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Anti-Radiation Performance Assessment of Satellite Units Based on the Weiner Process

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ABSTRACT In satellite anti-radiation reinforcement designs, it is necessary to specify the anti-radiation reinforcement index of the selected electronic components to ensure that the satellite has enough anti-radiation adaptability. Traditional probability distribution models or 0-1 models use only the radiation dose at the moment of unit failure, and so, in the case of a small sample size, it may be difficult to obtain a credible estimation of the unit anti-radiation. Furthermore, due to the uncertainties of environmental conditions and manufacturing processes as well as the individual differences of various products, there exist differences and uncertainties for the anti-radiation abilities of individual units. Consequently, in this paper, a performance degradation model based on the Wiener process is constructed to characterize the law of the unit anti-radiation performance changes along with the total radiation dose levels. Finally, the anti-radiation performance of STRM60N20FSY is evaluated by the model proposed in this paper, and the average anti-radiation, survival probability, and survival function of the unit product are also obtained.

INDEX TERMS Reliability, satellites, radiation monitoring, anti-radiation performance, Wiener process.

I. INTRODUCTION

In the study of the anti-radiation ability of a system, the anti-radiation of the included devices and materials is the foundation and prerequisite to calculate that of the system. The anti-radiation model describes the ability of a unit to meet its requirements and perform its intended function within a defined radiation environment and a set time. The purpose of modeling the unit anti-radiation is to establish a model to describe the relationship of the unit anti-radiation, radiation environment and run time by a statistical method. The modeling process is realized by using the data of the unit anti-radiation test, actual operations and simulations. Because of the different types of data available for modeling, the radiation damage mechanism may be different, and the type as well as the change rules of the radiation-sensitive parameters will differ. Therefore, suitable models should be selected to describe anti-radiation performances according to the data and unit characteristics.

The unit-level anti-radiation performance evaluation is mainly based on radiation experiments. The file data, expert judgment and the information concerning the manufacturing process are usually fused to make up for the inadequacy of the test sample size. There are many methods for using historical, similarity and Radiation Lot Acceptance Testing (RLAT) data [1]–[6]. The radiation effect study and analysis group of the NASA Goddard Space Flight Center (2005) [7] support the use of the file data for rationally restraining the patent distribution, providing the variability of different batches and determining the shape of the distribution of the anti-radiation (such as the location, width, higher order moments, the extreme values of the distribution, etc.). Identifying radiation by file data in the RLAT requires the use of a big enough radiation design margin (RDM=failure dose/mission dose). To address this problem, Ladbury et al. (2009) [5] found that statistical selection models based on AIC compensate for the bias between file data and RLAT data. For the RHA problems that rely on small sample sizes when flight lots are large and reliability requirements are ultra-high, Ladbury et al. (2005a) [4] showed that the file data can enhance the results of RLAT and that sampling errors arising from the small sample size and systematic errors can be bounded. Ladbury et al. (2005b) [8] provided a cursory introduction to the broad applicability of Bayesian analyses for radiation hardening guarantee (RHA) issues, both for single-event effects (SEE) and for degradation phenomena such as total ionizing dose (TID). Furthermore, they noted that, based on the same level of radiation, the priori distribution structure constructed by reinforcing the logical data and expert judgment can make up for the inadequacy of the test data. Thuesen et al. (2003) [9] note that, under the condition of high survivability, the overstress test used can effectively reduce the sample size. The applicability of implementing the Qualified Manufacturers List (QML) for radiation hardness assurance had been studied by Winokur et al. (1990 [10], 1993 [11]). To be more specific, the costly end-of-the-line IC test can be avoided by controlling the following key technique processes: the statistical process control (SPC) of radiation parameters, test structure of the IC correlation, and extrapolations from laboratory to threat scenarios. While studying the lot uniformity and small sample size problems in RHA, Namenson (1988) [1] noted the need to use 2 or 4 parts with no failures as a test acceptance condition. In recent years, the increasing demand for products with high reliability has motivated the development of degradation analysis. Due to the test conditions, expense limitations, the radiation tests are infeasible and only a small size of radiation test sample is applicable. Thus, the traditional probability model is not able to evaluate the unit-level anti-radiation performance. Under this situation, it is essential to evaluate the anti-radiation performance by using degradation data. There are many models proposed for modeling and analyzing degradation processes [12]–[19]. Song et al. (2017) [20] adopted the Gamma process to describe the degradation of satellite unit with radiation. Wang (2010) [21] studied the maximum likelihood inference on a class of Wiener processes with random effects for degradation data. The traditional Wiener process was extended to a one with positive drifts compounded with i.i.d. Gaussian noises in the paper of Ye et al. (2013) [22], and the results showed that its estimation efficiency was better than that of the existing inference procedure.

