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An Adaptive Reliability Prediction Method for the Intelligent Satellite Power Distribution System

JUN WANG AND YUBIN TIAN
School of Mathematics and Statistics, Beijing Institute of Technology, Beijing100081, China

Corresponding author: Yubin Tian (tianyubin2017@hotmail.com)

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ABSTRACT The accurate prediction of reliability for long-time running intelligent satellite power distribution systems is crucial in engineering. In this paper, an adaptive method is proposed to achieve this goal. Based on lifetime and degradation data, an estimator of the reliability for the system is derived by mainly using an additive degradation model of combined Poisson and Gaussian processes. A locally c-optimal approach to choosing effective data from the real-time data flow is given. Associated with the sequence of observed lifetime and degradation data, a robust criterion is proposed to determine an appropriate data subset for reliability prediction. A simulation study shows that the proposed method gives superior performance over the traditional method. Benefiting from adaptive and optimal strategies, the reliability predictions for 16 to 20 years obtained from the proposed method are convincing even if the initial models fitted by the ground test data have deviations from the true models.

INDEX TERMS Satellite, intelligent power distribution system, reliability prediction, adaptive estimation, recursive maximum likelihood.

I. INTRODUCTION

The intelligent satellite power distribution system, dubbed ISPDS for brevity, is an energy management system that was developed for new satellites. Since it operate work 15∼20 years in orbit, a more precise prediction method is one of the most important issues concerning field use.

For such long-running systems, reliability prediction has attracted more and more interest in reliability analysis. Mori and Ellingwood [1] used the adaptive importance sampling method to evaluate the time-dependent reliability of a structural system. In their paper they updated the estimation of the mean vector of the optimal importance variable until no significant improvement in accuracy was obtained. Wong *et al.* [2] proposed an adaptive design approach for non-linear finite element analysis to predict the reliability levels of structures. Xu *et al.* [3] provided a real-time reliability prediction method for a dynamic system based on the hidden degradation process identification by the recursive maximum likelihood method. Ma *et al.* [4] presented monotone degradation models and applied the Bayesian method to update the estimation of parameters for real-time reliability analysis. Fan *et al.* [5] proposed the degradation-data- driven method to predict the reliability of high-power white light–emitting diodes based on a general degradation model and nonlinear least squares estimation. Peng *et al.* [6] investigated a Bayesian approach, which combined lifetime data with degradation data to analyze and predict system reliability. Jiang *et al.* [7] proposed a novel time-variant reliability analysis method based on stochastic process discretization which is extremely useful for assessing design reliability of a complex structure. Zhang *et al.* [8] proposed an interval PHI2 method to creatively solve the time-dependent reliability for random problems with the interval distribution parameters. Liu *et al.* [9] established a non-linear and non-Gaussian state space model, predicted the degrading tendency by the particle filter algorithm, and then calculated the conditional reliability based on a Bayesian frame. Hao *et al.* [10] proposed a new degradation model with a random effect independent increment process and iteratively updated the parameters by using the Bayesian method. Zhang *et al.* [11] proposed a novel approach with response surface to estimate the time-dependent reliability for nondeterministic structures by effectively generating a Gaussian stochastic process. Cai *et al.* [12] proposed a WCF approach to estimate the lower confidence limit of the reliability for Solid State Power Controller which is a part of the ISPDS. Pan *et al.* [13] proposed a reliability estimation approach based on the EM (Expectation Maximization) algorithm and the Wiener process.

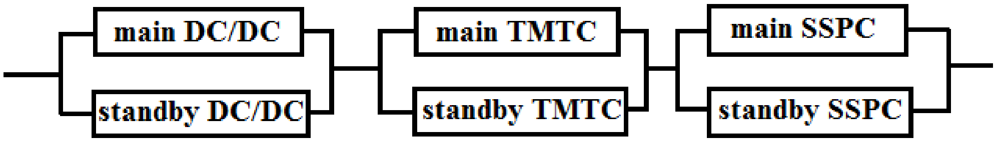

FIGURE 1. Structure of the intelligent satellite power distribution system

For primary satellite power distribution systems, engineers often use accelerated degradation ground test data to establish a degradation model and then predict the reliability of the system for 15∼20 years. However, the predicted results are not typically convincing, because no real-time data are used. If real-time observations of the system could be obtained, a prediction based on a combination of ground test data and real-time observations might be more accurate. It is fortunate that intelligent satellite power distribution systems (ISPDS) can record operating data so that we can obtain the real-time data flow. The difference is that the degradation model of its main component is an additive model of the Gauss and Poisson processes. Another important factor is that we can obtain a real-time data flow. How to extract useful information from the real-time data flow to develop a good reliability prediction has received scant attention in the literature.

The main purpose of this paper is to develop a new adaptive method that can predict the reliability of ISPDS more accurately by efficiently exploiting the information from ground test data and real-time data flow in orbit. The method includes a locally c-optimal procedure and a robust criterion to choose effective data from real-time data flow and develop an adaptive reliability prediction based on the recursive maximum likelihood estimation. In section II, a reliability model for the intelligent satellite power distribution system is given based on exponential distributions and an additive degradation model of Poisson and Gaussian processes. In section III, a locally c-optimal procedure and a robust criterion are proposed methods for choosing effective data from data flow. Thus, the explicit expression of the reliability prediction is developed based on the real-time lifetime data and the real-time degradation data. Section IV gives one example to illustrate the key steps of the proposed method. Simulation comparisons of the proposed method with traditional predictions used in practice are given in Section V. Concluding remarks are given in Section VI.

II. THE RELIABILITY MODEL FOR ISPDS

The intelligent satellite power distribution system is composed of a power convert module, an intelligent management module, and a solid-state power controller module. The power convert module contains a main DC/DC converter (DC/DC) and a warm standby redundancy. The intelligent management module uses a cold standby redundant structure with two telemetry and telecontrol devices (TMTC). The solid state power controller module has a main solid state power controller (SSPC) and a warm standby SSPC. Fig. 1 shows the basic structure of the intelligent satellite power distribution system.

Suppose that the lifetime $T_{DC/DC}$ of DC/DC and the lifetime T_{TMTC} of TMTC follow the exponential distributions,

$$T_{DC/DC} \sim f_1(t) = \lambda_1 e^{-\lambda_1 t}, \quad (1)$$

$$T_{TMTC} \sim f_2(t) = \lambda_2 e^{-\lambda_2 t}. \quad (2)$$

where λ_1 and λ_2 are the failure rates of DC/DC and TMTC, respectively.

The lifetime T_{SSPC} of SSPC is determined by the degradation value of the Rdson $r(t)$ of its main component, MOSEFT,

$$T_{SSPC} = \inf\{t : r(t)/r(0) \geq l, t > 0\}, \quad (3)$$

where $x(t) = \ln r(t) = \beta n_1(t) + \gamma n_2(t) + \alpha t + x(0) + \varepsilon$, $n_1(t)$ is the number of switches of the MOSEFT, $n_2(t)$ denotes the number of short circuits, $r(0) = \exp(x(0))$ is the initial value of Rdson, and ε is the error. In engineering research, the following assumptions have been commonly used: ε is normally distributed with mean 0 and variance σ^2, and $n_1(t)$ and $n_2(t)$ follow the Poisson processes with parameters τ_1 and τ_2, respectively. Note that when the main SSPC is still operating, the redundant SSPC is on warm standby and is also connected to the loads, but it does not suffer the shocks of switches and short circuits.

