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Applying Bayesian Reliability Demonstration Testing to Downhole Electronics: An Effective Approach for Performance Validation

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The increasing reliability and performance requirements of permanently installed downhole completion tools is necessitating the development of advanced approaches for assessing and demonstrating reliability. Traditional reliability testing methods often rely on frequentist approaches which require a large sample size to achieve statistically significant results. For satisfying high reliability targets, demonstration using classical reliability demonstration test (RDT) approaches are practically challenging primarily due to large sample size (cost, test execution complexity, etc.). This paper explores an application of Bayesian Reliability Demonstration Test (BRDT) as an advanced methodology for evaluating system reliability in real-world conditions. Bayesian method leverages prior reliability to optimize samples required to satisfy high reliability target. The proposed framework leverages a non-parametric Bayesian statistical technique based on beta distribution to combine prior information such as historical performance data or expert opinions, with sample data (empirical test results) to update reliability estimate. In a non-parametric context, prior reliability data only influences sample size and acceleration factor impacts the test time. This paper further examines the acceptance criterion for prior reliability data with the goal of using a prior reliability distribution that reflects a reasonable level of uncertainty or conservatism as it helps to avoid overconfidence. By updating beliefs about reliability performance through a dynamic posterior distribution, the Bayesian RDT results in sample size which is significantly lower than a classical RDT especially when the prior reliability is comparable to target reliability. A case study involving a permanently installed downhole electronics module is presented to demonstrate the application of this methodology, showcasing its potential to improve reliability estimates, reduce testing costs, and enhance confidence in system performance. The paper highlights the advantages and limitations of Bayesian RDT in ensuring that systems meet stringent reliability criteria, contributing to more efficient and effective product development cycles.

Keywords: Reliability Demonstration Test, Bayesian Methods, Prior Reliability, Permanently Installed Downhole Electronics, Intelligent Completions.

1. Permanently Installed Downhole Electronics Module in Completion Tools

In well completion tools, permanently installed downhole electronics modules are integrated systems that enable real-time monitoring, control, and data collection during well installation and production phase. These tools are part of the equipment that allows operators to manage and optimize production over the life of the well. The permanent downhole electronics module in these completion tools are essential for improving the efficiency, safety, and longevity of the well operations. These electronics modules are typically rated for high temperature and can continuously measure well parameters such as temperature, pressure, flow rates, and other subsurface conditions. This information helps operators to adjust production strategies and optimize well performance.

Key function of electronics module is to enable reservoir monitoring where it can help track the behavior of the reservoir over time, including production, pressure variations, and temperature fluctuations. This data is valuable for reservoir management and enhancing recovery techniques of hydrocarbons. These electronics modules typically help with enhancing reservoir management where well operators can make more informed decisions about reservoir pressure, stimulation and recovery methods. (Shrivastava Pankaj et al. 2016)

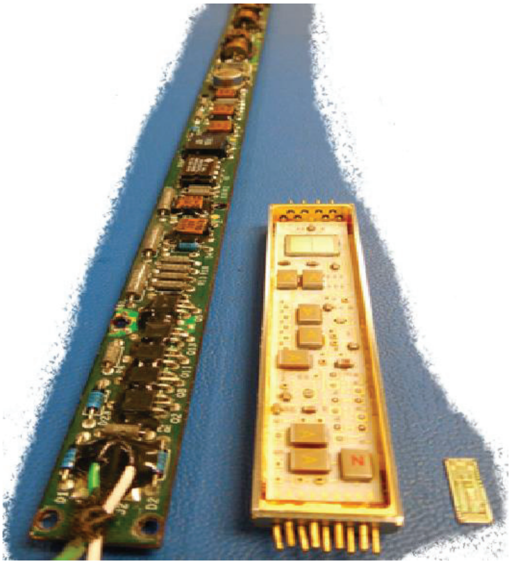

Fig. 1. Design Evolution of Downhole Electronics Technology

There has been a significant development in downhole electronics technology over the last decade Figure 1 shows the electronics technology development starting with the PCB from a decade ago. PCB electronics were integrated in the hybrid circuit with a length reduction of around 80%. The ASIC chip is now taking 70% of the components on the hybrid chip into one ASIC. However, the size of the hybrid is not changing due to added functionality in the electronics. (Shrivastava Pankaj et al. 2021). The key functions of downhole electronics module in well completions are summarized below.