The construction of a unit anti-radiation model in the space radiation environment is the foundation for evaluating the anti-radiation performance of the system. Since the performances of the spacecraft's sensitive materials or electronic components will show different degrees of changes after experiencing high-energy particle radiation, unit anti-radiation performance measurement and evaluation models based on the Wiener degradation process are proposed in this paper. The model is able to describe the law of the unit anti-radiation changes along with the total radiation dose levels under the total dose effect and the displacement damage effect. The anti-radiation of STRM60N20FSY3, which is produced by STM, is analyzed by the above model. The evaluation results of the average anti-radiation, survival probability and survival function are obtained and compared with those of the traditional probability model.

II. WIENER DEGRADATION PROCESS MODEL

If a stochastic process $\{X(t), t \geq 0\}$ satisfies the following properties, it is called a Wiener process with a drift function $\mu(t)$ and diffusion parameters σ:

(1) $X(0)=0$;
(2) $X(t)$ has stationary independent increments;
(3) $X(t)$ obeys a normal distribution with mean $\mu(t)$ and variance $\sigma^2 t$.

The Wiener process with a drift coefficient is expressed in the following form:

$$X(t) = \mu(t) + \sigma B(t) \tag{2.1}$$

where $\{B(t), t \geq 0\}$ is a standard Wiener process or a standard Brownian motion process.

According to this definition, the Wiener process with the stated drift coefficient has the following properties:

(1) The increment between time t and $t + \Delta t$ follows a normal distribution, namely, $\Delta X = X(t + \Delta t) - X(t) \sim N(\mu(t + \Delta t) - \mu(t), \sigma^2 \Delta t)$;

(2) For any two disjoint time intervals $[t_1, t_2]$, $[t_3 t_4]$, $t_1 < t_2 \leq t_3 < t_4$, the increment $X(t_4) - X(t_3)$ is independent of $X(t_2) - X(t_1)$.

A normal Wiener process $\{B(t), t \geq 0\}$ describes the movement of particles with liquid interiors (such as pollen grains) due to the cumulative effects of the collisions of a large number of tiny liquid molecules. Owing to the large number of collisions, we can state that the displacement of the particles obeys a normal distribution based on the central limit theorem. Similarly, if the degradation of a product $\Delta X = X(t + \Delta t) - X(t)$ at time t and $t + \Delta t$ is a uniform and gentle degradation process caused by the sum of many independent random microperformance losses ν_i, namely, $\Delta X = \sum_{i=1}^{n} \nu_i$, and the number of these small losses n is proportional to Δt, then the process ΔX obeys a normal distribution and we can state that the Wiener process describes the degradation process of the product.

Due to the property that the increment ΔX obeys a normal distribution at time t and $t + \Delta t$, the increment ΔX can be greater than, equal to or less than zero, which implies that the one-dimensional Wiener process X (t) is not a strictly regular degradation process. However, when μ and σ are relatively large, the probability that ΔX has a negative value is negligible, and the degradation process can be approximated as a monotone process. The Wiener process is a good choice when it is necessary to describe the degradation process of non-monotonically degraded products.

For a given critical level l, the Wiener degradation of the product life T first reached or exceeded l at a time of X (t), that is, $T = \inf\{t: X(t) \geq l\}$. It is difficult to give the analytic form of the distribution of T for the general drift function $\mu(t)$. However, for the linear case, namely, the case of the drift function $\mu(t) = \mu t$, $\mu > 0$, it can be proved that the case follows an inverse Gaussian distribution, whose distribution function and density function, respectively, are

$$F_T(t) = \Phi(\frac{\mu t - 1}{\sigma\sqrt{t}}) + \exp(\frac{2\mu 1}{\sigma^2})\Phi(\frac{-1 - \mu t}{\sigma\sqrt{t}}) \tag{2.2}$$

$$f_T(t) = \frac{1}{\sqrt{2\pi\sigma^2 t^3}} \exp[-\frac{(1 - \mu t)^2}{2\sigma^2 t}] \tag{2.3}$$

The mean and variance of T are:

$$E(T) = \frac{1}{\mu}, \quad Var(T) = \frac{l\sigma^2}{\mu^3} \tag{2.4}$$

The degradation of the performances of certain products at the initial moment satisfies $X(0) \neq 0$. At this time, the product failure threshold should be assumed to be l-X (0), which transforms the case into one wherein the initial degradation performance is zero. Therefore, when the Wiener process is used to describing a degradation process, the degradation performance at the initial time is assumed to be zero.

