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Review on accelerated life testing plan to develop predictive reliability models for electronic components based on design-of-experiments

Fatima-Ezahra Indmeskine  | Laurent Saintis | Abdessamad Kobi

University of Angers, LARIS, SFR
MATHSTIC, Angers, France

Correspondence

Fatima-Ezahra Indmeskine, LARIS,
Polytech Angers, 62 Av. de Notre Dame du
Lac, 49000 Angers, France.
Email: [fatima-ezahra.indmeskine@
etud.univ-angers.fr](mailto:fatima-ezahra.indmeskine@etud.univ-angers.fr)

Abstract

Accelerated testing has been commonly used for the assessment of reliability of products or systems. In particular, it has been used to produce models for predicting the reliability of electronic components as a function of design and environmental parameters, or to qualify reliability. Extensive literature exists on different aspects ranging from defining type of stresses and type of censoring data, to optimizing test plans for efficient and relevant testing. On the other hand, design of experiments methodology is commonly used for studying the robustness of systems and for quality applications. This being said, combining both approaches, taking into account the system's physics of failure, is scarcely put into practice in a context of reliability prediction. Yet, this could significantly improve reliability prediction, especially in the case of electronic components which constantly go through technological progress with new parameters or properties to consider. After first presenting existing predictive reliability guides, models and parameters related to accelerated life testing, the purpose of this article is to provide a review of what has been done concerning the combination of such approaches.

KEYWORDS

accelerated life test, design of experiments, physics of failure, reliability prediction

1 | INTRODUCTION

Accelerated life testing (ALT) is a method commonly used for the assessment of reliability of products. Since it enables the manufacturer to observe failures in shorter times, it is notably useful for high reliability products intended for domains such as the military, the automotive and the biomedical. There exists extensive literature on ALT with single and multiple stresses and different types of censoring,^{1,2} There has not been, however, many works on the application of design of experiments on ALT. In fact, integrating quality concepts into the study of reliability of a product is a way to potentially enhance the optimization of test planning and to more accurately estimate the parameters of concern. Despite this, test planners of ALTs often do not take full advantage of design of experiments methods due to the difficulties which arise from the

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differences of reliability and quality approaches in handling experiments' data (extrapolation methods, life distribution, etc.). Alternatively, the physics of failure has been efficiently employed in numerous works to build a reliability model for products (e.g., this has been widely applied in power electronics). There even exists guides for predictive reliability, such as FIDES and MIL-HDBK 217F. However, reliability prediction is still subject to many lacks and pitfalls that come with technological advancements. The industry of electronic implantable medical devices is a substantial example of an actively growing field with a keen tendency towards miniaturization. Despite this, it uses mostly standards from other domains to assess reliability.³

The objective of this paper is to provide an overview of existing methods for obtaining a reliability model for a given type of electronic component, as a function of design and environmental factors, based on ALT and design of experiments. This paper also aims to discuss the drawbacks of each of these methods present in the state-of-the-art.

To concretely justify the need for better methodologies when comprehensive reliability handbooks and standards^{4–8} already exist and are seemingly working enough, a discussion will be given in Section 2 of the existing predictive reliability guides, their specifications with respect to electronic components, and their lacks. The rest of the article will be organized as follows: Section 3 will provide a quick look into the physics of failure. Section 4 will provide a brief review on ALT planning methodologies under multiple stress factors and will discuss the different lacks associated. Section 5 will explore the applications of design of experiments on ALTs. Finally, Section 6 will conclude the article with remarks on future perspectives.

2 | RELIABILITY PREDICTION GUIDES

This section aims to introduce predictive reliability guides for the purpose of pinpointing their limits with respect to design parameters of products, particularly electronic components. An example about ceramic capacitors will be given to further shed light on how critical of a role can these design parameters play in the reliability of the component. This serves as an emphasis on including the effects of these design parameters in reliability assessment by intersecting design factors through DoE methodology with environmental factors through ALT, to generate a reliability prediction guide as the output of interest.

MIL-HDBK-217 is one of the guides used for reliability estimation of electronic and electrotechnical components in the military field assuming that they follow an exponential lifetime distribution⁹ with a constant failure rate model.¹⁰ This assumption is very controversial and is considered unreliable by several manufacturers since it is based on heuristic analyses¹¹ and does not provide results depending on the technology and the exact conditions of use of the product. For instance, the ceramic capacitor model considers as design factors only the component's capacitance, and environmental factors are divided into general categories according to whether the component is used in mobile ground applications, fixed ground applications, sheltered naval applications, etc. Operational conditions (ambient temperature and ratio of operating voltage to rated voltage) are taken into account in the model's base failure rate. However, the guide is still used to have a figure of merit for the reliability of some electronic components, such as ceramic and tantalum capacitors.¹²

Another predictive reliability data handbook is UTE C 80-810 (RDF 2000) developed by French telecommunication industry.¹³ It relies on the mission profile of a given electronic component to define its failure rate, taking into account a base failure rate and the contributions of the significant operational and environmental factors of each phase of the mission profile. It also focuses only on failure during the useful life stage of the product. Yet, it is deficient in terms of mechanisms of failure and the types of environments it is intended for (limited sources of field data, limited environmental factors considered influencing, etc.).

