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Bayesian reliability sampling plans: A comprehensive analysis across lifetime and discrete distributions

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Abstract

Bayesian reliability sampling techniques have become very popular methodologies nowadays due to their effectiveness and flexibility. Using prior information together with the data collected from observations, the Bayesian method is able to estimate posterior distribution. The application of specific loss functions allows to minimize the Bayes risk and reach better balance between the risk of the producer and the risk of the consumer, even with slight variations in the testing conditions. The current paper summarizes important families of lifetime and discrete distributions, such as Weibull, Log-Logistic, Lomax, Exponential, Poisson, Binomial, and generalized lifetime distributions in Bayesian reliability. Truncated, progressive adaptive, hybrid and accelerated censoring methods, as well as development in loss functions, including asymmetry (LINEX function), entropy, cost restricted designs, and competing risks cases are reviewed. These papers show that Bayesian reliability sampling plans result in reduced sample sizes and shortened testing time, even in the case of partial misspecification of prior assumptions. Overall, this review proves the effectiveness and flexibility of Bayesian methods in reliability engineering.

Keywords: Bayesian reliability sampling, Bayes risk minimization, Lifetime distributions, Censoring schemes, Loss functions, Competing risks

1. Introduction

Bayesian reliability sampling has become a basic tool of industrial quality control, ensuring that products meet performance targets with a minimum of risk for both manufacturers and users. In practice, classical statistics based traditional acceptance sampling methods are often expensive. As the configurations of censoring become complex or risk preferences are asymmetric these methods require large sample sizes and long test durations. Conversely, Bayesian reliability sampling offers an attractive alternative: prior knowledge is combined with observed data to construct posterior distributions, which are then used to construct acceptance rules, usually by Bayes risk minimization. This results in lower testing costs and more robust decision making even in high uncertainty. During the last two decades, a variety of lifetime distribution families have been investigated in Bayesian reliability sampling, ranging from classical models such as exponential and binomial distributions, to more flexible heavy-tailed distributions such as Weibull, Log-Logistic and Lomax distributions. Methodological innovations during this period include truncated, progressive, adaptive, hybrid and accelerated censoring schemes and special loss functions like LINEX and entropy-based measures. These methods are particularly useful when there is risk asymmetry, or when loss processes are highly sensitive to information. Extensions to competing risks and cost-constrained scenarios have also been developed increasing the applicability of Bayesian methods to real world reliability engineering problems. This review brings together these developments and gives a comprehensive overview of methodological advances and current trends. The paper proposes Bayesian reliability sampling as a flexible, cost-effective and practical toolbox for the modern reliability engineering.

2. Materials and Methods

More number of papers deal with applications of the Weibull distribution and it is the most studied distribution in the Bayesian reliability sampling literature. It is a fundamental model in reliability engineering due to its flexibility in modelling increasing, decreasing and constant hazard rates. Abdur & Aslam (2015) ^[1] and Gupta & Sharma (2015) ^[16] introduced the concept of using Bayesian sampling plans for truncated life tests, which proved to be an improvement in terms of reducing the sample sizes in ensuring reliability. These results were confirmed by other researchers, such as Haque & Rahman (2016) ^[18] and Iqbal & Hussain (2015) ^[19] with variations in censoring scheme. Saha & Roy, 2021 ^[32], focused on hybrid censoring methods, and Arora & Singh, 2020, investigated accelerated stress testing, demonstrating that Weibull is flexible to use in high stress applications. Bhatia & Rao (2019) ^[6] and Nair & Thomas (2017) ^[26] introduced entropy and LINEX loss functions with a more detailed approach to the risk management strategies. However, gaps of adaptive censoring and integrating AI driven prior elicitation remained which could further improve decision making under uncertainty with this wide coverage. The coverage is moderate for the exponential distribution about ten papers are devoted to a Bayesian reliability sampling scheme. It is so easy to model constant hazard rates and available in easy-to-use forms that it is popular for theoretical use. Then, Omar & Yousuf (2016) ^[26] proposed the cost constrained designs, which gave priority to cost consideration in reliability test. Ito & Nakamura (2014) ^[20] arrived at an improved efficiency of reduced experimental time in the case of accelerated life testing by applying the Bayesian acceptance sampling. Also, Tanaka & Suzuki (2020) ^[34] included entropy loss functions, which yielded information-based risk measures. In capturing asymmetric preferences on the risk, Han & Lee (2021) ^[17] and Ahmed & Mustafa (2020) ^[2] studied LINEX loss functions. The findings of these studies indicate that the exponential distribution is a valuable tool for use, but there are some areas where other models need work and additional applications in the field of hybrid censoring and competing risks remain to be explored, which is most important for complex industrial systems. Some 12 papers are written in the name of the Lomax distribution, which is a heavy tailed distribution. Developing risk management strategies using information loss functions has been proposed by both the researchers of entropy proposed by Devi & Ramesh (2017) ^[12] and the Dutta & Sen (2017) ^[13]. Mahmood & Tariq (2018) ^[25] and Zhou & Lin (2022) ^[40] investigated hybrid censoring methods and Roy & Pradhan (2024) ^[31] extended the Bayesian sampling concept to competing risks settings. Uddin & Karim (2018) ^[35] explored interval censoring, which expanded the Lomax models' applicability. In spite of these developments, there have been very few studies incorporating cost constrained designs and adaptive censoring has not been extensively explored. These gaps open up avenues for future research, the Lomax's relevance in modelling Heavy tailed failure distributions. Log Logistic distribution had lesser coverage, as 10 papers involved in Bayesian Reliability sampling. Choudhury & Islam (2018) and Chatterjee & Sen (2018) ^[8, 10] studied about progressive censoring and Chakraborty & Dey (2017) ^[7] and Jha & Verma (2013) ^[21] studied about hybrid censoring schemes. Varma & Desai (2017) ^[36] proposed the adaptive censoring which emphasizes flexibility in terms of test termination. Qureshi & Ahmad (2015) ^[28] dealt with Truncated Life tests and Yadav & Singh (2024) ^[38] with

