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Time-Censored Test Plan Design and Risk Analysis Based on Two-Level ”Component–System” Collaboration

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In reliability tests, timed censored tests are the most widely used type. How to formulate system-oriented test plans and calculate the test plan risks are current research hotspots. In this paper, a two-level collaborative timed censored test framework of ”component-system” is constructed to achieve collaborative search and risk calculation of ”component-system” test schemes. Firstly, based on the assumption of exponential distribution, this paper establishes a failure probability model of series systems and derives the system-level risk integral formula considering the prior distribution of components. Secondly, an adaptive dimension hybrid integrator is proposed, which realizes the adaptive switching among three methods: sparse grid, Gauss-Legendre and Monte Carlo, and was used to solve high-dimensional coupled integrals. In addition, this study developed a two-level simulation verification process of ”component-system” for the collaborative search of two-level schemes of ”component-system”. Finally, taking the dual-exponential component series system scenario as an example in this paper, the algorithm has completed the risk curve calculation and the collaborative optimization of the test plan. The results show that the proposed framework can get the two-level test plans while meeting the risk constraints, providing theory and algorithm for system reliability tests.

Keywords: time censored test, risk calculation, Monte Carlo Simulation, series system, exponential distribution.

1. Introduction

Reliability Qualification Test (RQT) is a mandatory process to verify whether a product meets its design requirements and is usually conducted during the development phase. Current studies on RQT are extensive: by test type they include type-I censored, type-II censored and sequential censored tests; by lifetime distribution, exponential[1-5], Weibull, normal, and binomial models; and by system complexity, component-level and system-level reliability tests. Among these, component-level fixed-time censored tests assuming an exponential lifetime distribution have received the greatest attention, and a variety of relevant test standards have been established both domestically and internationally.

At present, domestic and international reliability qualification tests are conducted primarily according to GJB 899A-2009[6] or MIL-STD-781[7]. Both standards presume that lifetime follows an exponential distribution and formulate test plans accordingly. They prescribe three censored test plans—Type-I (time-censored), Type-II (failure-censored), and sequential tests. Among these, the Type-I censored plan only requires the total test duration to be fixed in advance; the accumulated number of failures is subsequently compared with a pre-specified acceptance threshold to decide whether to accept or reject the product. Owing to its administrative simplicity, this test plan is frequently implemented in engineering practice.

The traditional design methods for timed censored test plans, such as those specified in the standards, mainly rely on the Poisson distribution for risk calculation, as it is generally believed that the lifetime of electronic products follows an exponential distribution. When calculating the timed censored test plans in practice, it is necessary to specify the upper and lower limits of the test for the average time between failures (MTBF) to be verified, as well as the producer risk and the consumer risk . Through calculation, the test scheme is obtained, where is the test time and is the number of qualified judgments. In GJB899A, the schemes that do not exceed two types of risks and can be found through discrimination comparison. However, the test schemes provided in the standard documents have problems such as long test times for low-risk schemes and high risks for short-time schemes.

To alleviate various problems associated with standard test plans, contemporary research has increasingly turned to integrating prior information into reliability testing and evaluation. During actual testing processes, test subjects often exhibit certain accessible prior information, encompassing historical data, expert judgments, and parameters derived from similar systems. By utilizing this prior information in parameter estimation for lifetime distributions and the determination of prior distributions, the theoretical accuracy and stability of reliability test plans can be substantially improved.

How to effectively synthesize prior information to optimize test schemes—simultaneously improving reliability while reducing testing costs—represents a critical research challenge. In existing literature, researchers have explored using component-level prior information for parameter estimation of prior distributions in reliability testing. The fusion methodologies include: maximum entropy methods for hyperparameter determination of prior distributions based on expert judgments [8], moment-based methods for expectation estimation of prior distributions utilizing historical data [9], and total probability Bayesian formulas for posterior distribution computation with statistical data [10]. These approaches share a common limitation: they typically address only a single information category, essentially extracting statistical characteristics from existing data to estimate prior distribution parameters. Consequently, they prove inadequate when confronting parameter estimation scenarios where multiple information sources present conflicts or redundancies.