- Data Acquisition: Collects real-time data of downhole conditions such as pressure, temperature, vibration, flow rates, etc. And monitors the performance of the completion tools and the reservoir.
- Communication: Transmits data to surface through wired or wireless telemetry systems. Receives commands from surface for controlling downhole tools or adjust their settings.
- Control and Automation: Enables remote operation of downhole tools such as interval control valves, safety valves, etc.
- Diagnostics and Health Monitoring: Tracks the health and performance of downhole equipment. Detects faults and failures allowing for intervention or maintenance.
- Power Management: Manages power supply for downhole electronics module (e.g. interface or controller card).

1.1. *Reliability Requirements of Downhole Electronics Module*

The reliability requirements of downhole electronics module are exceptionally stringent due to the extreme environments in which they operate. Downhole tools are subjected to high temperatures, high pressures, corrosive fluids, along with mechanical shock and vibration – with being located thousands of feet below the surface. Any failure can result in costly interventions or lost production. Therefore, downhole electronics module must meet rigorous reliability standards to ensure long-term performance and minimal downtime.

For lifetime stressors of downhole electronics, temperature is considered to play a key role. Downhole electronics are expected to operate reliably at temperature ranging from 150°C to over 200°C depending on the well depth and geographic location, typically for over 25 years of well life. Electronic components must withstand high temperature exposure for long life and prevent degradation over time. Well conditions also involve high pressure and corrosive environments, but sealing and packaging of electronics module typically prevents fluid ingress and maintain structural integrity. Electronics must be hermetically sealed to prevent moisture, gases or fluids from entering and causing damage. And seals must maintain integrity under extreme pressure and temperature conditions.

Electronic modules are also expected to survive shock and vibration during installation, operation and retrieval. Electronic components must possess mechanical durability to prevent failure due to physical impact. Power consumption must be minimized to extend the life and effective heat dissipation is critical to prevent overheating and ensure stable operation. In some cases, critical systems may incorporate redundant electronic design feature or fail-safe mechanisms to ensure continued operation. Fault-tolerant design also help to mitigate the risk of catastrophic failure. (Crowe D et al. 2001).

The reliability requirements for downhole electronics are among the most challenging in any industry. Meeting these requirements involves a combination of robust design, rigorous testing, and adherence to industry standards. By ensuring high reliability, downhole electronics can deliver consistent performance, reduce operational risks, and maximize the economic value of oil and gas wells. (Shrivastava Pankaj et al. 2015)

1.2. *Reliability Testing Strategies for Downhole Electronics Module*

Reliability testing of downhole electronics is a critical process to ensure that these components can withstand the extreme conditions encountered in oil and gas wells. Downhole electronics are exposed to high temperatures, high pressures, corrosive fluids, mechanical shocks, and vibrations, making reliability testing essential to validate their performance and longevity. These tests simulate downhole conditions and stress the electronics to identify potential failure modes and ensure they meet stringent reliability requirements.

Key objectives of reliability testing involve (a) identifying failure modes by detecting potential weaknesses in the design or materials, (b) validating performance to ensure that the electronics operate within performance specifications under extreme downhole conditions, (c) estimating the operational life of the components using accelerated test techniques. (Wayne Nelson 1990).

Accelerated life testing is commonly used to simulate long-term operation in a shorter time frame by testing the electronics module at elevated temperature to accelerate aging, predict lifetime and identify wear-out mechanisms.

Reliability testing is a crucial step in the development and qualification of downhole electronics. By subjecting these components to rigorous testing, manufacturers can ensure they meet the demanding requirements of downhole environments, ultimately improving the efficiency and longevity of oil and gas operations.

1.2.1. *Limitations of Reliability Demonstration Test for High Reliability Target*

Traditional reliability testing methods often rely on frequentist approaches which require a large sample size to achieve statistically significant results. For satisfying high reliability targets (upside of 95%), demonstration using classical reliability demonstration test (RDT) approaches are practically challenging primarily due to large sample size because of the cost of test specimens, test execution complexity, etc. (Shrivastava Pankaj et al. 2020). For example, a reliability requirement of 96.3% with 80% confidence for 27 years lifetime at 125°C use case will require more than 40 samples to be tested for over 15 months. In this scenario, reliability demonstration using classical approach is practically challenging.