Let T_{11} and T_{12} be the lifetimes of the main DC/DC and the standby DC/DC, T_{21} and T_{22} be the lifetimes of the main TMTC and the standby TMTC, and T_{31} and T_{32} be the lifetimes of the main SSPC and the standby SSPC, respectively. Furthermore, let T_1 be the lifetime of the power convert module, T_2 be the lifetime of the intelligent management module, and T_3 be the lifetime of the solid-state power controller module. Thus, the lifetime T of ISPDS can be written as

$$T = \min\{\max(T_{11}, T_{12}), T_{21} + T_{22}, T_3\}. \quad (4)$$

If we know that the system is in operation at time t, the reliability model of the system at time y is given by

$$\begin{aligned} R(y; t) &= P\{T > y | T > t\} \\ &= P\{\max(T_{11}, T_{12}) > y | T_1 > t\} \\ &\quad \cdot P\{T_{21} + T_{22} > y | T_2 > t\} \\ &\quad \cdot P\{T_3 > y | T_3 > t\}. \quad (5) \end{aligned}$$

From the exponential distribution, we have

$$\begin{aligned} &P\{\max(T_{11}, T_{12}) > y | T_1 > t\} \\ &\quad = 1 - P\{\max(T_{11}, T_{12}) \leq y | T_1 > t\} \\ &\quad = 1 - \frac{P\{\max(T_{11}, T_{12}) \leq y, \max(T_{11}, T_{12}) > t)\}}{P\{\max(T_{11}, T_{12}) > t\}} \end{aligned}$$

$$
\begin{aligned}
&= 1 - \frac{P\{t < T_{11} \le y\}P\{T_{12} \le y\}}{1 - P\{T_{11} \le t\}P\{T_{12} \le t)\}} \\
&\quad - \frac{P\{T_{11} \le y\}P\{t < T_{12} \le y\}}{1 - P\{T_{11} \le t\}P\{T_{12} \le t\}} \\
&\quad + \frac{P\{t < T_{11} \le y\}P\{t < T_{12} \le y\}}{1 - P\{T_{11} \le t\}P\{T_{12} \le t\}} \\
&= 1 - \frac{(e^{-\lambda_1 t} - e^{-\lambda_1 y})(2 - e^{-\lambda_1 t} - e^{-\lambda_1 y})}{1 - (1 - e^{-\lambda_1 t})^2}. \quad (6)
\end{aligned}
$$

Since T_{21} and T_{22} are independent and both follow exponential distribution with failure rate λ_2, then $T_{21} + T_{22}$ follows $Gamma(2, \lambda_2)$ distribution; thus, we have

$$
\begin{aligned}
&P\{T_{21} + T_{22} > y | T_2 > t\} \\
&= 1 - P\{T_{21} + T_{22} \le y | T_2 > t\} \\
&= 1 - \frac{P\{t < T_{21} + T_{22} \le y\}}{P\{T_{21} + T_{22} > t\}} \\
&= 1 - \frac{(1 - \lambda_2 y e^{-\lambda_2 y} - e^{-\lambda_2 y}) - (1 - \lambda_2 t e^{-\lambda_2 t} - e^{-\lambda_2 t})}{1 - (1 - \lambda_2 t e^{-\lambda_2 t} - e^{-\lambda_2 t})} \\
&= e^{-\lambda_2 (y-t)} \frac{\lambda_2 y + 1}{\lambda_2 t + 1}. \quad (7)
\end{aligned}
$$

If the main SSPC is still working at time t, we obtain

$$
\begin{aligned}
&P\{T_3 > y | T_{31} > t\} \\
&= P\{T_{31} \le y, T_{32} > y | T_{31} > t\} + P\{T_{31} > y | T_{31} > t\} \\
&= \frac{1}{y-t} \int_t^y P(t < T_{31} \le z, T_{32} > y | T_{31} > t) dz \\
&\quad + \frac{P\{T_{31} > y\}}{P\{T_{31} > t\}} \\
&= \frac{1}{y-t} \frac{\int_t^y P(t < T_{31} \le z) P(T_{32} > y) dz}{P(T_{31} > t)} + \frac{P\{T_{31} > y\}}{P\{T_{31} > t\}} \\
&= \frac{\int_t^y A_1(z;t) A_2(y;z) dz}{(y-t) P\{x(t) - x(0) < \ln l\}} \\
&\quad + \frac{P\{x(y;t) - x(0) < \ln l\}}{P\{x(t) - x(0) < \ln l\}}, \quad (8)
\end{aligned}
$$

where

$$
\begin{aligned}
A_1(z;t) &= P\{x(t) - x(0) < \ln l, x(z;t) - x(0) \ge \ln l\} \\
A_2(y;z) &= P\{\tilde{x}(y;z) - x(0) < \ln l\} \\
x(t) &= \beta n_1(t) + \gamma n_2(t) + \alpha t + x(0) + \varepsilon_1, \\
x(z;t) &= x(t) + \beta n_1(z-t) + \gamma n_2(z-t) + \alpha(z-t), \\
\tilde{x}(y;z) &= \beta n_1(y-z) + \gamma n_2(y-z) + \alpha y + x(0) + \varepsilon_2, \\
&\qquad \varepsilon_1, \varepsilon_2 \ i.i.d. \sim N(0, \sigma^2).
\end{aligned}
$$

If the main SSPC failed at time $t_0 \le t$, then we obtain

$$
\begin{aligned}
P\{T_3 > y | T_3 > t\} &= P\{T_{32} > y | T_{32} > t\} \\
&= \frac{P\{T_{32} > y\}}{P\{T_{32} > t\}} \\
&= \frac{P\{\bar{x}(y) - x(0) < \ln l\}}{P\{\bar{x}(t) - x(0) < \ln l\}}, \quad (9)
\end{aligned}
$$

where

$$
\bar{x}(z) = \beta n_1(z - t_0) + \gamma n_2(z - t_0) + \alpha z + x(0) + \varepsilon_3, \quad \varepsilon_3 \sim N(0, \sigma^2).
$$

Let $i_{SSPC}(t, t_{SSPC,0}) = 1$ or 0 denote the switch status of the main SSPC at time t, switch (occurred at time $t_{SSPC,0}$), or not switch ($t_{SSPC,0} = 0$). Then, the two above formulas can be combined as follows:

$$
\begin{aligned}
&P\{T_3 > y | T_3 > t\} \\
&= \left\{ \frac{\int_t^y A_1(z;t) A_2(y;z) dz}{(y-t) P\{x(t) - x(0) < \ln l\}} + \frac{P\{x(y;t) - x(0) < \ln l\}}{P\{x(t) - x(0) < \ln l\}} \right\} \cdot \{1 - i_{SSPC}(t; t_{SSPC,0})\} \\
&\quad + \frac{P\{\bar{x}(y) - x(0) < \ln l\}}{P\{\bar{x}(t) - x(0) < \ln l\}} i_{SSPC}(t; t_{SSPC,0}) \quad (10)
\end{aligned}
$$