System-level reliability qualification testing, conversely, concentrates on estimating system reliability indices by leveraging field data from component-level reliability tests. However, the majority of existing studies either adopt classical distribution assumptions—such as exponential distribution assumptions—for system lifetime distributions, or fit empirical distributions based on simulation data, without considering their specific analytical distributions [11-16, 19].

Based on current research, three critical issues are identified: (1) multi-source prior information fusion is compromised by complex or conflicting component data; (2) risk calculation based on system structure and component distribution remains scarce, with most studies relying on classical assumptions lacking interpretability; (3) collaborative planning between component and system-level tests is limited, focusing on post-test evaluation rather than pre-test guidance.

To address these, our previous work proposed a PSO-MEM framework for fusing conflicting information. This study extends to system-level risk modeling, constructing a ”component-system” two-level framework for collaborative test planning.

The paper is organized as follows: Section 1 introduces the hierarchical framework; Section 2 presents an adaptive integrator and simulation framework; Section 3 demonstrates via case study; Section 4 concludes with limitations and future directions.

2. System-Level Risk Modeling

2.1. *Risk Modeling for Series Systems*

2.1.1. *Failure Count Probability Modeling*

The structural characteristic of series systems requires that all components operate normally; when any single component fails and ceases operation, the entire system fails and stops functioning. Consequently, the system failure count equals the sum of individual component failure counts.

Based on the relationship between system failure determination and component failures under the aforementioned series structure, let the system failure count be denoted as random variable N_s, and the failure count of component i as random variable N_i. According to the association between system and component failure counts, the following equation holds,

$$Z = \sum\nolimits_{i=1}^{m} X_i \tag{1}$$

Therefore, taking a two-component series system as an example, the probability density function of the system failure count Z is equivalent to the convolution of the failure counts X_i of all components, while the cumulative probability function of the system failure count Z is the sum of discrete probability density functions.

$$\begin{cases} P_s(Z=k) = \sum\limits_{r=0}^{k} P_1(X=r)P_2(Y=Z-r) \\ P_s(Z \le C) = \sum\limits_{0 \le n \le C} P_s(Z=k) \end{cases} \tag{2}$$

Given the convolution closure property of the Poisson distribution, the system failure count Z over a time period still follows a Poisson distribution:

$$P_s(Z=k) = \frac{\exp(-\sum_{i=1}^{m} \lambda_i T_s) \cdot (\sum_{i=1}^{m} \lambda_i T_s)^k}{k!} \tag{3}$$

where m is the count of units for a series system.

2.1.2. *Prior Probability Modeling for Parameters*

This study conducts test plan risk modeling and calculation from both system-level and component-level perspectives. In the preceding component-level research, risk calculation and scheme searching were implemented for exponential and Weibull distributions based on failure count probabilities and parameter prior probability models. The system-level parameter prior distribution builds upon the prior formulas of individual components, with particular emphasis on the fusion calculation of prior probability models for multiple components.

From the previous step, it is established that the system failure count follows a Poisson distribution. Based on the relationship between the exponential and Poisson distributions, the time between failures T_s of the series system follows an exponential distribution:

$$F_s(T_s) = 1 - \exp(-\sum\nolimits_{i=1}^{m} \lambda_{e,i} T_s) \tag{4}$$

where λ_i represents the failure rate of component i, and the mean time between failures (MTBF) corresponds to the expectation of this exponential distribution:

$$\widehat{\theta}_s = 1/\sum\nolimits_{i=1}^{m} \lambda_i \tag{5}$$

In industrial production, estimation of product failure rates typically relies on sampling inspection results, where frequency is often substituted for probability. However, small-sample product testing tends to introduce substantial deviation errors. To address this issue, recent studies have generally replaced the traditional assumption of ”constant failure rate” with ”failure rate as a random variable following a specific distribution,” with common distribution types including the Gamma distribution Gamma(a, b) and the Uniform distribution Uniform(a, b), among others.