To overcome the limitations of large sample size for high reliability targets, a Bayesian approach was considered for demonstrating high reliability expectations of downhole electronics module.

2. Bayes' Rule

Bayes' rule provides a mechanism for combining prior information with sample data to make inferences on model parameters and produce a posterior distribution. Combinations of extensive experience, physical and chemical theory, expert opinions, etc. can provide information to form a framework for inference and decision making. At times, it’s necessary to combine prior information with limited additional observational or experimental data. This posterior can be used to quantify uncertainty about the model parameters.

Equation 1 provides a simplified approach to comprehend Bayes' rule with the probabilities of event A and event B.

$$P(A/B) = \frac{P(A) \times P(B/A)}{P(B)} \tag{1}$$

Where, P(A) is the probability of observing event A without any given conditions which is also the prior, the initial degree of belief in A. P(B) is the probability of observing event B without any given conditions. P(B/A) is the probability of event B occurring given that A is true which is also interpreted as the likelihood of

A given B. Therefore, P(A/B) is the probability of event A occurring given that B is true. Also, called the posterior probability of A given B.

Bayes' rule provides a strong foundation for a logical process in modern data science because it allows analysts to systematically update their beliefs about a hypothesis based on new evidence, essentially incorporating prior knowledge with observed data to arrive at more informed conclusions especially in scenarios with uncertainty – making it a powerful tool for decision-making. (Meeker, W.Q et al. 1998).

2.1 *Baye's Logical Approach*

Figure 2 illustrate the logical approach of bayes' rule. This approach can be effectively applied to the reliability testing principles using Bayesian statistics. A four step Bayesian approach is listed below.

1. Start with a hypothesis and a degree of belief in the hypothesis based on prior knowledge.
2. Gather data or evidence to update initial beliefs.
3. If the data support the hypothesis, the probability goes up.
4. If data does not support, then probability goes down.

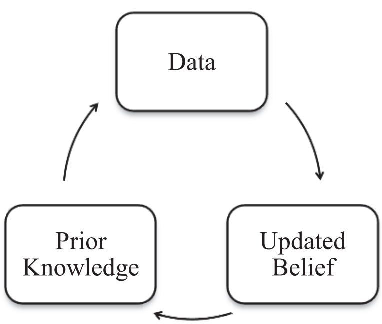

Fig. 2. Baye's Rule – A Logical Approach.

3. Bayesian Reliability Demonstration Test

A Bayesian Reliability Demonstration Test (BRDT) is a statistical method used to assess the reliability of a product or system by combining prior knowledge (prior distribution) with observed test data (likelihood) to update the reliability estimate (posterior distribution). This approach is particularly useful when sample sizes are small or when prior information about the system's reliability is available.

BRDT allows for a more informed decision on whether the product meets specified reliability targets, and updating the probability of acceptance as more data is collected throughout the testing process. Traditional frequentists methods rely solely on the test results themselves whereas BRDT uses the Bayesian statistics where the prior belief is updated with new information to produce a posterior probability distribution.

3.1. *Sources of Prior Information*

The process of designing a BRDT plan starts with a "prior distribution" which represents the initial belief about the product reliability based on design features, experience, or expert opinions. The sources of prior information can come from various areas, and they essentially inform the shape and characteristics of the prior probability distribution.

The choice of the prior is crucial because it influences the posterior distribution (which is the updated belief after incorporating data). The primary sources of prior data are listed below.

- <u>Subject Matter Expertise</u>: Prior knowledge or experience with the system/process being tested. These are subjective assessments from domain experts about the reliability of the concerned product. Prior reliability estimates are based on engineering judgement.
- <u>Non-informative Prior</u>: Typically considers equal probability to all possibilities. When no strong prior information is available, non-informative (e.g. uniform distribution) can be used to let the data dominate the analysis. Probability density function of non-informative prior is constant over the range of model parameters. They are also called as "vague prior" and "diffuse prior".
- <u>Empirical Prior</u>: Reliability data from similar system or components with similar design, materials or operating conditions.
- <u>Bayesian Model Averaging</u>: Average across multiple prior with expert agreement which account for uncertainty in the prior data.

The choice of prior can be highly influential in Bayesian analysis, and it's often a combination of available information and practical considerations that guides its selection. In many applications, analyst typically have useful and definite prior information (e.g. information from physical theory or experience deemed relevant through engineering or scientific knowledge), in such cases, information should be integrated into the analysis. Analysts must avoid the use of "hopeful thinking" as the prior information. The potential of generating misleading conclusions is high when experimental data is limited, and prior reliability dominates the performance evaluation of new product.