III. ADAPTIVE PREDICTION OF THE RELIABILITY

A. ESTIMATION OF THE RELIABILITY BY ADDING A NEW OBSERVATION

Let $Y(t) = \{t_{11}(t), t_{12}(t), i_{DC/DC}(t; t_{DC/DC,0}), t_{21}(t), t_{22}(t), i_{TMTC}(t; t_{TMTC,0}), x_1(t), x_2(t), n_1(t), n_2(t)$, and $i_{SSPC}(t; t_0)\}$ be the observed data of ISPDS at time t in orbit, where $t_{11}(t)$ and $t_{12}(t)$ are lifetimes (or truncated lifetimes) of the main DC/DC and the standby DC/DC, $t_{21}(t)$ and $t_{22}(t)$ are lifetimes (or truncated lifetimes) of the main TMTC and the standby TMTC, $x_1(t)$ and $x_2(t)$ are the degradation values for the Rdsons of MOSEFTs in the main SSPC and in the standby SSPC, and $n_1(t)$ and $n_2(t)$ are the number of switches and short-circuits suffered by the MOSEFTs, respectively. Similarly, we use $i_{DC/DC}(t; t_{DC/DC,0})$ and $i_{TMTC}(t; t_{TMTC,0})$ to denote the switch status of the main DC/DC and the main TMTC, respectively. Since the purpose of this paper is to predict the reliability of the system after t hours of operation, we always assume $t_{12}(t)$ and $t_{22}(t)$ are truncated lifetimes.

Assume we have collected data $Y_1, \ldots, Y_n$ at times $t_1, \ldots, t_n$. (This includes the case of not having any new observation in orbit, for which $n = 0$). Based on these data, we can compute the maximum likelihood estimates (MLEs) $\hat{\lambda}_1(t_1, \ldots, t_n)$ and $\hat{\lambda}_2(t_1, \ldots, t_n)$ of λ_1 and λ_2 based on the likelihood functions $L_1(t_1, \ldots, t_n)$ and $L_2(t_1, \ldots, t_n)$. Additionally, we have MLEs $\hat{\alpha}(t_1, \ldots, t_n)$, $\hat{\beta}(t_1, \ldots, t_n)$, $\hat{\gamma}(t_1, \ldots, t_n)$, and $\hat{\sigma}^2(t_1, \ldots, t_n)$ of α, β, γ, and σ^2 from the likelihood function $L_3(t_1, \ldots, t_n)$. If we only have the ground data ($n = 0$), the likelihood functions for DC/DC, TMTC, and SSPC are denoted by L_{01}, L_{02}, and L_{03}, respectively. The corresponding MLEs for λ_1, λ_2, α, β, γ, and σ^2 are $\hat{\lambda}_{10}$, $\hat{\lambda}_{20}$, $\hat{\alpha}_0$, $\hat{\beta}_0$, $\hat{\gamma}_0$, and $\hat{\sigma}_0^2$.

Let $\max\{\phi\} = 0$, where ϕ is an empty set. For DC/DC, adding the new observations $t_{11}(t)$, $t_{12}(t)$, and $i_{DC/DC}(t; t_{DC/DC,0})$ at $t > t_n$, the updated likelihood is given by

$$
\begin{aligned}
&L_1(t_1, \ldots, t_n, t) \\
&\propto L_{01} \cdot \{\lambda_1 e^{-\lambda_1 t_{DC/DC,0}} e^{-\lambda_1 t_{12}(t)}\}^{i_{DC/DC}(t, t_{DC/DC,0})} \\
&\quad \cdot \{e^{-\lambda_1 t_{11}(t)} e^{-\lambda_1 t_{12}(t)}\}^{1 - i_{DC/DC}(t, t_{DC/DC,0})} \quad (11)
\end{aligned}
$$

and the updated MLE $\hat{\lambda}_1(t_1, \ldots, t_n, t)$ of λ_1 can be obtained by minimizing $-\log L_1(t_1, \ldots, t_n, t)$. Thus, the reliability estimate of the power convert module is updated by

$$\begin{aligned}\hat{R}_1(y;t_1,\ldots,t_n,t) &= P\{T_1 > y|T_1 > t\}\\ &= 1-\frac{B_1(y;t_1,\ldots,t_n,t)B_2(y;t_1,\ldots,t_n,t)}{1-\left(1-e^{-\hat{\lambda}_1(t_1,\ldots,t_n,t)t}\right)^2}.\end{aligned} \quad (12)$$

where

$$B_1(y;t_1,\ldots,t_n,t) = e^{-\hat{\lambda}_1(t_1,\ldots,t_n,t)t} - e^{-\hat{\lambda}_1(t_1,\ldots,t_n,t)y},$$
$$B_2(y;t_1,\ldots,t_n,t) = 2-e^{-\hat{\lambda}_1(t_1,\ldots,t_n,t)t} - e^{-\hat{\lambda}_1(t_1,\ldots,t_n,t)y}$$

Similarly, we have the updated likelihood,

$$\begin{aligned}L_2(t_1,\ldots,t_n,t) &\propto L_{02}\cdot\{\lambda_2 e^{-\lambda_2 t_{TMTC,0}} e^{-\lambda_2 t_{22}(t)}\}^{i_{TMTC}(t;t_{TMTC,0})}\\ &\quad\cdot\{e^{-\lambda_2 t_{21}(t)}\}^{1-i_{TMTC}(t;t_{TMTC,0})},\end{aligned} \quad (13)$$

the estimate $\hat{\lambda}_2(t_1,\ldots,t_n,t)$ of λ_2 and the updated reliability estimate for the intelligent management module,

$$\hat{R}_2(y;t_1,\ldots,t_n,t) = e^{-\hat{\lambda}_2(t_1,\ldots,t_n,t)(y-t)}\frac{\hat{\lambda}_2(t_1,\ldots,t_n,t)y+1}{\hat{\lambda}_2(t_1,\ldots,t_n,t)t+1}. \quad (14)$$

Let For SSPC, adding the new observations $x_1(t)$, $x_2(t)$, $n_1(t)$, $n_2(t)$, and $i_{\text{SSPC}}(t;t_0)$, the updated likelihood function can be expressed as

$$\begin{aligned}L_3(t_1,\ldots,t_n,t) &\propto L_3(t_1,\ldots,t_n)\\ &\quad\cdot C_1(t;\alpha,\beta,\gamma)^{[1-i_{SSPC}(t;t_0)]}\\ &\quad\cdot C_1(t_0;\alpha,\beta,\gamma)^{i_{SSPC}(t;t_0)\cdot\{1-\max[i_{SSPC}(t_n;t_0),\ldots,i_{SSPC}(t_1;t_0)]\}}\\ &\quad\cdot C_2(t,t_0;\alpha,\beta,\gamma)^{i_{SSPC}(t;t_0)}\end{aligned} \quad (15)$$

where

$$C_1(t;\alpha,\beta,\gamma) = \frac{1}{\sigma}\exp\left\{-\frac{1}{2\sigma^2}[x_1(t)-(\beta n_1(t)+\gamma n_2(t)+\alpha t+x(0))]^2\right\}$$
$$C_2(t,t_0;\alpha,\beta,\gamma) = \frac{1}{\sigma}\exp\left\{-\frac{1}{2\sigma^2}[x_2(t)-(\beta n_1(t-t_0)+\gamma n_2(t-t_0)+\alpha t+x(0))]^2\right\}$$

which gives the updated MLEs $\hat{\beta}(t_1,\ldots,t_n,t)$, $\hat{\alpha}(t_1,\ldots,t_n,t)$, $\hat{\gamma}(t_1,\ldots,t_n,t)$, and $\hat{\sigma}^2(t_1,\ldots,t_n,t)$ of β,α,γ, and σ^2. Thus, the degradation curve of the Rdson of MOSFET is updated by

$$\begin{aligned}x(z;t_1,\ldots,t_n,t) &= \hat{\beta}(t_1,\ldots,t_n,t)n_1(z)+\hat{\gamma}(t_1,\ldots,t_n,t)n_2(z)\\ &\quad+\hat{\alpha}(t_1,\ldots,t_n,t)z+x(0)+\varepsilon,\\ &\qquad\varepsilon\sim N(0,\hat{\sigma}^2(t_1,\ldots,t_n,t)).\end{aligned} \quad (16)$$