The cumulative failure probability distribution for series systems has been presented in Eq.(4).

When calculating system risk, the numerator involves computing the joint probability distribution between the probability density function of the failure rate parameter and the probability density function of the failure count, that is $P(r_s < C,\ \theta_s < \theta_{s1})$.

Therefore, it is necessary to construct the probability density distribution of the series system failure rate. Existing research has provided the derivation process for the failure rate of exponential-type components in series structures [1] (Jiang, 2022), demonstrating that the series system failure rate equals the sum of individual component failure rates:

$$\lambda_s = \sum\nolimits_{i=1}^{m} \lambda_i \tag{6}$$

Regarding the modeling of failure rates, it is first necessary to determine their respective probability distributions. Tan (2025) [18] compared three types of prior distributions and concluded that the uniform distribution, when serving as the prior distribution for the failure rate of an exponential distribution, exhibits favorable stability and approximation properties. Therefore, we have:

$$\lambda_i \sim \text{Uniform}(a_i,\ b_i) \tag{7}$$

where a_i and b_i are the parameters of the uniform distribution. The probability density function of the component failure rate can be further derived as:

$$f_{\lambda_i}(\lambda) = \frac{1}{b_i - a_i} \cdot \mathbb{I}_{[a_i, b_i]}(\lambda) \tag{8}$$

where $\mathbb{I}(\cdot)$ denotes the indicator function, which equals 1 when $a_i \leq \lambda_i \leq b_i$ and 0 otherwise.

The uniform distribution assumption is generally applied when no prior information or historical data is available; specific justifications should be consulted in relevant literature to clarify the prior distribution for the parameter λ of the exponential distribution. Subsequent research could analyze the impact of component priors on their posterior estimation and system-level effects under different prior distributions, such as the Gamma distribution and Negative Log-Gamma (NLG) distribution. In summary, the joint probability distribution of the system under different prior parameter combinations is directly represented by multiplying the probability distributions of individual prior parameters, denoted as $\pi(\boldsymbol{\theta})$, where $\boldsymbol{\theta}_i$ represents the complete set of prior parameters associated with a particular component. For exponentially distributed components, $\boldsymbol{\theta}_i = \{a_i, b_i\}$; for Weibull-distributed components, $\boldsymbol{\theta}_i = \{a_i, b_i, c_i, d_i\}$.

$$\pi_s(A) = \prod_{i=1}^{n} \pi_i(A) \tag{9}$$

2.1.3. ***System Risk Calculation Formulas***

Since a system comprises multiple components with specific structural characteristics, its failure count and failure rate during the test duration differ in modeling from those at the component level. However, the fundamental definitions of system-level test risks remain identical to those at the component level. Jiang (2022) and Wang (2024) [19] have provided definitions for the two types of risks in component-level testing: Type I risk α represents the probability that a test subject meeting the qualification criteria fails to pass the predetermined acceptance criterion, also known as the ”producer’s risk” or probability of rejecting a true hypothesis; Type II risk β represents the probability that a test subject failing to meet the qualification criteria passes the predetermined acceptance criterion, also known as the ”consumer’s risk” or probability of accepting a false hypothesis.

Based on the previously derived system failure rate probability modeling and failure count probability modeling, combined with risk formulas from prior research, the derivation process for the two types of risks in series systems is presented below:

$$\begin{aligned}\alpha_s &= P(r > C_s \mid \theta_s > \theta_{s0}) \\ &= \frac{P(r > C_s, \theta_s > \theta_{s0})}{P(\theta_s > \theta_{s0})} \\ &= 1 - \frac{P(r \leq C_s, \theta_s > \theta_{s0})}{P(\theta_s > \theta_{s0})} \\ &= 1 - \frac{\sum_{r=0}^{C_s} \int_{\theta_s > \theta_{s0}} P_s(r) \cdot \pi_s(A)\, dA}{\int_{\theta_s > \theta_{s0}} \pi_s(A)\, dA}\end{aligned} \tag{10}$$