On the other hand, FIDES is a guide produced by the FIDES group made up of: AIRBUS France, Eurocopter, Nexter Electronics, MBDA France, Thales Systèmes Aéroportés SA, Thales Avionics, Thales Corporate Services SAS, Thales Underwater Systems.¹⁴ It proposes a methodology for predicting the failure rates of electronic systems, based on the physics of failures, analysis of test data (especially in the military and civil aviation), feedback from different manufacturers, and existing models of acceleration of failure mechanisms. It considers that the failure rates vary throughout the life cycle of the product from its manufacture to its destruction following a “bathtub” curve.

The FIDES guide excludes periods of infancy and wear-out from its reliability prediction models and considers only the normal life of the product with a constant failure rate (more precisely an average failure rate) (Weibull beta=1) based on the following model:

$$\lambda = \lambda_{physical} \times \Pi_{PM} \times \Pi_{Process} \quad (1)$$

- $\lambda_{Physical}$ represents the physical contributions (thermal, electrical, mechanical, or chemical stresses),
- Π_{PM} represents the manufacturing quality of the product,
- $\Pi_{Process}$ represents the quality of the various processes involved in the life cycle of the product (development, manufacturing, and use).

As a matter of fact, for each electronic component (or subsystem), a model of reliability is built based on field data from different manufacturers. The physical contributions of each type of stress are respectively calculated through the acceleration models corresponding to the relevant failure mechanisms of the product. Each acceleration model includes a basic failure rate ($\lambda_{Physical}$ in Equation 1) given depending on the relevant design factors of the product (e.g., for each type of ceramic material for ceramic capacitors). On the other hand, the quality of manufacturing (Π_{PM} in Equation 1) and the quality of process ($\Pi_{Process}$ in Equation 1) are quantified according to some questionnaires related to manufacturing practices and process.

The advantage of FIDES compared to MIL-HDBK-217 is the fact that it is more up to date with regard to electronic components' technologies and manufacturing processes. However, it is also based on a constant failure rate model which ended in 1994 with the memorandum issued by Secretary of Defense William Perry eliminating most defense standards.¹⁰ It has been recommended since then to rely essentially on failure physics to model the reliability of electronic components.

The FIDES guide was created to replace MIL-HDBK-217 which deviated from real life conditions, but it has many gaps which are not well addressed.¹⁵ Its shortcomings include:

1. The failure rate in real life conditions is not constant, contrary to the model's assumption.
2. Failure modes and mechanisms are not explained. It is not quite clear how physics of failure was incorporated into the models with respect to environmental and design factors. Although it is not the purpose of the guide, a clear representation of the physics of failure could make it useful to take advantage of the guide for designing reliability experiments complemented with up-to-date state-of-the-art in electronics.
3. The methodology does not take into account the materials and the chemical composition as well as the dimensions of the components whereas these factors can have a very important role in their failure (for ceramic capacitors for example).

Despite the existence of predictive reliability guides for electronic systems and subsystems, the accuracy of the models and parameters proposed in these guides is not guaranteed¹⁶ given the extremely rapid evolution of electronic technology as well as the complexity of qualification of the reliability of the electronic subsystems which increases with it. In addition, it is fundamental to note that FIDES reliability models are constructed for electronic components which are destined for severe or harsh conditions environments, such as the components intended for military and avionic use. They do not necessarily consider environments with completely different type of settings and constraints, such as medical implantable devices (miniaturization, biocompatibility, polymer usage trend, sterilization, coatings). To illustrate this, an example of ceramic capacitors is taken. Based on the model of physical failure rate established by FIDES shown in Equation (2), it can be understood that only the contributions of physical stresses related to thermo-electrical, thermal cycling, and mechanical phenomena, while humidity related failure mechanisms are neglected.

$$\lambda_{Physical} = \lambda_{0_Capacitor} \times \sum_i^{Phases} \left(\frac{t_{annual}}{8760} \right)_i \times (\Pi_{Thermo-electrical} + \Pi_{TCy} + \Pi_{Mechanical})_i \times (\Pi_{Induced})_i \quad (2)$$