From the above updated curve, the reliability estimate for the solid state power controller module becomes

$$\begin{aligned}\hat{R}_3(y;t_1,\ldots,t_n,t) &= P\{T_3 > y|T_3 > t\}\\ &= \left\{\frac{\int_t^y A_3(z;t_1,\ldots,t_n,t)A_4(y,z;t_1,\ldots,t_n,t)dz}{(y-t)P\{x(t_1,\ldots,t_n,t)-x(0)<\ln l\}}\right.\\ &\quad\left.+\frac{P\{x(y;t_1,\ldots,t_n,t)-x(0)<\ln l\}}{P\{x(t_1,\ldots,t_n,t)-x(0)<\ln l\}}\right\}\\ &\quad\cdot\{1-i_{SSPC}(t;t_{SSPC,0})\}\\ &\quad+\frac{P\{\bar{x}(y;t_1,\ldots,t_n,t)-x(0)<\ln l\}}{P\{\bar{x}(t;t_1,\ldots,t_n,t)-x(0)<\ln l\}}i_{SSPC}(t;t_{SSPC,0}),\end{aligned} \quad (17)$$

where

$$\begin{aligned}A_3(z;t_1,\ldots,t_n,t) &= P\{x(t_1,\ldots,t_n,t)-x(0)<\ln l,\\ &\qquad x(z;t_1,\ldots,t_n,t)-x(0)\geq\ln l\},\\ A_4(y,z;t_1,\ldots,t_n,t) &= P\{\tilde{x}(y,z;t_1,\ldots,t_n,t)-x(0)<\ln l\},\\ x(t_1,\ldots,t_n,t) &= \hat{\beta}(t_1,\ldots,t_n,t)n_1(t)+\hat{\gamma}(t_1,\ldots,t_n,t)n_2(t)\\ &\quad+\hat{\alpha}(t_1,\ldots,t_n,t)t+x(0)+\varepsilon_1(t_1,\ldots,t_n,t),\\ x(z;t_1,\ldots,t_n,t) &= x(t_1,\ldots,t_n,t)+\hat{\beta}(t_1,\ldots,t_n,t)n_1(z-t)\\ &\quad+\hat{\gamma}(t_1,\ldots,t_n,t)n_2(z-t)+\hat{\alpha}(t_1,\ldots,t_n,t)(z-t),\\ \tilde{x}(y,z;t_1,\ldots,t_n,t) &= \hat{\beta}(t_1,\ldots,t_n,t)n_1(y-z)\\ &\quad+\hat{\gamma}(t_1,\ldots,t_n,t)n_2(y-z)+\hat{\alpha}(t_1,\ldots,t_n,t)y\\ &\quad+x(0)+\varepsilon_2(t_1,\ldots,t_n,t),\\ \bar{x}(z;t_1,\ldots,t_n,t) &= \hat{\beta}(t_1,\ldots,t_n,t)n_1(z-t_{SSPC,0})\\ &\quad+\hat{\gamma}(t_1,\ldots,t_n,t)n_2(z-t_{SSPC,0})+\hat{\alpha}(t_1,\ldots,t_n,t)z\\ &\quad+x(0)+\varepsilon_3(t_1,\ldots,t_n,t),\\ \varepsilon_1(T_1,\ldots,T_n,t),\ &\varepsilon_2(T_1,\ldots,T_n,t),\ \varepsilon_3(T_1,\ldots,T_n,t)\, i.i.d.\\ &\qquad\sim N(0,\hat{\sigma}(t_1,\ldots,t_n,t)^2).\end{aligned}$$

Combining Eqs.(12), (14) and (17), we obtain the reliability estimate of the system,

$$\begin{aligned}\hat{R}(y;t_1,\ldots,t_n,t) &= \hat{R}_1(y;t_1,\ldots,t_n,t)\cdot\hat{R}_2(y;t_1,\ldots,t_n,t)\\ &\quad\cdot\hat{R}_3(y;t_1,\ldots,t_n,t).\end{aligned} \quad (18)$$

B. A LOCALLY C-OPTIMAL APPROACH TO CHOOSE THE SEQUENCE OF OBSERVATIONS

Based on the data $Y_1,\ldots,Y_n$ at times $t_1,\ldots,t_n$, for effective reliability prediction of the system in future y hours, we choose the new observations at time t_{n+1} by the following scheme:

$$t_{n+1} = \arg\min_t Var\left\{\hat{R}(y; t_1, \ldots, t_n, t)\right\}$$
$$= Var\left\{\hat{R}_1(y; t_1, \ldots, t_n, t) \cdot \hat{R}_2(y; t_1, \ldots, t_n, t) \cdot \hat{R}_3(y; t_1, \ldots, t_n, t)\right\}, \tag{19}$$

where the variance is calculated under the joint distribution of observations at time t and conditioned on $Y_1, \ldots, Y_n$.

Clearly, the variance in Eq.(19) is difficult to compute with the exact joint distribution of observations at time t. Therefore, we resort to approximation by the sequential bootstrap method. The approximation is completed in six steps:

(1) Simulate the observation $t_{11}(t)$, $t_{12}(t)$, $i_{DC/DC}(t; t_{DC/DC,0})$ of DC/DC according to the exponential distribution with parameter $\hat{\lambda}_1(t_1, \ldots, t_n)$. Let $T_{11} \sim Exp(\hat{\lambda}_1(t_1, \ldots, t_n))$ and $T_{12} \sim Exp(\hat{\lambda}_1(t_1, \ldots, t_n))$. Then,

$$t_{11}(t) = \min(T_{11}, t), \tag{20}$$
$$t_{12}(t) = \min(T_{12}, t), \tag{21}$$
$$i_{DC/DC}(t; t_{DC/DC,0}) = \begin{cases} 1, & T_{11} < t \\ 0, & T_{11} \geq t, \end{cases} \tag{22}$$
$$t_{DC/DC,0} = \begin{cases} T_{11}, & T_{11} < t \\ 0, & T_{11} \geq t. \end{cases} \tag{23}$$

Similarly, simulate the observations of TMTC. Let $T_{21} \sim Exp(\hat{\lambda}_1(t_1, \ldots, t_n))$ and $T_{22} \sim Exp(\hat{\lambda}_1(t_1, \ldots, t_n))$. Then,

$$t_{21}(t) = \min(T_{21}, t), \tag{24}$$
$$i_{TMTC}(t; t_{TMTC,0}) = \begin{cases} 1, & T_{21} < t \\ 0, & T_{21} \geq t, \end{cases} \tag{25}$$
$$t_{TMTC,0} = \begin{cases} T_{21}, & T_{21} < t \\ 0, & T_{21} \geq t. \end{cases} \tag{26}$$