The above equation represents the Type I risk formula α_{sys} for series systems, where $P_{N_s}(r_s \leq$

$C_s|\boldsymbol{\lambda}, T_s)$ denotes the failure count probability distribution of the series system, with different probability models selected according to with-replacement or without-replacement test modes. $\pi(\boldsymbol{\lambda})$ represents the joint prior probability distribution of the parameter set in the series system; since the parameters are mutually independent, the individual distribution functions are directly multiplied. Similarly, the Type II risk formula for series systems is given as:

$$\begin{aligned}\beta_s &= P(r \leq C_s | \theta_s \leq \theta_{s1}) \\ &= \frac{P(r \leq C_s,\ \theta_s \leq \theta_{s1})}{P(\theta_s \leq \theta_{s1})} \\ &= \frac{P(r \leq C_s,\ \theta_s \leq \theta_{s1})}{P(\theta_s \leq \theta_{s1})} \\ &= \frac{\sum_{r=0}^{C_s} \int\limits_{\theta_s \leq \theta_{s1}} P_s(r) \cdot \pi_s(A) dA}{\int\limits_{\theta_s \leq \theta_{s1}} \pi_s(A) dA}\end{aligned} \tag{11}$$

For the aforementioned integral, since the parameter set $\boldsymbol{\lambda}$ contains multiple mutually independent parameters, this integral constitutes a multiple integral. Furthermore, the integration region in the risk formula involves an inequality concerning the system mean time to failure (MTTF), which must be formulated as a function of the prior parameter set. This transformation maps the integration domain from the MTTF to each dimension of the parameter set. The mapping relationships and dimensions are determined by the component types and quantities within the series system. Variations in component types and quantities lead to differences in the shape of integration regions across different scenarios, necessitating case-specific analysis.

3. Risk Calculation and plan Searching Based on Monte Carlo Methods

3.1. *Theoretical Foundations*

For component-level risk integral calculation, since the exponential distribution contains only one parameter λ, one-dimensional numerical integration methods can be directly applied. Although the integrand form is complex, low-complexity computation can still be achieved through discretization. For Weibull-type components, the Weibull distribution possesses two parameters (λ, k), yet the integral of complex risk formulas can still be realized through layer-by-layer integration. The specific approach involves first discretizing the value range of parameter k, then transforming the inner-layer integral into a one-dimensional integral problem with respect to λ alone when k is fixed. The two-dimensional risk integral result for Weibull-type components can be obtained by accumulating the inner-layer integral results through outer-layer loops over k.

Unlike component level risk calculation, system level calculation involves multiple components, where the integration region typically forms a simplex region constrained by inequalities composed of individual component parameters. This leads to progressively increasing integration dimensions as the number of components grows. Moreover, due to the complex form of the integrand and the difficulty in separating integrated variables, single-layer numerical integration becomes necessary, thereby substantially increasing computational difficulty, as shown in Eq.(12):

$$F(x, y) = \iint\limits_{\theta(A,B)<\theta_0} p(x, y) A(x) B(y) \mathrm{d}x \mathrm{d}y \tag{12}$$

Furthermore, because system failure modes are correlated with individual components, the failure count probability distribution function in the integrand becomes a coupled common factor encompassing all parameters. This disrupts the box-shaped integration region required for layer-by-layer integration, rendering such an approach ineffective and necessitating overall numerical integration or Monte Carlo methods.

Beyond the difficulties in layer-by-layer integration caused by coupled common factors, the growth in integration dimension with increasing component numbers substantially raises problem complexity. In low-dimensional scenarios, sparse grids can achieve high-precision integral estimation. However, as dimensionality increases, grid partitioning grows exponentially, resulting in substantial computational costs. In such cases, interval-truncated Gauss-Legendre integration methods can be employed. When dimensions exceed 10, Monte Carlo methods are adopted due to their superior generality, though their precision is comparatively lower than the former two methods. Additionally, Monte Carlo Simulation methods inherently exhibit noise, requiring smoothing treatment.