Aside from these physical contributions calculated based on physical acceleration laws, FIDES guide also provides basic failure rates associated with components. However, according to the guide, these differ only from dielectric material class to another and from a CV product (Capacity * Rated Voltage of the capacitor) to another. No reference to the internal electrode materials is present even though this significantly impacts failure mechanisms. In fact, there has been a transition from the material used in the internal (layered) electrodes of capacitors under the miniaturization constraint.¹⁷ As a result, nickel electrodes BME (Base Metal Electrode) have been the most widely used in industry since 2000, except for the defense and aerospace industries which still use electrodes made of precious metals such as silver and palladium PME (Precious Metal Electrode) due to strict reliability specifications. These two types of electrodes differ to some degree in their failure mechanisms and modes, and therefore require different qualification protocols. Results have shown that BME ceramic capacitors are more susceptible to degradation than PME ones under autoclave conditions (high humidity and high temperature) due to the fact that BME capacitors have higher oxygen vacancies.¹⁸ It is straightforward to notice how can this relate to the reliability of ceramic capacitors used in implantable medical devices under high humidity and

miniaturization constraints. Added to this is the impact of the material used in the ceramic dielectric which depends on the material of the internal electrodes,¹⁹ the percentage of dopants used in the dielectric,²⁰ the difference in the acceleration model followed (especially for the BMEs),²¹ and the variety of cracks which are the main causes of failure in ceramic capacitors.²² Of course, not all design factors of electronic components should be taken into account but extended application-specific research on physics of failure could immensely benefit reliability prediction. FIDES guide could also be enriched with newer popular technologies, such as Micro-Electro-Mechanical Systems (MEMS) which are of a huge interest in medical applications.

Therefore, to get a more holistic predictive reliability model for electronic subsystems, there needs to be an updated understanding of the physics of failure that comes with the technological advances. This means conducting life tests that take into account more environmental and technological design factors, especially those related to miniaturization. For this purpose, ALT is a good candidate to obtain a model taking into account environmental factors. Planning such tests could be time- and resources-consuming if we consider all design factors but employing design of experiments methods could be useful for that.

3 | ALT BASED ON THE PHYSICS OF FAILURE

Most of reliability studies conduct accelerated tests based on test plan optimization and on statistical methods without studying the physics of failure and the failure mechanisms of the product.²³ Highly accelerated life tests (HALT) are usually conducted to determine the product's operation limits and to identify the dominant failure modes. In fact, most ALTs are designed with one or two stress factors (mostly assumed independent) while electronic components are subject to multiple stressors, which sometimes interact with each other. Establishing a Failure Modes, Mechanisms, & Effects Analysis (FMMEA) enables the test planner to understand the physics of failure of the product to better identify the relevant combination of stressors, possibly their levels, censoring times, and methods to be used, as well as to facilitate the data analysis.

FMMEA (unlike FMEA, Failure Modes & Effects Analysis) investigates the failure mechanisms to assess their role in accelerating the product's failure. It sorts them by criticality to model the interaction between environmental variables during the product's life cycle and its lifetime.²⁴ Establishing an FMMEA helps to identify the type of test to perform and to understand the effect of the test on the failure mechanisms. Failure Mode Verification Testing (FMVT) is a method used in reliability assessment in automotive domain to accelerate the product's failure.²⁵ This method employs the stressors identified through the physics of failure and applies simultaneously these stressors to the product starting from operational level up until a predetermined maximum level of each stress. However, Yadav et al.²⁶ point out the lack of existing models (some of which were applied to semi-conductor devices) that assist in an effective choice of type of test, choice of component or subsystem, and choice of number of units allocated to each test. They argue that there needs to be a systematic understanding of a system's functional structure as well as that of failure behavior, including the criticality and the effect of failure mechanisms on each element of the system, physically and functionally. They proposed a methodology to help product designers plan effective and robust reliability demonstration tests based on existing information. This methodology is a three-dimensional combination of physical structure, functional requirements, and degradation behavior over time. Li et al.²³ take this further by considering systems under multiple stresses exhibiting multiple failure modes. They propose an Analytic Hierarchy Process (AHP) methodology to design an Accelerated Reliability Demonstration Testing (ARDT) plan and accelerated test profile based on stress-strength interference (SSI). The AHP is used to allocate reliability for each type of environmental stress which is potentially failure-provoking, with weights distributed based on field and warranty data. It takes into account the unknown effect of interdependence between stresses as well. Even so, the proposed methodology depends heavily on the environment profile and the application of the product, thus making it complicated to design a test plan for electronic components potentially used in a range of types of environments (e.g., components used in neuro-implants with respect to components used in pacemaker).