III. PARAMETER ESTIMATION OF THE WIENER DEGRADATION PROCESS

Assume that there is no error in the measurement of the degraded data and that there are no random effects or individual differences in the overall degradation processes. According to the properties of the Wiener process, it is easy to get

$$\Delta X_{ij} \sim N(\mu(t_{ij}) - \mu(t_{i,j-1}),\ \sigma^2 \Delta t_{ij}). \tag{3.1}$$

Then, on the basis of the degradation of the data Xij=xij (which is equivalent to ΔXij $=$ Δxij), we can obtain the likelihood function of the model parameters as follows:

$$L = \prod_{i=1}^{n}\prod_{j=1}^{m_i} \frac{1}{\sqrt{2\sigma^2\pi\Delta t_{ij}}} \exp[-\frac{(\Delta x_{ij} - (\mu(t_{ij}) - \mu(t_{i,j-1})))^2}{2\sigma^2\Delta t_{ij}}] \tag{3.2}$$

and the log-likelihood function is

$$l = -\sum_{i=1}^{n}\sum_{j=1}^{m_i} \times [\frac{1}{2}\log(2\sigma^2\pi\Delta t_{ij}) + \frac{(\Delta x_{ij} - (\mu(t_{ij}) - \mu(t_{i,j-1})))^2}{2\sigma^2\Delta t_{ij}}]. \tag{3.3}$$

Solving the extremes of the likelihood estimate, the unknown parameters can be estimated. Here are a few special examples.

A. LINEAR MODEL

In this case, the log-likelihood function is

$$l(\mu, \sigma^2) = -\sum_{i=1}^{n}\sum_{j=1}^{m_i}[\frac{1}{2}\log(2\sigma^2\pi\Delta t_{ij}) + \frac{(\Delta x_{ij} - (\mu(t_{ij}))^2}{2\sigma^2\Delta t_{ij}}] \tag{3.4}$$

The maximum likelihood estimations of the drift parameter μ and the diffusion parameter σ^2 can be obtained directly from the above equation.

$$\hat{\mu} = \frac{\sum_{i=1}^{n} X_{im_i}}{\sum_{i=1}^{n} t_{im_i}},$$
$$\sigma^2 = \frac{1}{\sum_{i=1}^{n} m_i}[\sum_{i=1}^{n}\sum_{j=1}^{m_i}\frac{(\Delta X_{ij})^2}{\Delta t_{ij}} - \frac{(\sum_{i=1}^{n} X_{im_i})^2}{\sum_{i=1}^{n} t_{im_i}}] \tag{3.5}$$

From equation (3.5), we can know that the estimation of the average degradation rate is only true in relation to the length of the test time and the performance of the sample at the end of the test and is independent of the number of measurements and the interval time; the estimation of the diffusion coefficient is related not only to the test time but also to the measurement scheme. In actuality, assuming that the test is performed using a timed censoring method, we can calculate the variance of the estimator as follows:

$$Var(\hat{\mu}) = \frac{\sigma^2}{\tau} \tag{3.6}$$

where $\tau = \sum_{i=1}^{n} t_{im_i}$ is the total test time and the constant confirmed before the test. Assuming the measurement interval is δ and measurement time is m for the case of equal interval measurements and the same test times for each sample, we can get

$$Var(\hat{\sigma}^2) = \frac{1}{\sigma^2}Var\{\frac{1}{mn}\sum_{i=1}^{n}\sum_{j=1}^{m_i}(\Delta X_{ij})^2 - \left(\frac{1}{mn}\sum_{i=1}^{n}\sum_{j=1}^{m_i}\Delta X_{ij}\right)^2\} \approx \frac{2\sigma^4}{mn}. \tag{3.7}$$