If $t_{TMTC,0} \neq 0$, we get

$$t_{22}(t) = \min\{T_{22}, t - t_{TMTC,0}\}. \tag{27}$$

(2) Calculate the updated estimates for R_1 and R_2 based on the above simulated observations,

$$\hat{R}_1(y; t_1, \ldots, t_n, t) = 1 - \frac{B_1(y; t_1, \ldots, t_n, t) B_2(y; t_1, \ldots, t_n, t)}{1 - \left(1 - e^{-\hat{\lambda}_1(t_1, \ldots, t_n, t)t}\right)^2} \tag{28}$$

$$\hat{R}_2(y; t_1, \ldots, t_n, t) = e^{-\hat{\lambda}_2(t_1, \ldots, t_n, t)(y-t)} \frac{\hat{\lambda}_2(t_1, \ldots, t_n, t)y + 1}{\hat{\lambda}_2(t_1, \ldots, t_n, t)t + 1}. \tag{29}$$

(3) Simulate $n_1(t)$ and $n_2(t)$ according to $Poisson(\tau_1 \cdot t)$ and $Poisson(\tau_2 \cdot t)$. Simulate $\varepsilon_1(t_1, \ldots, t_n)$ from the normal distribution $N(0, \hat{\sigma}^2(t_1, \cdots, t_n))$. Calculate the Rdson values $x_1(t)$ based on the regression function

$$x_1(t) = \hat{\beta}(t_1, \ldots, t_n) n_1(t) + \hat{\gamma}(t_1, \ldots, t_n) n_2(t) + \hat{\alpha}(t_1, \ldots, t_n) t + x(0) + \varepsilon_1(t_1, \ldots, t_n). \tag{30}$$

If $x(t) - x(0) \geq \ln l$, it indicates that $i_{SSPC}(t; t_{SSPC,0}) = 1$. From the Poisson process, the arriving times of $n_1(t)$ switches are the realized values of order statistics $u_{11} < \ldots < u_{1n_1(t)}$ generated from uniform distribution $U(0, t)$. Similarly, the arriving times of $n_2(t)$ short-circuits are values $u_{21} < \ldots < u_{2n_2(t)}$ generated from uniform distribution $U(0, t)$. From these values and the regression function Eq.(30), we calculate the switch time $t_{SSPC,0}$ and $n_1(t_{SSPC,0})$ and $n_2(t_{SSPC,0})$. Then, we simulate $n_1(t - t_{SSPC,0})$ and $n_2(t - t_{SSPC,0})$ from $Poisson(\tau_1 \cdot (t - t_{SSPC,0}))$ and $Poisson(\tau_2 \cdot (t - t_{SSPC,0}))$, respectively. Then, we simulate $\varepsilon_2(t_1, \ldots, t_n)$ with normal distribution $N(0, \hat{\sigma}^2(t_1, \ldots, t_n))$. Calculate $x_2(t)$ from the regression function

$$x_2(t) = \hat{\beta}(t_1, \ldots, t_n) n_1(t - t_0) + \hat{\gamma}(t_1, \ldots, t_n) n_2(t - t_0) + \hat{\alpha}(t_1, \ldots, t_n) t + x(0) + \varepsilon_2(t_1, \ldots, t_n). \tag{31}$$

(4) Calculate $\hat{R}_3(y; t_1, \ldots, t_n, t)$ according to Eq.(17).

(5) Calculate

$$\hat{R}(y; t_1, \ldots, t_n, t) = \hat{R}_1(y; t_1, \ldots, t_n, t) \cdot \hat{R}_2(y; t_1, \ldots, t_n, t) \cdot \hat{R}_3(y; t_1, \ldots, t_n, t) \tag{32}$$

(6) Repeat the above steps and get 1000 reliability estimates $\hat{R}^{(1)}(y; t_1, \ldots, t_n, t), \ldots, \hat{R}^{(1000)}(y; t_1, \ldots, t_n, t)$. The approximation of $Var\{\hat{R}(y; t_1, \ldots, t_n, t)\}$ is given by

$$\frac{1}{999} \sum_{i=1}^{1000} [\hat{R}^{(i)}(y; t_1, \ldots, t_n, t) - \bar{\hat{R}}(y; t_1, \ldots, t_n, t)]^2,$$
$$\bar{\hat{R}}(y; t_1, \ldots, t_n, t) = \frac{1}{1000} \sum_{i=1}^{1000} \hat{R}^{(i)}(y; t_1, \ldots, t_n, t). \tag{33}$$

Usually, the designed lifetime of ISPDS is 15 years, i.e., 131400 hours. We will stop selecting the new observations at t_n, when $t_n \leq 131400$ but $t_{n+1} > 131400$. For searching each t_i, we use the grid searching method with one hour as a grid.

C. SELECT AN APPROPRIATE SUBSET OF THE DATA FOR RELIABILITY PREDICTION

For reliability prediction of the system after a long operating time, the observations at earlier times may not fit the current degradation curve well and will make the prediction radical. We need to delete some of the early observations after we have all observations at times $t_1, \ldots, t_n$. Our goal is to find an appropriate subset of the data at times $t_m, \ldots, t_n$, which can make the prediction most robust.

Based on observations $t_{11}(t_m)$, $t_{12}(t_m)$, $i_{DC/DC}(t_m; t_{DC/DC,0})$, …, $t_{11}(t_n)$, $t_{12}(t_n)$, and $i_{DC/DC}(t_n; t_{DC/DC,0})$ for

DC/DC at time $t_m, \ldots, t_n$, the likelihood function is

$$\begin{aligned} &L_1(t_m, \ldots, t_n) \\ &\quad \propto L_{01} \cdot \{\lambda_1 e^{-\lambda_1 t_{DC/DC,0}} e^{-\lambda_1 t_{12}(t_n)}\}^{i_{DC/DC}(t_n, t_{DC/DC,0})} \\ &\qquad \cdot \{e^{-\lambda_1 t_{11}(t_n)} e^{-\lambda_1 t_{12}(t_n)}\}^{1-i_{DC/DC}(t_n, t_{DC/DC,0})}. \end{aligned} \tag{34}$$

which gives the MLE $\hat{\lambda}_1(t_m, \ldots, t_n)$ of λ_1.