The physics of failure approach used on electronic products relies on²⁷:

1. Defining the product's requirements and operational and environmental conditions.
2. Identifying failure roots, failure sites, failure modes, and failure mechanisms through a stress analysis.
3. Fitting a failure mechanism model which can be validated through ALTs. If no model exists, new ones can be developed by applying design of experiment methods to find the relationship between relevant design factors and lifetime.
4. Assessing reliability by calculating the time-to-failure for each failure mechanism.

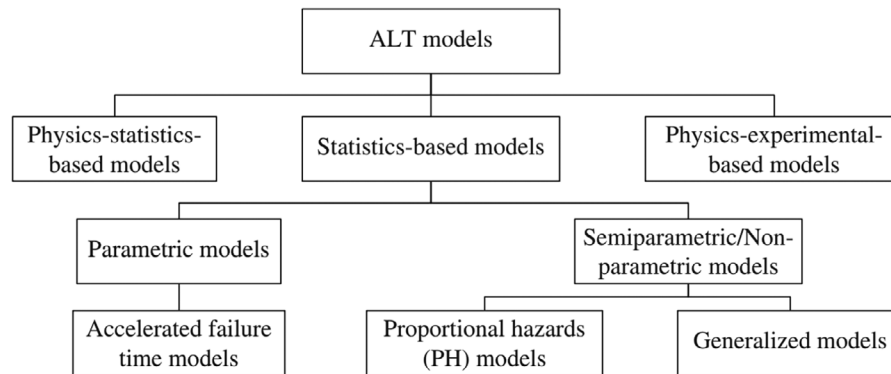


FIGURE 1 Classification of ALT models.³⁴

5. Deriving useful data: appropriate ALTs conditions, sensitivity to stresses, safe region of operation at normal conditions.

The idea of relying on the product's mission profile to predict its reliability based on the physics of failure is not novel. Liu et al.²⁸ review existing lifetime models for super-capacitors to incorporate it in a reliability-oriented design procedure. Ma et al.²⁹ discuss the existing methods for reliability modeling and testing based on physics of failure applied to power electronics.

Furthermore, physics of failure plays an important role in ALT plan. Further details about accelerating life testing planning will be discussed in Section 4. Evidently, being conscious of the failure mechanisms and their interactions helps to identify the significant accelerating factors and to design their combinations as well as to avoid issues potentially related to missing a failure mode in ALT^{30,31}. In fact, setting up stress limits ensures that the dominant failure mechanisms during nominal life cycle do not shift to different ones during the accelerated life test.³² Some detailed examples of interactions between accelerating stressors are covered by Hu et al.³²

4 | REVIEW ON ALT PLANNING

ALT consists of subjecting a product to higher stresses (variables) than it normally is subjected to during the operating conditions. This so that its degradation is accelerated, and that failure happens faster than it otherwise would. The purpose of performing an accelerated life test can include: identifying failure for design improvement (HALT), detecting manufacturing defects to assess quality, burn-in to eliminate early failures, estimating reliability parameters (mean time to failure, failure rates, etc), developing and validating the statistical models that represent the physical failure processes through data analysis, etc³³... or to demonstrate that the product meets reliability target (RDT).

Accelerated life tests can be classified according to Figure 1 to the following models:

- **Physics-statistics based models:** which are models that describe the physical relationship between stresses and failure rate of a product under test. These include models that depend on the type of the environmental stress. For instance, Arrhenius model² and Eyring model² can be used to describe the failure of a product accelerated by temperature, and Inverse Power model² is usually used to describe failure accelerated by voltage or pressure.
- **Statistics-based models:** used when the physical relationship between stresses and failure time is not known. These can be categorized according to their assumptions and failure time distribution as follows (also see Table 1 which shows how hazard rates are calculated for each model based on its assumptions, expressed as a baseline hazard rate times an acceleration factor):
 - **Parametric models:** most commonly using exponential, Weibull, normal, lognormal, gamma, and extreme value failure-time distributions (failure time following the same distribution at different levels of stress). A linear or non-linear life-stress relationship is assumed to statistically estimate parameters by adopting accelerated failure time (AFT) models.³⁴
 - **Nonparametric/semiparameteric models:** more suitable to model failure-time for complex failure processes or small number of runs, since they are “distribution-free”. These mainly include the linear models and proportional hazard models (which is more flexible than the traditional failure time regression model³⁵).

TABLE 1 Most commonly used ALT models (Section 4).