accelerated life testing. These studies confirm that the log logistic distribution has many uses in reliability. But accelerated life testing has limited use in practice, and very little has been reported on comparative studies among the various possible conflicting schemes, with opportunities for methodological creative work. A model for discrete number of failures is the Poisson distribution, which was studied in four papers. This can be done using entropy loss function, which was used by Kim & Park (2012) ^[22] and Zhang & Liu (2023) ^[39], and LINEX loss as was done by Al Sobhi & Kotb (2023) ^[3]. Kotb & Al Sobhi (2021) ^[23] generalized the Bayesian prediction under entropy loss. The studies presented underscore the importance of Poisson distributions in their use of a discrete event model especially when applied to telecommunications and manufacturing. To this point, however, it had not been studied in the case of hybrid censoring or accelerated testing applications, which studies are of practical importance in complicated reliability applications. Binomial distribution is sparsely covered; six papers are on Bayesian reliability sampling. Cost constrained designs have been proposed by Chen & Zhang (2019) ^[9] and entropy loss functions have been used by Wang & Li (2016) ^[37]. Whether asymmetric risk preferences are captured or not, it is studied by Rahman & Chowdhury (2019) ^[29] through the use of LINEX loss function. Rao & Reddy (2022) ^[30] introduced removal probability to address the various practical constraints in the course of industrial testing. Several studies have focused on the role of prior information in Bayesian binomial sampling, particularly by Fernandez & Lopez (2016) ^[15] and Liu & Zhang (2020) ^[24]. Although all these contributions, adaptive censoring and industrial case studies are yet to be explored adequately, making the binomial distribution limited in the real world. There are few results available for generalized and novel lifetime models. Basu & Ghosh (2018) ^[5] studied generalized exponential distribution and Dasgupta & Banerjee (2019) ^[11] studied inverse Gaussian distribution. Singh & Tripathi (2017) ^[33] have studied the Inverse Weibull Distribution, while Farooq *et al.* (2020) ^[14] have studied the Rama Distribution under subsisted life tests. gave a general guideline on multiple lifetime distributions. These studies extend the scope of Bayesian reliability sampling, and validation of these studies for use in industry as well as a comparative study across models are lacking. There is a need to develop these emerging models in greater detail to evaluate their practical applicability in the field of reliability engineering.