Obviously, the higher the number of measurements, the higher the accuracy of the estimation of the diffusion coefficient. To obtain the reliability estimation of the product, the point estimation of the survival function can be solved by taking $\hat{\mu}$, $\hat{\sigma}^2$ into the reliability expression of task time t. That is,

$$R(t) = 1 - F(t; \hat{\mu}, \hat{\sigma}) = \Phi(\frac{1 - \hat{\mu}t}{\hat{\sigma}\sqrt{t}}) - \exp(\frac{2\hat{\mu}l}{\hat{\sigma}^2})\Phi(\frac{-1 - \hat{\mu}t}{\hat{\sigma}\sqrt{t}}) \tag{3.8}$$

B. NONLINEAR MODEL

Assume $\mu(t)=at^b$. Then, $X(t) \sim N(at^b, t\sigma^2)$. In addition, the degenerate increment is

$$\Delta X_{ij} \sim N(at_{ij}^b - at_{i,j-1}^b, \Delta t_{ij}\sigma^2) \tag{3.9}$$

TABLE 1. The specific value for the test conditions.

The test conditions	Value
Test temperature	20±5 at room temperature
Test time	300 hours
Radiation source	cobalt 60 (γ rays)
Particle energy	1.173 MeV, 1.332 MeV
Radiation dose rate	5.9 rad(Si)/min

TABLE 2. The test sample number and bias conditions.

Bias conditions ID	Descriptions	Sample number
BC1	V_{DS}=0 V, V_{GS}=+15 V	013, 014, 015, 016, 017
BC2	V_{DS}=+160 V, V_{GS}=0 V	008, 009, 010, 011, 012
BC3	V_{DS}=0 V, V_{GS}=0 V	001, 002, 003, 004, 005
BC4	V_{DS}=+200 V, V_{GS}=-20 V	020, 021, 022, 023, 024
BC5	V_{DS}=0 V, V_{GS}=+12 V	018, 019

TABLE 3. The parameter estimations of the Wiener degradation process.

ID	Model I				Model II			
	a	b	σ	MSE	a	b	σ	MSE
BC1	1.134×10^2	0.7227	12.995	0.0434	4.724×10^3	-0.0113	24.11	0.0960
BC2	40.1442	0.83134	10.4066	0.1200	3.357×10^3	-0.0082	4.4945	0.0633
BC3	41.1957	0.8172	10.3713	0.0677	3.2397×10^3	-0.0081	7.8153	0.0426
BC4	68.1971	0.8180	8.4449	0.0851	5.5830×10^3	-0.0075	9.6851	0.0851

Thus, the likelihood function of the model parameters can be obtained:

$$l(a, b, \sigma^2) = -\sum_{i=1}^{n}\sum_{j=1}^{m_i}[\frac{1}{2}\log(2\pi\Delta t_{ij}\sigma^2) + \frac{(\Delta x_{ij} - (at_{ij}^b - at_{i,j-1}^b))^2}{2\sigma^2\Delta t_{ij}}]. \tag{3.10}$$

Taking the first order of equation (3.10) with respect to a and σ^2, the following equation is then obtained.

$$a = \sum_{i=1}^{n}\sum_{j=1}^{m_i}\frac{\Delta x_{ij}(t_{ij}^b - t_{i,j-1}^b)}{\sigma^2\Delta t_{ij}} \Big/ \sum_{i=1}^{n}\sum_{j=1}^{m_i}\frac{(t_{ij}^b - t_{i,j-1}^b)^2}{\sigma^2\Delta t_{ij}} \tag{3.11}$$

$$\sigma^2 = \sum_{i=1}^{n}\sum_{j=1}^{m_i}[\frac{(\Delta x_{ij} - (t_{ij}^b - t_{i,j-1}^b))^2}{\Delta t_{ij}}] \Big/ \sum_{i=1}^{n} m_i \tag{3.12}$$

This means that a and σ^2 are both functions of b. Substituting the above into the log-likelihood function (3.10), we can get the univariate function of the unknown parameter b and further obtain the estimation of b by solving for its extremum value. In addition, taking this estimation result into equation (3.11) and (3.12), the maximum likelihood estimations of a and σ^2 can be obtained. Similarly, for $\mu(t) = a(1 - e^{tb})$, we can get the maximum likelihood estimation.