3.2. *Design of Adaptive Dimension Integrator*

The adaptive-dimension integrator is a general numerical integration framework that "first automatically switches numerical algorithms based on the dimension d of the integration domain, then refines and iterates according to error estimates during runtime."

The core of this framework comprises three integral functions, implementing sparse grid-based integration, Gauss-Legendre integration, and Monte Carlo sampling algorithms, respectively. During actual computation, a main function needs to be developed for specific experimental scenarios to control the iterative update of test time T within the test plan (T,C) , thereby enabling continuous calculation of risk curves and facilitating subsequent comparison with the system risk simulation verification framework.

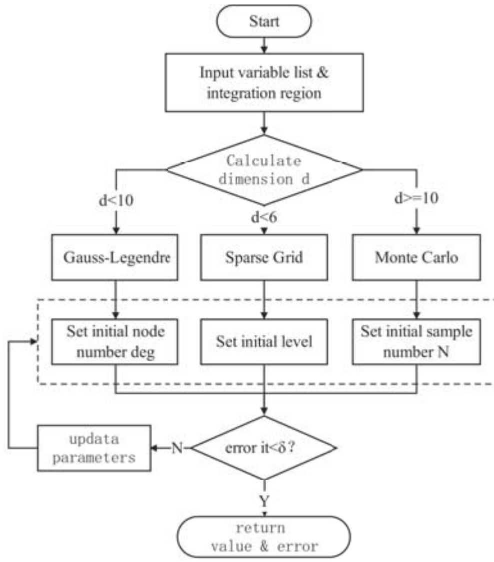

Fig. 1. The Adaptive dimension hybrid integrator

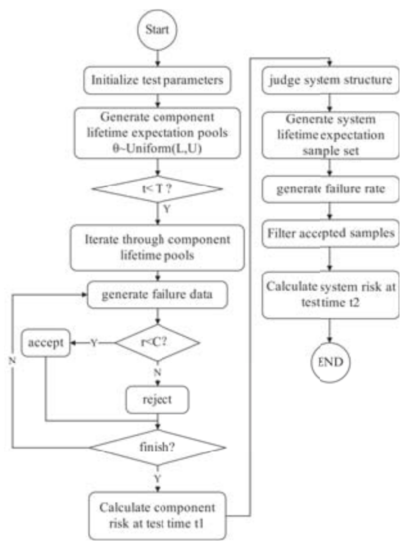

Fig. 2. Flowchart of system risk simulation verification

3.3. *System Risk Simulation Verification*

Based on the risk integral results obtained from the aforementioned integrator, sampling, approximate integration, and interval truncation techniques are employed during the computation process. Consequently, a quantitative error bound metric cannot be provided regarding accuracy. It is therefore necessary to model the "component-system" two-level test execution process and simulate results according to actual test procedures, thereby reflecting the empirical probability distribution of risks in system tests through large-scale statistical outcomes. This facilitates quantitative analysis of the computational accuracy of the adaptive high-dimensional integrator.

3.3.1. *Simulation Process and Algorithm Design*

To quantitatively assess the propagation effect of component-level risks on system-level risks and verify the accuracy of the adaptive high-dimensional integrator proposed in section 3.2, this paper designs a "component-system" two-level simulation framework.

The overall workflow is illustrated in Figure 2, comprising five core steps: generation of lifetime expectation parameter pools, component-level test simulation, system-level test simulation, risk in-

Table 1. Several numerical integrators with their applicability

Numerical Method	Dimension	Characteristics
Sparse Grid	< 5	High precision, computational cost increases with dimension
Gauss-Legendre	5–10	High precision, limited interval width
Monte Carlo Sampling	> 10	Lower precision, applicable for high dimensions

dex calculation, and result output.