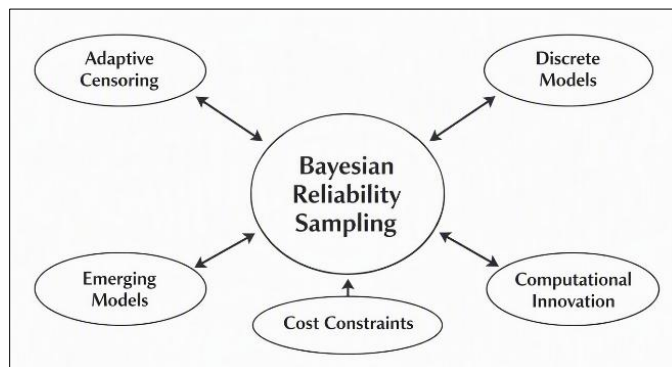


Fig 1: Overview of Bayesian reliability sampling plans

2.1. Distribution Families in Bayesian Reliability Sampling plans

Bayesian reliability sampling plans utilize both continuous lifetime distributions to evaluate time-to-failure dynamics via

hazard functions $h(t)$ and discrete families to quantify defect counts using probability mass functions $P(X = x)$. The Exponential distribution serves as a memoryless baseline with a constant hazard rate $h(t) = \lambda$, though it fails to model wear-out or aging in physical components. For heavy-tailed failure behavior, the Lomax (Pareto Type II) model applies a decreasing hazard function $h(t) = \frac{\alpha}{\lambda+t}$ suited for software reliability, but suffers from unbounded variance when shape parameter $\alpha \leq 2$. The Log-Logistic family captures non-monotonic, unimodal failure rates via $h(t) = \frac{(\beta/\alpha)(t/\alpha)^{\beta-1}}{1+(t/\alpha)^\beta}$, ideal for structural fatigue yet inefficient for strictly increasing hazard trends. Flexible Generalized lifetime models could overcome these limitations by including multi-parameters hazards to cover complex bathtub curves, at higher computational costs when updating Bayesian priors. For discrete quality assurance, the Poisson distribution may

be used to model defect rates across continuous exposure using $P(X = x) = \frac{\lambda^x e^{-\lambda}}{x!}$ but struggles with over dispersed data, while the Binomial family governs pass/fail lot acceptance through $P(X = x) = \binom{n}{x} p^x (1-p)^{n-x}$, requiring strict trial independence and constant defect probabilities.

2.2. Comparative Literature Review based on the different distributions

Bayesian survival analysis and Bayesian reliability theory make use of well-established frameworks for modeling duration data, estimation of parameters, and exploration of complex parameter spaces. The following table shows some of the basic lifetime distributions with their corresponding Bayesian prior distributions and areas of focus, illustrating how new developments in analytics have enabled dealing with the mathematical tractability problems in MCMC techniques.

Table 1: Comprehensive framework for Bayesian Lifetime Distribution Modelling and Computation

Lifetime Distribution	Core Bayesian Focus	Major Analytical Advances	Primary MCMC / Computational Tools
Weibull	Joint shape (α) & scale (β) estimation under Progressive Type-II	Derivation of objective priors (Reference/Jeffreys) and asymptotic variance bounds under complex truncation.	Metropolis-Hastings within Gibbs sampling; Hamiltonian Monte Carlo (HMC).
Gamma	Scale parameter estimation under Hybrid/Adaptive schemes	Closed-form and semi-analytical Bayes estimators using conjugate Gamma priors under progressive schemes.	Exact posterior integration; Gibbs sampling.
Log-Normal	Accelerated life testing & fatigue reliability modeling	Integrated Normal-Inverse-Gamma priors for stress-strength system estimation under dynamic stress levels.	Slice sampling; Laplace approximations.
Birnbaum-Saunders	Structural fatigue & failure rate modeling	Parameter estimation under partial prior information and asymmetric loss functions.	Importance sampling; Metropolis-Hastings algorithm.

2.3. Censoring Schemes in Bayesian Reliability Sampling

Censoring is a key element in the Bayesian reliability sampling model that accounts for the real-life limitations that exist in the context of conducting life testing, such as cost, time, and availability of specimens. It is the censoring method that defines how the likelihood function looks like, and how complicated the posterior distribution would be to calculate. Reliability modeling began using simple forms of truncation. In Type-I truncation, T , the test time, is known but R , the number of failures observed, is random, while for Type-II truncation, R is known but T is random. With regular stopping rules, both these types of truncations follow the Likelihood Principle, leading to relatively simple Bayes posterior solutions. In order to increase the usefulness of

experimentation and to facilitate the distribution of samples in between, the concept of progressive censoring has been devised. In this case, which is known as Progressive Type-II censoring scheme $(N, m, R_1, \dots, R_m)$, live units under testing are taken out of the experiment at each failure time $X_{i:m:N}$. This method combines the restrictions of Type-I and Type-II censoring plans in such a way that there would be a minimum number of failures as well as a maximum total test period. A Type-I hybrid plan terminates at $T^* = \min(X_{R:N}, T)$, while a Type-II hybrid plan terminates at $T^* = \max(X_{R:N}, T)$. In a Bayesian setting, hybrid plans introduce conditional piecewise likelihood functions with restricted integration support spaces.