IV. EMPIRICAL STUDY

In an experiment assessing anti-radiation ability, three kinds of data may be collected: the binary data, the failure data and the degradation data. While testing a batch of products, we continue increasing the threat level (e.g., the cumulative doses) and test the product performances at regular intervals or under certain threat levels. The performance data is defined as the degradation data. With a regression analysis of the degradation data, the functional relationship between the product performance and time or threat level can be obtained. In this paper, the degradation data is chosen as a basis for analysis. The N-channel MOSFET power device named STRH60N20FSY3 and produced by STM was used to perform the radiation test. The test setting, test data and the preliminary analysis results are reported in ESA_QEC RA0572. The test sample in this study is taken from the "lot 3922168" prototype product. The information provided by the manufacturer shows that the package type of the prototype product is TO3 and that its time code is 30946A. To better evaluate the recovery/rebound performance of the device after radiation, aging and annealing tests are also performed.

The total sample size is 24, excluding the reference sample used for comparison. The experiment scheme is as follows: under the test conditions shown in Table 1, measure the electrical parameters of the sample while the radiation dose reaches 0, 3, 10, 20, 30, 50, 75, 85, 110 krad (Si), +/−10% of the total dose. The Unimet 3000 (s/n 0639001) is used during the measurement.

After the radiation test, anneal the samples at room temperature for 166 hours, and measure the electrical parameters at 30 hours, 77 hours and 166 hours. In addition, perform the aging procedure at 100° for 830 hours in order to complete the investigation of other similar equipment with the time dependent effects (such as the N-channel MOSFET device maned STRH40N6SY3; see report RA558). The electrical

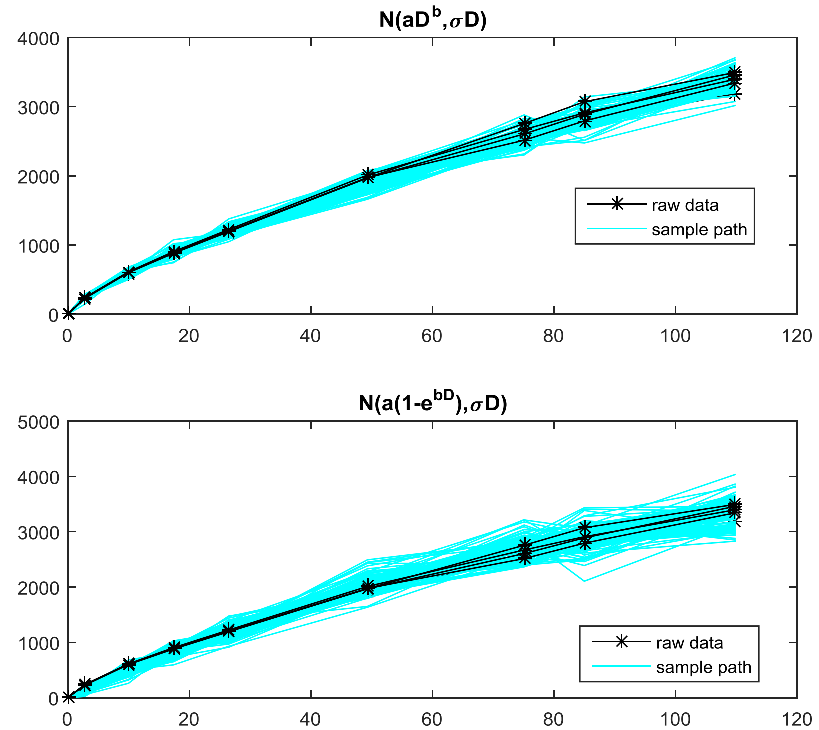

FIGURE 1. The imitative effect comparison under the bias condition BC1.

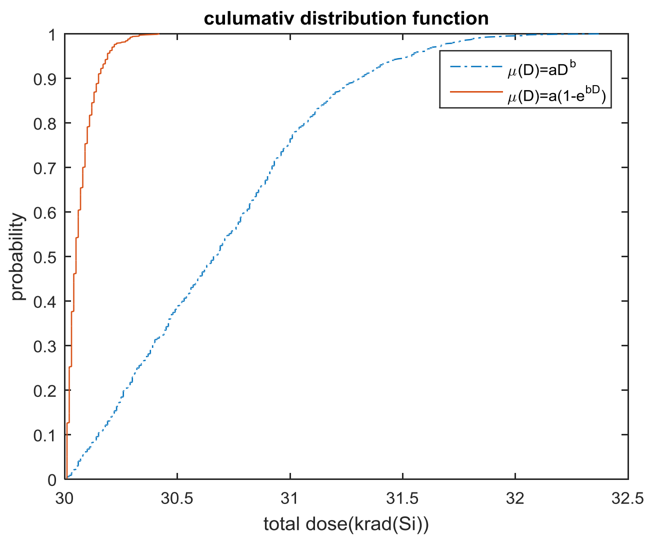

FIGURE 2. The survival function of different models under BC1.