Model	Assumptions	Parameters
AFT	<ul style="list-style-type: none"> The log-lifetime depends on the applied stress via: $Y = \log(T) = \mu(\mathbf{z}) + \sigma\epsilon$. The location parameter follows some assumed life-stress relationship: $\mu(\mathbf{z}) = \beta_0 + \beta_0 z_0 + \dots + \beta_n z_n$. The covariates (applied stresses) act multiplicatively on the failure time, or linearly on the log failure time, rather than multiplicatively on the hazard rate: $\lambda(t; \mathbf{z}) = \lambda_0(e^{\beta z} t)e^{\beta z}$. The times to failure are inversely proportional to the applied stresses. 	<ul style="list-style-type: none"> T: the lifetime. \mathbf{z}: a stress vector of n stress functions z_i. $\mu(\mathbf{z})$: the distribution location parameter which depends on a stress \mathbf{z}. $\sigma > 0$: the distribution scale parameter which is constant. ϵ: a random variable whose distribution doesn't depend on \mathbf{z}. β_1, \dots, β_n: regression coefficients.
PH	<ul style="list-style-type: none"> The basic Proportional Hazards model is given by: $\lambda(t; z_1, \dots, z_n) = \lambda_0(t)e^{\beta_1 z_1 + \dots + \beta_n z_n}$. The failure rates are proportional to the applied stresses. No assumption needed on failure-time distribution. The hazard rate functions for different units when tested at different stress levels must be directly proportional to one another (the ratio doesn't vary with time). The covariates act multiplicatively on the hazard rate (they can be time-dependant as well). 	<ul style="list-style-type: none"> $\lambda(t; z_1, \dots, z_n)$: the hazard rate at time t for a unit under regressor covariates. z_1, \dots, z_n: regressor covariates. β_1, \dots, β_n: regression coefficients. $\lambda_0(t)$: unspecified baseline hazard-rate function.
Linear	<ul style="list-style-type: none"> The linear model is typically modeled as: $T_i = \alpha + \beta^T \mathbf{z}_i + e_i (i = 1, \dots, n)$. t_z is assumed to have the same distribution as: $t_z = e^{\beta^T \mathbf{z}_i} T_{i_0}$. The hazard rate of t_z: $\lambda_z(t) = \lambda_0(e^{\beta^T \mathbf{z}_i} t)e^{\beta^T \mathbf{z}_i}$. 	<ul style="list-style-type: none"> T_i: the time to failure of the ith unit. \mathbf{z}_i: the vector of the covariates (stresses) associated with time to failure T_i. β^T: the vector of regression coefficient. e_i: error coefficients following the same distribution. t_z: the survival time under stress vector \mathbf{z}.

- **Physics-experimental-based models:** based on the physics of failure mechanisms either theoretically or experimentally. The most widely used ones for time-to-failure prediction are electromigration model, humidity model, and fatigue failure model.³⁴

Most ALT models used currently belong to the parametric statistics-based models' category. Especially those that estimate the location-scale distribution and the linear stress-life relationship using the maximum likelihood estimation (MLE) method, being the most advanced theory.³⁶ However, as can be noticed from assumptions in Table 1, the parametric models basically consider the same failure time distribution for different stress levels, while real life conditions can prove to be more complex.

To determine the most suitable ALT model for qualification of the parameters of electronic components, it is crucial to have an exhaustive understanding of their functionality, the failure mechanisms taking place, the failure modes, as well as the accelerating factors. For this, an FMMEA must be evaluated for each electronic component of interest. This includes identifying (a) the factors, related to process or to environmental conditions, which accelerate the failure of the component, (b) the physical, chemical, biological, and/or electrical phenomena taking place, (c) the failure location, (d) the effect by which the failure is observed (failure mode),³⁷ (e) the criticality of the failure, and (f) the potential inter-dependency between the different failure mechanisms. Due to eventual limitations in time, in cost, and in literature resources, the choice of test methods can be made based on the most critical failures.

Based on the final FMMEA performed on the product, the following step of the design of accelerated test is to identify the main acceleration stresses (environment variables), their respective levels, how these stresses are applied, for how long, and how many product samples are used per test.

After identifying the accelerating factors, the next step is to fix the lowest and the highest levels of each stress in such a way that the failure mechanisms of the component are accelerated without going beyond its physical limitations nor generating failure mechanisms other than what can occur in normal operating conditions.

There are three types of stress loading for each accelerating factor^{33,38}:

1. **Constant stress:** each sample is subject to a constant level of the stress for the whole period of the test. Most ALT plans use this type of stress loading. They are easier to implement but require more test run time.
2. **Step stress:** each sample is subject to a series of increasing levels of stress. In other words, if the sample subject to initially a certain level of the stress does not fail after a period of time, the level of the stress is increased and applied to the sample for another period of time and so on. The duration of the period of application as well as the level of stress can differ from a sample to another.
3. **Progressive stress:** each sample is subject to a continuously increasing level of the stress. The rate of the rise can differ from a sample to another. This type of time independent stress, along with step stress, enable a quicker failure but suffer from poor estimation accuracy.

