption of the moisture in the atmosphere by soluble salts in the deposited dust, and the ion concentration of the water film is also changed, so the SIR between the circuits is reduced once the PCB samples covered by salts are put into an environment with a high temperature and humidity, as the initial SIR curves shown in Fig. 3.

Under the bias voltage between two electrodes on the PCB surface, the condensed water is electrolyzed and OH^- moves to the anode to form a weak alkaline environment, then ECM starts from the corrosion of the anodic metal materials. Soluble salts, such as NaCl, can accelerate the chemical reaction on the immersion silver-finished copper anode. Not only the silver finish is corroded, but the exposed copper substrate on the intrinsic defects on the electrode edge is also dissolved into the water film on the PCB surface. Both copper and silver cations migrate to the cathode driven by the bias voltage and are reduced to metal atoms. Since Ag on the surface finish migrates firstly, the main composition on the dendrites close to the cathode is Ag. As the exposed substrate copper cations migrate subsequently and reduced on the reduced silver dendrites, the main composition of the dendrites close to the anode becomes Cu, as shown in Fig. 5 and 6.

As a result, the parallel wires of PCB are shorted by the dendrites of ECM and the SIR curve drops sharply. If the thin dendrite is broken down by the current, the SIR immediately recovers the high resistance value, appearing the intermittent failure, as the fluctuation of SIR curves shown in Fig. 3. When the dendrites reach a sufficiently thick and strong state, the SIR of the PCB fails and cannot be recovered.

B. MODELING OF ECM LIFE OF PCB UNDER THE INFLUENCE OF SOLUBLE SALTS

The ECM of PCB is the result of electrochemical corrosion, it is closely related to the electrode materials, the coating quality, the bias voltage, and the environmental conditions (temperature, relative humidity, and soluble salt contamination). Because of the complexity of ECM failure of PCB under multi-factor conditions, it is difficult to establish the life model of ECM of PCB based on the failure physics. Therefore, the multivariate non-linear regression modeling based on the statistical method and the machine learning modeling based on data-driven were adopted and compared for life modeling of ECM of PCB.

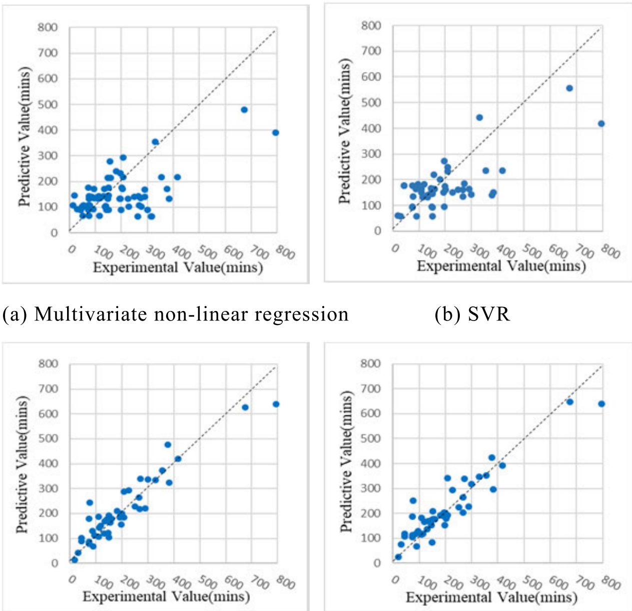
In the multivariate non-linear regression modeling, the known life model of a single independent variable, such as the temperature, the relative humidity, the bias voltage, and the concentration of the salt solution, was fully utilized to construct a function, which was then fitted by the experimental data to improve the accuracy of the life model.

In machine learning modeling, based on the characteristics of failure data with relatively small size, three algorithms, SVR, GBRT, and RFR, were used to predict the life of PCB based on ECM failure. The NMSE of the four modeling methods is compared in Table 3. The results show that the prediction performance of all three machine learning methods is better than that of multivariate non-linear regression modeling. Furthermore, the performance of the RFR and the GBRT is better than that of SVR, and the GBRT shows the best performance.

TABLE 3. NMSE values of four modeling methods.

Method	Multivariate non-linear Regression	SVR	GBRT	RFR
NMSE	0.531	0.371	0.091	0.111

The prediction performance of the four models is shown in Fig. 12a-12d respectively. The abscissa is the actual TTF and the ordinate is the predicted TTF by the different models. The dots on the dotted line in the figure represent the case where the experimental value is equal to the predicted value. The closer the data is to the dotted line, the closer the prediction value of the model is to the experimental value, that



(a) Multivariate non-linear regression (b) SVR

(c) GBRT (d) RFR

FIGURE 12. Prediction performance of four models for ECM.

is, the better the prediction performance of the model. It can be intuitively found that, on the whole, the modeling effect of machine learning is better than that of the multivariate non-linear regression. GBRT and RFR are better than SVR algorithm on predicting the ECM life of PCB. When the temperature, the relative humidity, the bias voltage and the NaCl solution concentration are moderate or lower, the TTF of ECM of PCB is extended, and the TTF extracted from the SIR curves in the experiments appears more discrete. At this condition, the modeling error based on multivariate non-linear regression is large. However, the prediction errors of GBRT and RFR models are small, because GBRT and RFR, as the ensemble learning methods, have excellent self-learning ability, and can effectively handle discrete data through iteration when the data volume is limited. Although SVR is suitable for small sample data, it has only one model, which is sensitive to the noise compared with the ensemble learning algorithms.

VI. CONCLUSION

Severe environmental pollution brings great risk to the insulation failure of high-density PCB based on the ECM mechanism, which not only reduces the reliability of electronic products but also has great security risks. In this article, the effect of the soluble salts in the airborne dust on ECM is studied through salt solution coverage and THB acceleration experiment. The ECM failure characteristics are analyzed from SIR curves, the morphologies, and the element compositions of dendrites formed on PCB. The TTF model of the ECM of PCB under four influencing factors is built by both the statistical regression method and various machine learning algorithms for comparison.

(1) The main ECM products are copper and a little silver. After silver on the top finish migrates firstly, the exposed copper substrate migrates intensively, which leads to the high content of silver in the dendrites close to the cathode and high content of copper in the dendrites close to the anode.

(2) The formation of dendrites between parallel circuits on the PCB causes shorting and the sharp drop of SIR. If the thin dendrite is broken down by the current, the SIR immediately recovers to the high resistance value, appearing intermittent failure. When the dendrites reach a sufficiently thick and strong state, the insulation failure of the PCB cannot be recovered.

(3) By defining the time when SIR reduces to $10^6\Omega$ for the first time as the TTF, the 213 life data of the PCB under 71 different experimental conditions are obtained. Two-thirds of the TTF data is taken as the training set, the else is the test set. The multivariate non-linear regression method, SVR, RFR, and GBRT are compared to predict the life of PCB under four influencing factors. The results show that the accuracy of machine learning modeling is much better than that of the multivariate non-linear regression modeling. The ensemble learning methods GBRT and RFR in machine learning have good application effects in a complex environment with limited data.

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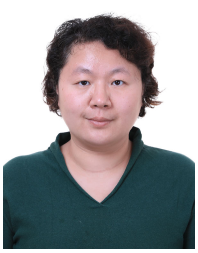

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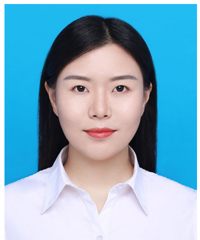

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