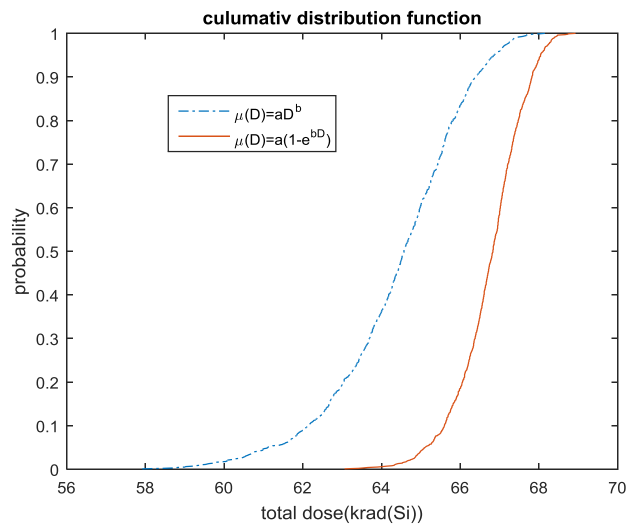

FIGURE 3. The survival function of different models under BC2.

parameters are measured at 5, 8, 24, 54, 76, 99, 188 and 355 hours. The test sample numbers and their bias conditions are shown in Table 2.

When the radiation dose reaches 2.8 krad(Si), samples 006 and 007 experienced critical failure. Therefore, they are replaced by the other five samples, namely 020, 021, 022, 023 and 024. No other critical failures are observed afterwards. Unit 018 and 019 are tested under bias condition BC5. Since the degradation data under BC5 is too small, we only perform the analysis for other four bias conditions. Readers may refer to the report ''ESA-QEC RA0572'' and Song et al. (2017) for the detailed test setting, procedure, experimental data and preliminary analysis results. The figures of the relationship between threshold voltage and total dose under different bias conditions can also be found there. The intuitive analysis shows that different parameters have various dependences on the radiation doses and bias conditions. Selecting the threshold voltage VGS_th@ID 0.01 mA

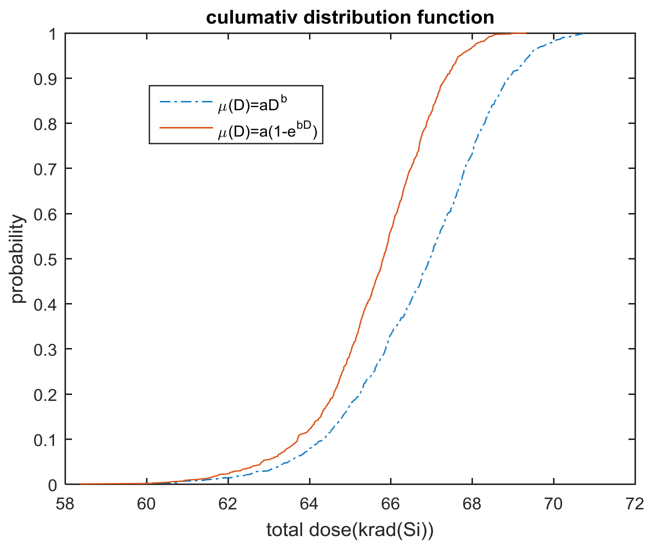

FIGURE 4. The survival function of different models under BC3.