To collect the desired information from an accelerated life test, the resulting data of the test must be analyzed. In the ideal situation where all tested units fail, complete data can be analyzed. Otherwise, data is “censored”. Typically, the tests are run for a fixed period of time T at the end of which the units are inspected for failure or survival, and the exact times of failure are collected. The resulting data is called “censored type I” data (time censoring). During the period of the test T , there can be units that showed no failure, which means that their failure time falls after the fixed time. The data obtained from these units is called “right censored” data. Alternatively, the tests can be run until a certain fixed number of failures occur. The resulting data is called “censored type II” data (failure censoring). In some cases, the exact times of failure of the failed units are not known, only the interval in which the failure occurred if the inspection is done more than once. The resulting data is thus “interval”, “grouped”, or “read-out” data. The ALT test mode most often used is Constant Stress Accelerated Life Test (CSALT) with single stress and time censoring.³⁶

The technical problems of reliability testing (ALT) are determining the stress levels at which the tests should be performed, as well as the selection of combinations of these levels, which requires the development of a design of experiments. The statistical problem is to estimate the parameters of life distribution under use conditions based on collected failure/degradation data from accelerated life tests, while considering the various configurations mentioned previously.³⁹

ALTs are mostly used for reliability determination purposes, using constant single stress with type I censoring.³⁶ However, with the ever-growing evolution in technology, products, especially electronic components, are becoming more and more robust and reliable which makes it more and more difficult to estimate their lifetime using a single stress variable, especially since real life conditions are complex and involve more than one stress factor (multi-stress tests can also accelerate faster the failure). It is, therefore, more interesting to plan ALTs with two or more stress variables.

Escobar and Meeker⁴⁰ were the first to plan ALTs for more than one stress variable. They, along with numerous other authors, designed test plans based on the precision around a quantile estimate or hazard functions, using Monte Carlo analysis (instead of power analysis) for more detailed evaluation of test plan statistical characteristics.⁴¹ Escobar and Meeker⁴⁰ presented a compromise plan when two stress factors without interaction were considered (with straightforward extension to a greater number of factors) where the highest level of each factor are restricted. They optimized the plan using C-optimality and D-optimality (by minimizing the standardized asymptotic variance of MLE for a given quantile) but it becomes problematic when there are more than two accelerating factors. Park and Yum⁴² also considered two stresses in their work and arranged the test points with a full factorial design. The interaction effects of the two stresses were also considered using the generalized Eyring model. Elsayed and Zhang⁴³ designed an ALT with multiple stressors based on a proportional hazard model (allegedly the first, they used a full factorial design to arrange test combinations). The upper bounds of stresses are pre-specified, whereas two levels for each stress are to be optimally determined while minimizing the variance of the reliability prediction at normal operating conditions. Yang and Pan³⁵ applied the proportional hazard model on failure times to transform the problem of ALT planning with interval censoring to the problem of experimental design for generalized linear model (GLM) (used to simplify the derivation of information matrix used for test plan optimization). They considered the interaction effects of two stress variables. A broad review of ALT methods is made by Limon et al.¹ and a brief review of multi-stress ALT methods by Zhang et al.⁴⁴

There also exists different optimization methods to obtain an optimal test plan by minimizing or maximizing the objective of interest under given constraints applied to a presupposed model⁴⁵. For instance, a D-optimal design, as mentioned earlier, maximizes the determinant of the Fisher information matrix of MLE. This optimality criterion

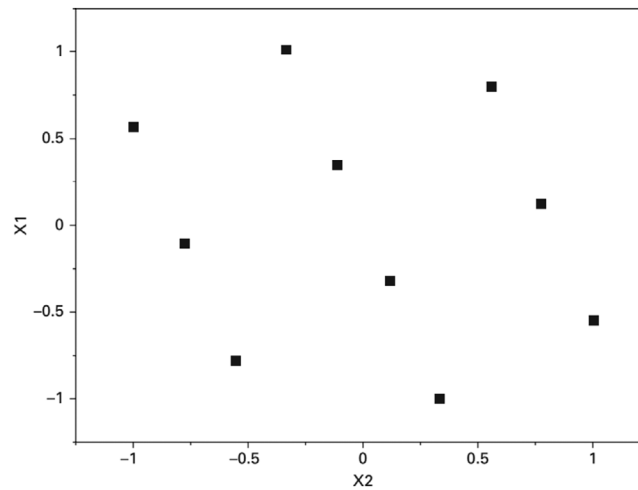


FIGURE 2 A 10-run Latin Hypercube design.⁴⁵

subsequently minimizes the generalized variance of the model's estimated coefficients. A V-optimal design, for example, minimizes the average variance over a set of finite experimental points while I-optimal design minimizes it over the use condition points. An economical approach can also be considered including test activities cost and warranty cost.⁴⁶