4. Example Analysis

4.1. *Scenario Design*

Taking a two exponential component series scenario as an example, risk calculation for individual test plans is completed based on the adaptive dimension hybrid integrator. Subsequently, complete risk curves are plotted using the system risk simulation verification algorithm, and the influence of component test plan selection on system test plan risk is analyzed. The specific parameter settings are as follows: assuming the lifetime expectation of a batch of components is [value], the test party needs to conduct time-censored tests on the components before delivery. After delivery, time-censored tests need to be conducted on the dual-component series system they constitute. The specific test parameters are shown in Table 2.

Table 2. Verification scenario parameter settings

Parameter Name	Symbol	Value	Unit
Component test limit	$[\theta_{c0}, \theta_{c1}]$	[80, 240]	h
System test limit	$[\theta_{s0}, \theta_{s1}]$	[40, 120]	h
Component sample size	N_c	50,000	-
System sample size	N_s	50,000	-
Maximum test time	$T_{\max}$	500	h
Component allowable failures	C_c	1	-
System allowable failures	C_s	1	-

4.2. *Solution and Data Analysis*

By iterating through test times, the component-system test risk curves can be obtained as shown in Figure 3 and Figure 4. When identical test times are assigned to both components and the system, it is often difficult to simultaneously satisfy the risk requirements for both.

Therefore, different time variables can be assigned to components and the system. When the component test plan is fixed at $(T = 200\text{h}, C = 1)$, the minimum system test time is found to be approximately 200 hours. Precise test times and corresponding schemes can be obtained by consulting the data-exported spreadsheet.

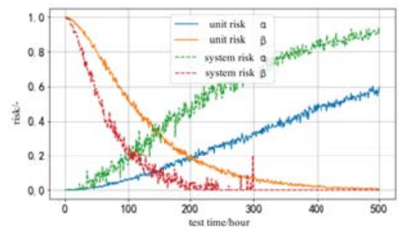

Fig. 3. Component-system test risk curves under the same test time

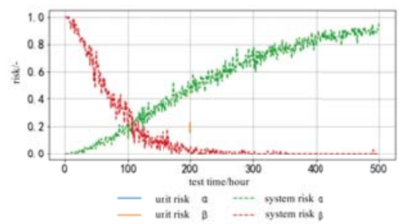

Fig. 4. System test risk curves under fixed component test time

Based on the above analysis, an optimal test plan combination satisfying the "component-system" two-level risk mapping theoretically exists. Consequently, an optimization problem is formulated as shown in Eq.(13):

$$\min T = T_c + T_s \tag{13}$$

$$s.t. \begin{cases} risk(T_c, C) < risk_c \\ risk(T_s, C) < risk_s \end{cases}$$

By solving the "component-system" two-dimensional risk surface, the set of feasible schemes satisfying test requirements and the optimal scheme are obtained. With a time step of Δt, all two-dimensional combinations of component test time and system test time are traversed. The scheme with the minimum total test time is finally obtained as shown in Table 3.Based on this, test plan points satisfying the four types of risk constraints are filtered.

Table 3. A list of feasible plans

Parameter	Symbol	Unit	Plan 1	Plan 2
Component test time	t_c	h	190	115
System test time	t_s	h	90	210
Total test time	t_{all}	h	280	325
Unit failure limit	C_c	-	1	1
System failure limit	C_s	-	1	1
Component Type I risk	α_c	-	0.1862	0.1897
Component Type II risk	β_c	-	0.1961	0.1824
System Type I risk	α_s	-	0.1429	0.1935
System Type II risk	β_s	-	0.1695	0.1569

5. Conclusion and future work

This paper investigates system-level time-censored testing and risk calculation. An adaptive dimension hybrid integrator is constructed to address complex coupling in multi-component risk integrals. A ”component-system” two-level collaborative framework is established for risk calculation and scheme selection, providing data and algorithmic support for two-level test planning.

Limitations remain: this study only considers dual exponential components in series. Future work will validate the framework for high-dimensional multi-component scenarios and extend to complex structures such as hybrid and voting systems.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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