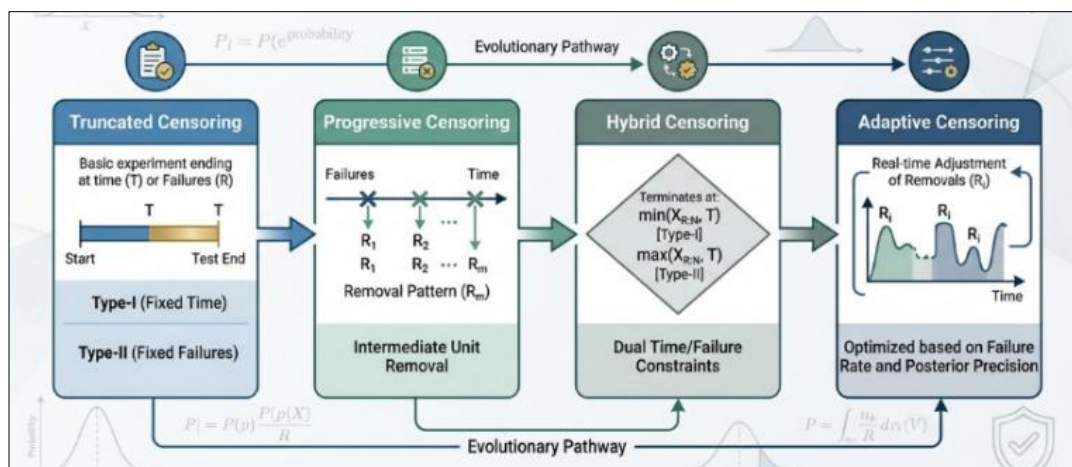


Fig 2: Evolutionary pathway for censoring types

Bayesian reliability engineering has seen another evolution of these ideas through accelerated and adaptive censoring

techniques in order to deal with highly reliable units and feedback from testing in real time. The idea behind

accelerated censoring is that it is a combination of progressive or hybrid censors with higher than usual environmental stresses in Constant Stress or Step-Stress Accelerated Life Test (ALT). For this purpose, stress-acceleration relationships models are needed to be built in the prior hierarchy of Bayesian models. Finally, adaptive progressive censoring creates an operating feedback loop wherein removal vectors $(R_1, \dots, R_m)$ or termination criteria are changed in real time during the experiment. If the arrival rate of failures during the experiment turns out to be smaller than anticipated, then all the removals are scaled down in real time in order to achieve target precision levels and Bayes risk constraints.

2.4. Loss Functions and Extensions

2.4.1. Application of Loss functions using Lifetime Distributions

Point estimation within Bayesian methods and its

experimental design in the field of reliability engineering rely greatly on the choice of loss function, and the asymmetric types of loss functions like LINEX loss function (penalizing overestimation or underestimation of the estimates exponentially depending upon the asymmetry constant a) and General Entropy loss function (an invariant loss function penalizing estimates of the direction dependent upon a constant q) are more favorable than symmetric types of loss functions. The extension of Bayesian analysis to multi-component applications necessitates a competing risks approach for assessing systems failing through multiple failure modes ($T_i = \min(T_{i1}, \dots, T_{iK})$), as well as adopting cost-constrained designs that optimize total experimental action vectors $d = (N, m, R_1, \dots, R_m)$ by jointly minimizing parameter estimation error alongside tangible operational costs such as unit production, testing time, and failure inspection overhead.