The issue with multiple stresses test planning is that the number of tests to run can increase significantly depending on the number of the stress factors and the number of levels for each stress factor. For instance, having three accelerating factors with four levels each would require $4^3 = 64$ runs to cover all the stress-level combinations. This is without taking into account other experimental factors which are usually included in the planning. One of the solutions to this is the Latin Hypercube Design (LHD) method, which is a space-filling design, proposed by Zhu and Elsayed.⁴⁷ Generally, space-filling designs have been one of the interesting alternatives to design an experiment when the experimenter does not have a solid preliminary knowledge of the response of the system under study across the experimental region, since they spread the design points uniformly over this region. Latin Hypercube is a common space-filling design that divides the range of k design variables of n levels into equally spaced intervals between each other. An array of n rows and k columns is then constructed by independently assigning a permutation of $\{1, \dots, n\}$ to each column⁴⁸ and the design is denoted LHD(n, k). Figure 2 is an example of an LHD of 10 runs and two variables whose levels fall between -1 and +1.⁴⁵ Applying this method would yield, based on the same example above, an experiment of only four runs, assuming the factors are mutually independents. Zhu and Elsayed⁴⁷ considered the LHD method in their study and obtained the optimal design for ALT with several stresses and several stress levels. When the LHD method is applied, the stress levels have to be predetermined and they are not treated as optimized variables.

The advantages of choosing an LHD over a full-factorial design include the ability to run smaller number of runs having many input variables while keeping a small variance on the response. This variance can be further decreased by methods that improve Latin Hypercube Sampling (LHS), such as the method introduced by Tang⁴⁹ which constructs an LHD based on an orthogonal array.

An LHD can be further optimized by adopting optimality criteria such as maximin distance criterion and entropy criterion. The former measures the scattering of the points across the experimental region and minimizes the distance between the experimental points and the design points. The reader can refer to the respective works of Joseph and Hung⁵⁰ and Fang et al.⁵¹ for more about maximin criterion or other criteria, of Viana⁵² for a review on the algorithms used for constructing optimal LHDs, of Giunta et al.⁵³ for an overview of modern DoE software, and of Beachkofski and Grandhi⁵⁴ for an improved Latin-Hypercube sampling.

5 | APPLICATION OF DOE ON ALTS: EXAMPLES AND CHALLENGES

From the examples of DoE methods' applications on ALTs prefaced at the end of the previous section, it can be noticed that they are applied using environmental stresses as factors of concern without considering the product's design factors, which are originally the factors of interest in DoE robustness studies. This is one of the limitations this section aims to discuss.

While the accelerated life tests enable primarily the reduction of time by using severe levels of stress, the design of experiments enables the reduction of resources by testing relatively few combinations of factors without losing information (or statistical efficiency). Combining these concepts would enable further optimization of time, resources, and overall cost. Especially since electronic components are subject to various types of stresses in most environments in which they are designed to operate. The bigger the number of stresses, the more complicated the planning of an ALT becomes.

Despite this, using design of experiments approaches for ALT planning does not seem popular. While there is an intensive literature on respectively both concepts, few publications exist on the combination of the two, as design of experiments approaches are not quite efficiently applied to reliability testing. Indeed, reliability testing takes into account many technicalities that make it difficult to merge with DoE methods. These include:

- The nature of reliability data.⁵⁵ While DoE approaches assume that data follow a normal distribution, failure time, which is usually the response of interest in ALTs, often follows Weibull distribution (skewed distribution)⁵⁶.
- Considerations in ALTs imbalance experiments' responses/experimental design such as censoring, sample size, stress level selection, sample allocation to stress levels.⁵⁶ These considerations are optimized using criteria that depend on the objective of the experiment.
- ALT extrapolation nature increases uncertainty in model estimation in nominal conditions.⁵⁶
- The extrapolation nature of failure time at the use conditions.⁵⁷
- Many DoEs use randomized designs while ALT plans are typically constrained by censoring time, unit size, and other parameters that make experiments not randomly run.⁵⁵ This results in what is called random effects which should be incorporated into the corresponding model.

Conventional DoE approaches such as factorial designs are often applied to ALT. However, they are not used in a way to accommodate the nature of ALT (censoring time, prediction at the use conditions, etc), which renders them inefficient (DoE typical applications on ALT does not fully exploit the advantages of DoE methods). Therefore, optimal design methods are more favorably used. Still, it is very useful to apply DoE methods on ALTs since the latter are very often, if not always, subjected to constraints related to time and cost.⁵⁷

In most planning methods of ALTs, observations (failures) are considered independent while that is not the case in real life. Therefore, a good test planning should take into account the restricted randomization in given conditions.⁵⁷ In fact, the classic three pillars of a proper experimental protocol, according to Vining⁵⁸ and Wu and Hamada,⁵⁹ are:

1. **Replication:** applying each treatment on experimental units that represent the whole population of concern.
2. **Blocking** (local control of error): controlling anything that might affect the response (e.g. using the same set-up for each run or running experiments the same day to eliminate day-to-day variation).
3. **Randomization:** running the experiments combinations at a random order (if blocking is not possible).