3.2. *Acceptance Criterion for Selecting Prior*

As there are multiple sources of prior reliability, it's of utmost importance to focus on the key acceptance criterion for selecting a prior. The goal is to select a prior reliability distribution that reflects a reasonable level of uncertainty or conservatism. It helps to avoid overconfidence.

The acceptance criterion ensures that the selected prior is consistent with the domain knowledge, does not lead to unrealistic results, and reflects the purpose of the reliability test. Listed below are the key acceptance criterion of selecting prior for designing BRDT especially for downhole electronics module.

1. Technology (design features and manufacturing/assembly processes) of the product is similar or improved as compared to prior.
2. In the prior test, accelerated test stresses were higher or equal to the stresses considered in the new test plan based on Bayesian methods.
3. Assumed test design parameters (activation energy, Weibull beta, etc.) are similar between the prior test and new test plan.
4. Expected failure modes and mechanisms of the new product and the prior are similar.

The prior reliability data reflects the initial knowledge or assumptions about the system's performance (e.g., failure rate, expected lifetime, etc.), and the acceptance criterion for selecting a prior ensures that the chosen prior is reasonable and does not overly influence the results.

3.3. *Non-Parametric Approach to Bayesian Reliability Demonstration Test*

A non-parametric reliability demonstration test is a statistical approach used to demonstrate the reliability of a system or component without assuming any specific parametric distribution (e.g. Weibull, normal, exponential, etc.). Unlike parametric methods, which rely on assumptions about the underlying distribution of failure times, non-parametric methods are more flexible and make fewer assumptions about the data, which is useful when the distribution of the data is unknown or difficult to model. (Meeker, W.Q et al. 2006). Classical cumulative binomial algorithm can be used to estimate the sample size for a given reliability and confidence level (equation 2).

$$1 - CL = \sum_{i=0}^{r} \binom{n}{i} . (1-R)^{i} R^{n-i} \qquad (2)$$

Where,

- CL: Confidence level
- r: Number of failures
- n: Total number of units in test
- R: Reliability to be demonstrated

A non-parametric Bayesian test design approach can be used to estimate the demonstrated reliability or confidence level that is expected from a specified test design. It can also be used to estimate the sample size needed to demonstrate a target reliability at a specified confidence level by considering the prior information.

In a Bayesian approach, the product reliability can be approximated with Beta distribution as shown in equation 3. Reliability is considered as a random number in a beta distribution. Prior distribution of reliability is widely approximated with a Beta distribution. When a Beta distribution is used as the prior distribution for reliability R_0, the posterior distribution of reliability R_{Post} also follows a beta distribution.

$$1 - CL = Beta(R, n-r, r+1) \qquad (3)$$

Posterior distribution for reliability R_{Post} can be considered as a function of prior reliability distribution R_0 with distribution parameters α_0 and β_0 (equation 4).

$$1 - CL = Beta(R_{Post}, n - r + \alpha_0, r + \beta_0) \quad (4)$$

Prior reliability (R_0) follows Beta distribution with parameters (α_0, β_0) as shown in equation 5 and 6.

$$\alpha_0 = E(R_0)\left[\frac{E(R_0) - E^2(R_0)}{Var(R_0)} - 1\right] \quad (5)$$

$$\beta_0 = (1 - E(R_0))\left[\frac{E(R_0) - E^2(R_0)}{Var(R_0)} - 1\right] \quad (6)$$

Where,

- $E(R_0)$ is the expected value of prior reliability
- $Var(R_0)$ is the variance of prior reliability

Its to be noted that in this framework, a non-parametric approach of BRDT only optimizes sample size (n) based on prior data. The test time is evaluated primarily based on the acceleration factor. (Jiang et.al 2009).

