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Modeling Optimal Reliability Test Planning Problem For Completion Technologies Under Development

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The recommended practice API 17Q (2018) presents a reliability demonstration test (RDT) approach for planning reliability tests capable of proving that a technology meets some target of reliability with a certain confidence level, whether in the development and/or production phase (Kim et al., 2019). However, for systems with high reliability, alternatives to standard RDTs should be investigated because test plans often require long test durations and pose high risks to producers and consumers (Jiang et al, 2022). Besides that, an RDT is typically limited to a set of components and failure mechanisms which can be covered by a single testing setup. This means that the reliability targets and respective RDT plans should be defined for each of them in order to demonstrate the reliability of a complex equipment at a system level. Otherwise, the reliability is assessed only for the failure mechanisms covered in the test.

In some real-world problems, reliability targets are determined at the system level, while multiple tests are performed at different hierarchical levels (component, subsystem, and system), each covering a distinct set of possible system failure mechanisms. Besides that, other source of reliability information may be available, such as expert opinions and historic of similar systems. Then, we have a multi-level problem with additional data source, where the various test must be planned and aggregated with extra reliability data to demonstrate the compliance with the reliability goal at a required confidence level. The primary objective of this paper is to propose an optimization model that achieves the desired target reliability while minimizing associated costs. Both producers and consumers risk are addressed (Zheng et al., 2023), requiring sophisticated approaches, and emphasizing the importance of optimal planning for comprehensive coverage (Fernández, 2022). This involves allocating resources efficiently across multiple test plans, each addressing one or more basic events.

We consider a system that can fail due to m distinct failure mechanisms. Each failure mechanism i ($i = 1, \dots, m$) has an associated reliability model $R_i(t|\theta_i)$ with parameter θ_i. Prior distributions for the parameters $\pi(\theta_i)$ are obtained from the additional source of information, such as expert's opinions and generic database, as in (Maior et al., 2022) and (Macedo et al., 2023). Thus, the problem consists of defining the plans for n different tests carried out on the components or subsystems, to minimize the total cost of the tests while the target for system reliability R_t with a confidence level CL are met, considering that each test covers only a subset of the m possible failure mechanism.

To enhance the effectiveness of the model, we propose the integration of Bayesian methodology for updating the parameters prior distributions $\pi(\theta_i)$, provided previously, for example, from expert opinion, historic of similar components, and functional standard tests, from the tests optimized in this modeling. This entails introducing the posterior distributions, allowing for dynamic modeling of reliability over time (Macedo et al., 2023). Then, given the posterior distribution $\pi(\theta_i|\text{multilevel tests})$, a distribution for the system reliability can be obtained by applying Monte Carlo (MC) techniques. From the MC a set of system reliability R_s is sampled.

The idea is that the CL^{th} percentile of the R_s is at least the target R_t. The optimization model is given as follows:

$\min_{n_k,t_k,s_k} TC = \sum_{k=1}^{n} CT_k(n_k, t_k, s_k)$,

subject to

$R_{s_{CL}} \geq R_t$

$n_k^l \leq n_k \leq n_k^u \; (k = 1, \ldots, n)$
$t_k^l \leq t_k \leq t_k^u \; (k = 1, \ldots, n)$
$s_k^l \leq s_k \leq s_k^u \; (k = 1, \ldots, n)$,

where the decision variables $\{n_k, t_k, s_k\}$ comprise respectively the specimens number, the test time and the stress level of test k $(k = 1, \ldots, n)$ with lower and upper limits described, respexctively, by $\{n_k^l,\ n_k^u,\ t_k^l,\ t_k^u,\ s_k^l,\ s_k^u\}$, $CT_k(n_k, t_k, s_k)$ is the cost of performing test k, and $R_{s_{CL}}$is the CL^{th} percentile of the posterior samples of R_s. The introduced decision variables and constraints form a mathematical model aimed at optimizing the total cost while meeting the necessary reliability validation requirements.

Our advanced testing planning method combines a systematic multilevel reliability model, optimal planning, and Bayesian methodology, creating a more efficient and adaptive strategy. Implementation of these concepts has the potential to lead to robust reliability validation, effectively meeting risks requirements with cost-effectiveness, for three reasons:

- the aggregation with additional information agrees for a less expensive testing plan to meet requirements;
- the component failure mechanism tests are easier to be performed in accelerated conditions, and you can even have several tests running simultaneously; and
- the use of a multilevel approach with prior information allows the anticipated identification of failure and/or design changes needs.

Difficulties and limitations consist of the need to define previously informative prior distributions for θ_i parameters, in addition to the need of estimating Bayesian posterior distribution in each optimization algorithm iteration, which can be computationally unfeasible if non-scalable methods are used for that end.

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