Similarly, with the data $t_{21}(t_m)$, $t_{22}(t_m)$, $i_{TMTC}(t_m; t_{TMTC,0})$, $\ldots$, $t_{21}(t_n)$, $t_{22}(t_n)$, and $i_{TMTC}(t_n; t_{TMTC,0})$ for TMTC, the MLE $\hat{\lambda}_2(t_m, \ldots, t_n)$ of λ_2 can be obtained by minimizing

$$\begin{aligned} &L_2(t_m, \ldots, t_n) \\ &\quad \propto L_{02} \cdot \{\lambda_2 e^{-\lambda_2 t_{TMTC,0}} e^{-\lambda_2 t_{22}(t_n)}\}^{i_{TMTC}(t_n, t_{TMTC,0})} \\ &\qquad \cdot \{e^{-\lambda_2 t_{21}(t_n)}\}^{1-i_{TMTC}(t_n, t_{TMTC,0})} \end{aligned} \tag{35}$$

For ease of notation, we write $t_{SSPC,0}$ simply as t_0. From the data $\{x_1(t_m), x_2(t_m), n_1(t_m), n_2(t_m)(\text{or } n_1(t_0), n_2(t_0), n_1(t_m - t_0), n_2(t_m - t_0)), i_{SSPC}(t_m, t_0), \ldots, x_1(t_n), x_2(t_n), n_1(t_n), n_2(t_n)(\text{or } n_1(t_0), n_2(t_0), n_1(t_n - t_0), n_2(t_n - t_0)), i_{SSPC}(t_n, t_0)\}$, we can compute the estimates $\hat{\alpha}(t_m, \ldots, t_n)$, $\hat{\beta}(t_m, \ldots, t_n)$, $\hat{\gamma}(t_m, \ldots, t_n)$, and $\hat{\sigma}^2(t_m, \ldots, t_n)$ of α, β, γ, and σ^2 based on the following likelihood function

$$\begin{aligned} &L_3(t_m, \ldots, t_n) \\ &\propto C_1(t_m; \alpha, \beta, \gamma)^{[1-i_{SSPC}(t_m;t_0)]} \\ &\quad \cdot C_1(t_0; \alpha, \beta, \gamma)^{i_{SSPC}(t_m;t_0)} \\ &\quad \cdot C_2(t_m, t_0; \alpha, \beta, \gamma)^{i_{SSPC}(t_m;t_0)} \\ &\quad \ldots \\ &\quad \cdot C_1(t_n; \alpha, \beta, \gamma)^{[1-i_{SSPC}(t_n;t_0)]} \\ &\quad \cdot C_1(t_0; \alpha, \beta, \gamma)^{i_{SSPC}(t_n;t_0)\cdot\{1-\max[i_{SSPC}(t_m;t_0),\ldots,i_{SSPC}(t_{n-1};t_0)]\}} \\ &\quad \cdot C_2(t_n, t_0; \alpha, \beta, \gamma)^{i_{SSPC}(t_n;t_0)} \end{aligned} \tag{36}$$

Then we refit the degradation curve of the Rdson of MOSFET in Eq.(37) and estimate R_3 for $y = t_n + s$ in Eq.(38),

$$\begin{aligned} x(y) &= \hat{\beta}(t_m, \ldots, t_n)n_1(y) + \hat{\gamma}(t_m, \ldots, t_n)n_2(y) \\ &\quad + \hat{\alpha}(t_m, \ldots, t_n)y + x(0) + \varepsilon(t_m, \ldots, t_n), y > t_n, \\ &\quad \varepsilon(t_m, \ldots, t_n) \sim N(0, \hat{\sigma}^2(t_m, \ldots, t_n)), \end{aligned} \tag{37}$$

$$\begin{aligned} &\hat{R}_3(y; t_m, \ldots, t_n) \\ &= \left\{ \frac{\int_t^{t_n+s} A_3(z; t_m, \ldots, t_n)A_4(t_n + s, z; t_m, \ldots, t_n)dz}{s \cdot P\{x(t_m, \ldots, t_n) - x(0) < \ln l\}} \right. \\ &\quad \left. + \frac{P\{x(t_n + s; t_m, \cdots, t_n) - x(0) < \ln l\}}{P\{x(t_m, \cdots, t_n) - x(0) < \ln l\}} \right\} \\ &\quad \cdot \{1 - i_{SSPC}(t; t_0)\} \\ &\quad + \frac{P\{\bar{x}(t_n + s; t_m, \ldots, t_n) - x(0) < \ln l\}}{P\{\bar{x}(t_n; t_m, \ldots, t_n) - x(0) < \ln l\}} i_{SSPC}(t_n; t_0), \end{aligned} \tag{38}$$

where

$$\begin{aligned} &x(t_m, \ldots, t_n) \\ &\quad = \hat{\beta}(t_m, \ldots, t_n)n_1(t_n) + \hat{\gamma}(t_m, \ldots, t_n)n_2(t_n) \\ &\qquad + \hat{\alpha}(t_m, \ldots, t_n)t_n + x(0) + \varepsilon_1(t_m, \ldots, t_n), \\ &x(z; t_m, \ldots, t_n) \\ &\quad = x(t_m, \ldots, t_n) + \hat{\beta}(t_m, \ldots, t_n)n_1(z - t_n) \\ &\qquad + \hat{\gamma}(t_m, \ldots, t_n)n_2(z - t_n) + \hat{\alpha}(t_m, \ldots, t_n)(z - t_n), \\ &\tilde{x}(t_n + s, z; t_m, \ldots, t_n) \\ &\quad = \hat{\beta}(t_m, \ldots, t_n)n_1(t_n + s - z) \\ &\qquad + \hat{\gamma}(t_m, \ldots, t_n, t)n_2(t_n + s - z) \\ &\qquad + \hat{\alpha}(t_m, \ldots, t_n)(t_n + s) + x(0) + \varepsilon_2(t_m, \ldots, t_n), \\ &\bar{x}(z; t_m, \ldots, t_n) \\ &\quad = \hat{\beta}(t_m, \ldots, t_n)n_1(z - t_0) \\ &\qquad + \hat{\gamma}(t_m, \ldots, t_n)n_2(z - t_0) + \hat{\alpha}(t_m, \ldots, t_n)z \\ &\qquad + x(0) + \varepsilon_3(t_m, \ldots, t_n), \\ &\varepsilon_1(t_m, \ldots, t_n), \varepsilon_2(t_m, \ldots, t_n), \varepsilon_3(t_m, \ldots, t_n), \ i.i.d. \\ &\quad \sim N(0, \hat{\sigma}(t_m, \ldots, t_n)^2). \end{aligned}$$

Thus, we have a reliability prediction for the system at $y = t_n + s$ based on the data at times $t_m, \ldots, t_n$,

$$\begin{aligned} &\hat{R}(y; t_m, \ldots, t_n) \\ &\quad = \left\{ 1 - \frac{B_3(t_n + s; t_m, \ldots, t_n)B_4(t_n + s; t_m, \ldots, t_n)}{1 - \left(1 - e^{-\hat{\lambda}_1(t_m,\ldots,t_n)t_n}\right)^2} \right\} \\ &\qquad \cdot \left\{ e^{-\hat{\lambda}_2(t_m,\ldots,t_n)s} \right\} \frac{\hat{\lambda}_2(t_m, \ldots, t_n)(t_n + s) + 1}{\hat{\lambda}_2(t_m, \ldots, t_n)t_n + 1} \\ &\quad \cdot \hat{R}_3(t_n + s; t_m, \ldots, t_n). \end{aligned} \tag{39}$$

where

$$B_1(t_n+s; t_m, \ldots, t_n) = e^{-\hat{\lambda}_1(t_m,\ldots,t_n)t_n} - e^{-\hat{\lambda}_1(t_m,\ldots,t_n)(t_n+s)},$$
$$B_2(t_n+s; t_m, \ldots, t_n) = 2 - e^{-\hat{\lambda}_1(t_m,\ldots,t_n)t_n} - e^{-\hat{\lambda}_1(t_m,\ldots,t_n)(t_n+s)}$$

We choose m such that $\left|\hat{R}(y; t_m, \ldots, t_n) - \hat{R}(y; t_{m-1}, \ldots, t_n)\right|$ is largest from $m = 2$ to $m = n$ and the final prediction is $\hat{R}(s; t_m, \ldots, t_n)$.