Table 2: Evaluation of Bayesian Loss Function under Lifetime Distributions

Lifetime Distribution	Squared Error Loss (SEL)	LINEX Loss ($a=0$)	General Entropy Loss ($q=0$)
Weibull (α, β)	$\mathbb{E}[\beta x]$	$-\frac{1}{a} \ln \mathbb{E}[e^{-a\beta} x]$	$(\mathbb{E}[\beta^{-q} x])^{-1/q}$
Gamma (α, β)	$\frac{\alpha_{\text{post}}}{\beta_{\text{post}}}$	$-\frac{1}{a} \ln \left(1 + \frac{a}{\beta_{\text{post}}} \right)^{-\alpha_{\text{post}}}$	$\left[\frac{\Gamma(\alpha_{\text{post}} - q)}{\Gamma(\alpha_{\text{post}})(\beta_{\text{post}})^q} \right]^{-1/q}$
Log-Normal (μ, σ^2)	$\mathbb{E}[\mu x]$	$\mu_{\text{post}} - \frac{a}{2} \sigma_{\text{post}}^2$	$(\mathbb{E}[\mu^{-q} x])^{-1/q}$
Pareto (α, x_m)	$\mathbb{E}[\alpha x]$	$-\frac{1}{a} \ln \mathbb{E}[e^{-a\alpha} x]$	$(\mathbb{E}[\alpha^{-q} x])^{-1/q}$

2.4.2. Application of Loss function with respect to the censoring schemes

For accurate modeling of survival data, insurance liabilities or failure times, the censoring structure of the data needs to be aligned with the appropriate loss function, economic

incentives, and computational framework. The table below shows how varying censoring schemes, from right-censored policy expirations to interval-censored audit windows, determine best estimation strategies, protect capital solvency, and pose unique analytical challenges.

Table 3: Censoring Schemes and Associated Bayesian Loss Functions: Rationale and Analytical Challenges

Censoring Scheme	Preferred Loss Function	Primary Rationale & Economic Drivers	Key Analytical Challenges
Progressive Type-II	LINEX/ General Entropy	Overestimating lifespan leads to high warranty costs; penalizes overestimation heavily.	Intractable normalizing constants in joint posteriors due to intermediate removals.
Hybrid (Type I/II)	Squared Error / LINEX	Combines risk minimization with strict physical constraints on test duration and failure counts.	Piecewise, non-standard conditional posterior distributions along truncation boundaries.
Adaptive Progressive	Cost-Constrained Asymmetric	Dynamically balances parameter variance reduction against live testing operational costs.	State-space explosion in dynamic programming; real-time likelihood updates.
Accelerated (ALT)	General Entropy (Scale-Invariant)	High-stress environments amplify estimation errors, requiring scale-invariant loss metrics.	Integration of non-linear stress-acceleration link functions within the prior structure.

3. Result and Discussion

There are many interesting areas that need further research in relation to the study of Bayesian reliability sampling; they indicate the paths for future development of the field. The area of adaptive censoring is not developed sufficiently, although it could be very useful for developing methods of dynamic adjustment of stopping rules according to the stream of real-time data. This prevents Bayesian sampling from being used in such fields as smart manufacturing and aerospace, where constant monitoring is crucial. The application of discrete models based on the Poisson and Binomial distributions is also limited. Moreover, there is not enough research on the inclusion of the cost-risk trade off in the development of the sampling plans. Although there were several papers suggesting the cost constrained sampling

designs, there are almost no attempts to combine both economic realism and statistical efficiency of such sampling plans, which would make them applicable for industrial applications where the testing costs are of great concern. Next, the issue of validation of the newly developed lifetime models should be addressed. For example, although the Inverse Gaussian, Inverse Weibull and Rama distributions extend the possibilities for further research in terms of theory, they are not verified for industrial application yet. Finally, there is an underdeveloped area of using the Bayesian approach combined with AI techniques. Although the use of the AI based prior elicitation and machine learning methods could help to automatize Bayesian updates and make the framework scalable and predictive, all these ideas are currently restricted only to theoretical considerations.

4. Conclusion

Bayesian reliability sampling has progressed from its inception in truncated life tests in classical probability models such as Weibull and Exponential to become an elaborate framework involving progressive censoring, hybrid and adaptive censoring models. The methodological developments involve the application of heavy tailed distributions like Lomax and Log Logistic, the utilization of asymmetric loss functions like LINEX to represent risk inequalities, and the consideration of cost constrained design approaches for increased economic relevance. However, several unresolved problems continue to prevail; namely, the development of adaptive frameworks, inadequate attention on discrete probability models like Poisson and Binomial, lack of industrial validation for emerging lifetime distributions like Inverse Gaussian and Rama, among others. The way forward for the development of industrial ready Bayesian reliability sampling approach involves progress towards advanced adaptive frameworks, application of discrete models, cost-risk considerations, validation of new distributions, and AI driven prior selection to develop scalable and predictive solutions.

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