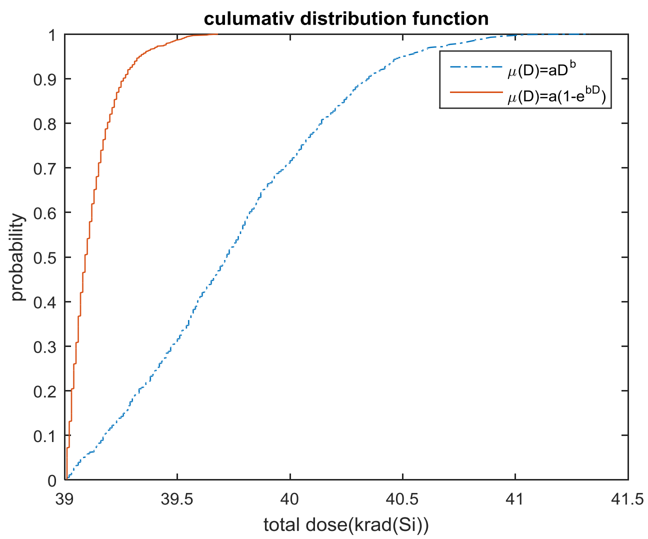

FIGURE 5. The survival function of different models under BC4.

as the radiation-sensitive parameter, the relationship between the anti-radiation ability and related factors are examined. According to the test data, the Wiener degradation model is constructed for the N-channel MOSFET power device named STRH60N20FSY3. Since the degradation process is nonlinear, a corresponding nonlinear Wiener degradation model is proposed. Specifically, under the cumulative dose D, the performance distribution is a normal distribution $X(D) \sim N(\mu(D), D\sigma^2)$, where $\mu(D)$ and $D\sigma^2$ denote the mean and variance, respectively. In addition, note that $\mu(D)$ is a nonlinear function of D.

Two types of average degradation are considered: $\mu(D) = aD^b$ and $\mu(D) = a(1 - e^{Db})$. According to the maximum likelihood estimation in Section 3, the estimation results for the parameters are shown in Table 3.

Figure 1 shows the simulation results of the different models under bias condition 1. The comparison is between 100 sample paths and the original data. It is obvious that both models perform well in fitting the experimental data, but the exponential model better matches the change trend, especially with large radiation doses.

TABLE 4. Performance evaluation results of the anti-radiation.

Bias condition	Model I	Model II
BC1	30.6946	30.0687
BC2	64.3963	66.7417
BC3	66.7344	65.6397
BC4	39.7495	39.1236

The mean square error (MSE) of the models is calculated to quantitatively evaluate the fitting effects. For a given degradation process model $\{X(t), t \geq 0\}$, MSE is defined as follows.

$$MSE = \sum_{i=1}^{n} \sum_{j=1}^{m_i} \left[\hat{F}(t_{ij}) - \tilde{F}(x_{ij})\right]^2$$

where $\hat{F}(t_{ij})$ denotes the estimated distribution of $X(t)$ and $\tilde{F}(x_{ij})$ denotes the empirical distribution function of $X(t)$ at time t_{ij}.

$$\tilde{F}(x_{ij}) = \frac{\begin{array}{c}\#(\textit{the number of measured values} \\ \textit{less than or equal to } x_{ij} \textit{ at time } t_{ij})\end{array}}{\#(\textit{the number of measured values at time } t_{ij})}$$

Table 4 displays the MSE values for two models. The results show that the exponential model generally performs slightly better than the polynomial model.

In the following, the anti-radiation performance based on the degradation process is evaluated; that is, the average anti-radiation and survival probability are tested. Because the drift function is nonlinear, the analytical form of the survival function is hard to obtain. Here, the Monte Carlo method is carried out to settle this problem. Table 4 shows the average anti-radiation evaluation results under different bias conditions, and Figures 2-5 display the corresponding survival functions.

V. CONCLUSION

In this paper, the unit anti-radiation performance measurement and evaluation models are proposed based on the Wiener degradation process. The models are applicable for describing the unit performance change rules along with the total radiation dose levels when there exist total dose effects and displacement damage effects. Our modeling process can make full use of the unit performance changes during the radiation test, which is conducive to obtaining credible estimates of the unit anti-radiation when the sample size is small. Furthermore, it is easy to calculate the following items: the radiation dose (or its probability distribution) when the unit anti-radiation fails, the distribution of the unit performance and the radiation-sensitive parameters at an arbitrary radiation dose, and the probability that the unit performance will exceed or fall below a specific value. Through the experimental analysis of the N-channel MOSFET power device named

STRH60N20FSY3, we verify that the proposed approach can provide a reliable description of the unit anti-radiation performance degradation process. In addition, various uncertainties concerning the unit anti-radiation performance are well reflected.

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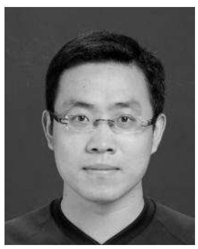

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