IV. ILLUSTRATION

From historical experience for MOSFET, the mean switch is 100,000 and the mean short circuit is 800. Then, we let $\tau_1 = 0.7610$ and $\tau_2 = 0.0061$ be the parameters of the two Poisson processes, respectively. From a large amount of historical data, the engineers at Beijing Spacecrafts constructed an emulator for ground tests with $\lambda_1 = 5.9 \times 10^{-7}$ for DC/DC, $\lambda_2 = 5.9 \times 10^{-7}$ for TMTC and $x(t) = \beta n_1(t) + \gamma n_2(t) + \alpha t + x(0) + \varepsilon$ for MOSFETs in SSPC, where $\beta = 1.046 \times 10^{-6}$, $\gamma = 4.924 \times 10^{-5}$, $\alpha = 5.124 \times 10^{-8}$, $\sigma^2 = 0.07223$, and $x(0) = 10.827$. From this emulator, the simulated lifetime data for DC/DC and TMTC are listed in Table 1 and Table 2, and the simulated degradation data are listed in Table 3.

Then, we took these simulated data as the ground data and applied the process for choosing an effective data subset, provided in Section 3, for reliability prediction of $15 + s$, $s = 1$ years. The first observing time was $T_1 = 2160$ and the simulated observations were

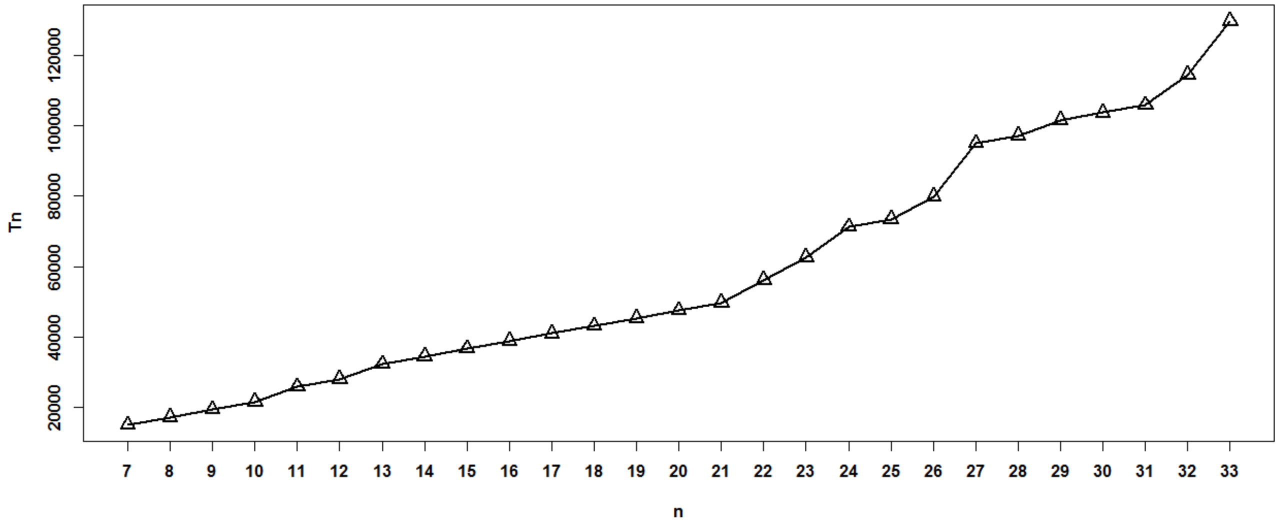

FIGURE 2. Graph of the effective observing times.

TABLE 1. The simulated lifetime data for DC/DC.

Number	Lifetime of DC/DC/hour	Number	Lifetime of DC/DC/hour
1	61882.6	2	632105.3
3	406474.6	4	1107514.1
5	144823.7	6	438572.2

TABLE 2. The simulated lifetime data for TMTC.

Number	Lifetime of TMTC/hour	Number	Lifetime of TMTC/hour
1	2858926.5	2	698169.2
3	565563.0	4	1961634.2
5	119313.7	6	1095738.8

TABLE 3. The simulated degradation data of Rdson for MOSFET.

Time/hour		Sample 1	Sample 2	Sample 3
1718	$n_1(t)$	1317	1332	1281
	$n_2(t)$	6	7	10
	$x(t)$	10.21992	10.97440	11.07855
2764	$n_1(t)$	2157	2125	2131
	$n_2(t)$	15	22	23
	$x(t)$	11.48351	10.50443	10.97649
3682	$n_1(t)$	2845	2812	2830
	$n_2(t)$	23	31	27
	$x(t)$	10.86539	11.27513	10.74453
4954	$n_1(t)$	3820	3735	3710
	$n_2(t)$	29	27	32
	$x(t)$	10.94788	10.72034	10.68273
5746	$n_1(t)$	4477	4342	4458
	$n_2(t)$	40	42	24
	$x(t)$	10.61243	10.91751	10.60554

$t_{11}(T_1) = 2160$, $t_{12}(T_1) = 2160$, $t_{21}(T_1) = 2160$, $t_{22}(T_1) = 0$, $i_{DC/DC}(T_1; t_{DC/DC,0}) = 0$, $i_{TMTC}(T_1; t_{TMTC,0}) = 0$, $n_1(T_1) = 1654$, $n_2(T_1) = 14$, $x_1(T_1) = 11.07574$, $x_2(T_1) = 10.26039$, $i_{SSPC}(T_1; t_{SSPC,0}) = 0$; the second observing time was $T_2 = 4320$, the simulated observations were $t_{11}(T_2) = 4320$, $t_{12}(T_2) = 4320$, $t_{21}(T_2) = 4320$, $t_{22}(T_2) = 0$, $i_{DC/DC}(T_2; t_{DC/DC,0}) = 0$, $i_{TMTC}(T_2; t_{TMTC,0}) = 0$, $n_1(T_2) = 3429$, $n_2(T_2) = 39$, $x_1(T_2) = 10.52651$, $x_2(T_2) = 10.68197$, $i_{SSPC}(T_2; t_{SSPC,0}) = 0$; …; the 33rd observing time, which was the last observing time was $T_{33} = 129600$, the simulated observations were $t_{11}(T_{33}) = 129600$, $t_{12}(T_{33}) = 129600$, $t_{21}(T_{33}) = 129600$, $t_{22}(T_{33}) = 0$, $i_{DC/DC}(T_{33}; t_{DC/DC,0}) = 0$, $i_{TMTC}(T_{33}; t_{TMTC,0}) = 0$, $n_1(T_{33}) = 98212$, $n_2(T_{33}) = 786$, $x_1(T_{33}) = 10.99811$, $x_2(T_{33}) = 10.88710$, $i_{SSPC}(T_{33}; t_{SSPC,0}) = 0$. The m we chose by using the robust criterion was 7, the 7th observing time was $T_7 = 15120$, and the simulated observations at this time point were $t_{11}(T_7) = 15120$, $t_{12}(T_7) = 15120$, $t_{21}(T_7) = 15120$, $t_{22}(T_7) = 0$, $i_{DC/DC}(T_7; t_{DC/DC,0}) = 0$, $i_{TMTC}(T_7; t_{TMTC,0}) = 0$, $n_1(T_7) = 11342$, $n_2(T_7) = 100$, $x_1(T_7) = 11.09100$, $x_2(T_7) = 10.70740$, $i_{SSPC}(T_7; t_{SSPC,0}) = 0$. So the effective data subset were the 7th to the 33rd observing time, and finally we got a series of 27 observing times shown in Fig. 2.