For downhole electronics, temperature is understood to be the key lifetime stressor. The Arrhenius life-stress relationship is probably the most common life stress relationship used in accelerated life testing. It has been widely used when the acceleration stress is thermal (i.e., temperature). Classical Arrhenius life-stress relationship is illustrated in equation 7 and 8.

$$AF_{Temp} = Exp\left\{\frac{E_a}{K_B}\left[\frac{1}{T_{Use}} - \frac{1}{T_{Stress}}\right]\right\} \quad (7)$$

$$\mathrm{Time}_{\mathrm{Accelerated}} = \frac{\mathrm{Time}_{\mathrm{Use}}}{\mathrm{AF}_{\mathrm{Temp}}} \quad (8)$$

Where,

- Ea: Activation energy
- K_B: Boltzmann constant
- T_{Use}: Nominal use temperature, Kelvin
- T_{Stress}: Accelerated test temperature, Kelvin
- $Time_{Use}$: Life at use conditions
- $Time_{Accelerated}$: Test time at accelerated conditions

3.4. *Key Steps to Design Bayesian Reliability Demonstration Test*

Bayesian test design approach leverages prior reliability to optimize samples required to satisfy high reliability target. The key steps of designing a reliability test based on non-parametric Bayesian approach are listed below.

1. Prior Reliability Data: Prior information is collected from similar electronics technology based on the acceptance criteria (listed in the previous section).
2. Non-Parametric Bayesian Test: Standard algorithm based on beta distribution is used to estimate sample size based on prior reliability data. Formulations shown in equation 2-8 can be used to optimize sample size based on prior data.
3. Acceleration Factor: Evaluation of test temperature is the key for successful reliability demonstration of the concerned product.
4. Test Time: Test time is function of acceleration factor and associated lifetime of the product.
5. Sample Size: Function of prior reliability data and the reliability requirement of the product.

4. Case Study of Bayesian Reliability Demonstration Test Design for Downhole Electronics Module

A new product has an average reliability target of 96.87% with 80% confidence for 27 years lifetime. Reliability target has a lower bound of 96.27% and upper bound of 99.12%. The product is expected to operate at 125°C. Historical test data from similar products are available. Prior reliability of the similar products was conservatively estimated to be 0.9953, 0.9926, 0.9644, 0.9280 with the same confidence level and operating conditions.

The average prior reliability can be estimated as AVG (0.9953, 0.9926, 0.9644, 0.9280) = 0.9701. The variance (a measure of statistical dispersion) in prior reliability of all products can be estimated as VAR (0.9953,0.9926,0.9644, 0.9280) = 0.000982.

Equation 2 can be used to estimate the sample size requirement for a non-parametric binomial test design. Equation 3-6 can be used to estimate the sample size for a non-parametric Bayesian test design.

As compared in Table 1, the sample size requirements for Bayesian test design are significantly lower than the non-parametric binomial test design – which essentially signifies the impact of using prior reliability data.

Table 1. BRDT Plan for New Product with Prior Reliability Data

	$Target_{Low}$	$Target_{Avg}$	$Target_{High}$
Product Reliability Target	96.27%	96.87%	99.12%
Sample Size 'Classical RDT'	42	51	182
Sample Size 'Bayesian RDT'	9	16	130
Test Time, Months	15	15	15

Equation 7-8 can be used to estimate the test time which is primarily the function of acceleration factor. With an Arrhenius-based acceleration factor of ~21, a test time of around 15 months will be required to satisfy the lifetime requirement of 27 years.

It's to be noted that in a non-parametric Bayesian approach, test time is related to use temperature, test temperature and associated lifetime. The prior reliability data does not necessarily help with the test time optimization.

This case study illustrates the Bayesian approach to reliability demonstration test design. By incorporating prior knowledge and updating beliefs with new data, more informed decisions about product reliability can be made.

9. Summary and Conclusions

The BRDT provides a powerful and flexible framework for evaluating the reliability of a product, especially when prior information or expert judgment is available. By combining prior knowledge and observed test data, it allows for a more comprehensive assessment of product reliability, providing insights that might not be attainable through traditional frequentist approaches.

For downhole electronics module, BRDT design helps in optimizing the test specimens especially for achieving high reliability target. However, prior reliability is based on engineering group's experience and judgement, and therefore, it may involve an element of subjectivity. A conservative approach of estimating prior reliability is typically preferred to avoid overconfidence in Bayesian updates. It's always important to perform a sensitivity analysis with uncertain input parameters in the test design models using Bayesian statistics.

Eventually, Bayesian reliability methods can be applied to any quantitative reliability test methods such as accelerated life test and degradation test to estimate posterior reliability. Bayesian reliability test design can also be leveraged for other lifetime stressors such as vibration, thermal cycling, etc.

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