Based on the simulated data at these observation times to predict the system reliability for 15 + 1 years, which is 0.9849781028. Note that the true reliability of the system is 0.9886399246.

V. SIMULATION STUDY

In this section, we investigate the performance of the proposed method using simulations. Three reliability models are used for generating the simulation samples: (1) the parameters λ_1, λ_2, β, γ, α, and σ^2 are smaller than the emulator parameters, i.e., $\lambda_1 = 5.9 \times 10^{-8}$, $\lambda_2 = 5.9 \times 10^{-8}$, $\beta = 1.046 \times 10^{-7}$, $\gamma = 4.924 \times 10^{-6}$, $\alpha = 5.124 \times 10^{-9}$, and $\sigma^2 = 0.007223$; (2) the parameters λ_1, λ_2, β, γ, α, and σ^2 are the same as their emulator parameters, $\lambda_1 = 5.9 \times 10^{-7}$, $\lambda_2 = 5.9 \times 10^{-7}$, $\beta = 1.046 \times 10^{-6}$, $\gamma = 4.924 \times 10^{-5}$, $\alpha = 5.124 \times 10^{-8}$, and $\sigma^2 = 0.07223$; and (3) the parameters λ_1, λ_2, β, γ, α, and σ^2 of the reliability model are bigger than their emulator parameters, i.e., $\lambda_1 = 1.18 \times 10^{-6}$, $\lambda_2 = 1.18 \times 10^{-6}$, $\beta = 2.092 \times 10^{-6}$, $\gamma = 9.848 \times 10^{-5}$, $\alpha = 1.025 \times 10^{-7}$, and $\sigma^2 = 0.14446$. Our objective is to predict the system reliability for $15+s$ years based on the data in 15 years, where $s = 1, 2, 3, 4, 5$. These predictions are of intrinsic interest to the investigators at Beijing Spacecrafts. We compare the performance of the proposed method with the traditional method, which predicts system reliability using only the ground data listed in Table 1 to Table 3.

For each reliability model, we simulated the data at $t_1, \ldots, t_n$ from the model with parameters τ_1, τ_2, λ_1, λ_2, β, γ, α, and σ^2 and predicted the system reliability for $15 + s$ years conditioned on the lifetime of the system longer than t_n. We simulated 1000 repeated samples and computed the mean and the mean squared error (MSE) of the 1000 predictions. Tables 4-6 show the simulation results under three models.

TABLE 4. Mean and MSE of prediction under $\lambda_1 = 5.9 \times 10^{-8}$, $\lambda_2 = 5.9 \times 10^{-8}$, $\beta = 1.046 \times 10^{-7}$, $\gamma = 4.924 \times 10^{-6}$, $\alpha = 5.124 \times 10^{-9}$, $\sigma^2 = 0.007223$.

Time /year	Mean	MSE	Prediction by the traditional method	True reliability
16	0.97429	0.0088191	0.84459	0.99999
17	0.97318	0.0087192	0.84278	0.99997
18	0.97203	0.0085938	0.84118	0.99996
19	0.96985	0.0089162	0.83974	0.99994
20	0.96772	0.0098305	0.83843	0.99993

From the simulation results shown in Tables 4, 5, and 6, we see that the proposed method performs uniformly better than the traditional method, with smaller bias of prediction and a low MSE, which shows that the prediction is accurate. The simulation study also clearly demonstrates the superior robustness of the proposed method against the model assumptions, as it performed well for both bad and good true models with the same ground data. Because the bias is a much smaller component of MSE, in terms of the MSE, the performance of the proposed method deteriorates as we move towards the far future. This is expected because any extrapolation technology for prediction should perform less well when the extrapolated time is further from the data range.

TABLE 5. Mean and MSE of prediction under $\lambda_1 = 5.9 \times 10^{-7}$, $\lambda_2 = 5.9 \times 10^{-7}$, $\beta = 1.046 \times 10^{-6}$, $\gamma = 4.924 \times 10^{-5}$, $\alpha = 5.124 \times 10^{-8}$, $\sigma^2 = 0.07223$.

Time /year	Mean	MSE	Prediction by the traditional method	True reliability
16	0.94992	0.018172	0.84459	0.98840
17	0.93620	0.021433	0.84278	0.97942
18	0.92808	0.022949	0.84118	0.97085
19	0.91257	0.028061	0.83974	0.96258
20	0.90499	0.026851	0.83843	0.95633

TABLE 6. Mean and MSE of prediction under $\lambda_1 = 1.18 \times 10^{-6}$, $\lambda_2 = 1.18 \times 10^{-6}$, $\beta = 2.092 \times 10^{-6}$, $\gamma = 9.848 \times 10^{-5}$, $\alpha = 1.025 \times 10^{-7}$, $\sigma^2 = 0.14446$.

Time /year	Mean	MSE	Prediction by the traditional method	True reliability
16	0.93819	0.019742	0.84459	0.96392
17	0.91918	0.018746	0.84278	0.93649
18	0.90188	0.020873	0.84118	0.91039
19	0.88070	0.027361	0.83974	0.88573
20	0.85731	0.033285	0.83843	0.86658

VI. CONCLUSION

Intelligent power systems are new power systems which have been developed for satellites and space stations and have been used widely on these aircrafts recently. The essential difference between the new systems and the primary systems is that the former can record the operating data and transform it to the ground if required. Consequently, it will make predictions of reliability be more accurate. In this paper, we propose an adaptive prediction method for reliability by using real-time lifetime data, real-time degradation data and the ground testing data before launching. The proposed method provides two optimal criteria for the selection of an effective subset of data and the time-dependent prediction of the reliability. Based on the real-time degradation, the updated additive model of the Gaussian and Poisson processes can also be obtained to describe the degradation of the solid-state power controller precisely. With this updated model, further reliability analysis for SSPC can be performed in the future.

A demonstrative example is given and simulations are conducted with various models to illustrate the efficiency of the proposed method and its superior performance over the traditional one. Simulation results also show that, regardless of whether the initial lifetime model and the degradation model fitted by the ground testing data are close to the true models or not, the proposed method provides better predictions of reliability for 16 to 20 years. The improvement is significant comparing to the traditional method. Future work on this aspect include exploring alternative optimal criteria to obtain more accurate prediction for long-running ISPDS, and potential extension of the proposed method to the reliability analysis of similar long-running systems which also have real-time data flow.

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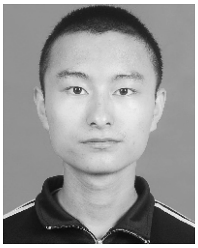

JUN WANG was born in China in 1990. He received the M.S. degree in statistics from the Beijing Institute of Technology in 2013. His research interests include reliability and high-dimensional data analysis.

YUBIN TIAN received the B.S. and M.S. degrees in mathematics from Beijing Normal University in 1987 and 1990, respectively, and the Ph.D. degree in mechatronical engineering from the Beijing Institute of Technology in 2000. She is currently a Full Professor with the School of Mathematics and Statistics, Beijing Institute of Technology. Her main interests are in reliability and statistics.