To effectively plan an ALT based on DoE, it is key to consider designs with sub-sampling, blocking, cluster, groups, split-plot... where random effects should be considered.⁶⁰ Ignoring the random effects model in ALT often results in the bias of shape parameter. Such bias is of significance because of the shape parameter's relationship to the underlying failure mechanism. Treating observations as independent like Meeker and Escobar did,⁶¹ results in the wrong experimental error and observational error.⁶²

Lv, He & Vining⁶⁰ provide a method for quality optimization using type I censoring sub-sampled lifetime data (since designed experiments are not usually completely randomized) while simultaneously optimizing reliability thanks to a desirability function. The quality characteristic is based on the response mean with respect to a quality target and the reliability characteristic on maximizing the location parameter. They applied a two-stage method that was previously used by Vining et al.⁵⁵ to integrate the random effects into the analysis (the contribution of the newer paper is the bias correction for the shape parameter). Wang et al.⁶³ propose an improved method of Freeman and Vining's two-stage approach to further reduce bias on estimates and calculate confidence intervals of low percentiles by bootstrapping.

In another example of incorporating DoE concepts into ALT planning,⁵⁶ a GLM framework is used to calculate easily the ML estimators (a similar use is mentioned in Section 4). This method employs iteratively weighted least-square (IWLS) approach which improves test planning by linking between the design factors and the response of the system. This method also enables the consideration of more than two factors as well as their interactions. This clearly immensely makes test planning more efficient and reduces the cost given the complexity of conventional test plan methods that increases with the addition of stress factors.

Another approach commonly used in DoE is statistical power analysis. It is not specific to DoE in itself, but it is more ubiquitous in quality evaluation than reliability assessment. Statistical power is the ability of a significance test to detect an effect given there really is one (The Probability of Test Success). For most reliability experiments, the purpose is to understand the effect of a factor on the response (usually the lifetime of the product), therefore power analysis is very useful. This is in contrast with quality control applications which focus on precision.⁴¹ Still, using statistical power analysis is challenging for reliability testing because lifetime data are usually Weibull or log-normally distributed while the power analyses studies exist for normally distributed data.⁶⁴

All the examples previously mentioned still do not take full advantage of how DoE methods could contribute to ALT plan optimization. The rest of this section will highlight some more useful applications of DoE to ALT by introducing first, one of DoE statistical methods widely applied, although controversial, in various domains, which are Taguchi methods. The latter can be used for instance for efficiently determining the dominant factor among complex interacting design factors affecting the quality of a system or a process, enabling a more robust design. This can be done by experimentally estimating the effects of noise factors based on a defined criterion to be optimized.⁶⁵ This criterion can be the s-expected loss (the effect of the noise factors at a certain combination of control factor levels) and can be calculated according to Equation 3:

$$L(x_{control}) = \int l(Y(x_{control}, x_{noise})).f(x_{noise})dx_{noise} \quad (3)$$

- $l(.)$ is the loss function.
- $Y(x_{control}, x_{noise})$ is the response at the combination of control factor levels $(x_{control}, x_{noise})$
- $f(.)$ is the joint pdf of noise factors.

The main application of Taguchi methodology is to make a product or a process robust against noise factors by finding optimal settings of control factors and the dominant quality factors. Such methods can be exploited in ALT contexts. For instance, Taguchi robust design methods were previously applied⁶⁶ on an evaporator tubing system while performing ALTs to define the levels of the control parameters. More inclusively, by using Taguchi product array approach, one can implement experiments using reliability as a response and set design factors (e.g., manufacturing, technological characteristic) as an inner array of controllable factors and set environmental stressors as an outer array of uncontrollable factors. An interesting example of this is applied to avionics⁶⁷ to improve product integrity. Despite the fact that in this example such approach is used solely for identifying the design factors' levels that enable maximum reliability under all operating environments, it provides a starting ground for potential extension to ALTs. Condra attempted this on surface mount capacitors in his book,⁶⁸ albeit general. The results from this example were used to choose the optimum design factors for the inner array factors and predict mean time to failure during operating conditions of SMD capacitors. The same book, which is a pioneer in the subject, contains other examples of improving reliability using DoEs.

Such applications could be even further enhanced by taking into account the physics of failure of products and incorporating FMMEA or FMEA. Su et al.⁶⁹ proposed a three-stage methodology to improve the reliability of an Electronic Paper Display (EPD) using FMEA and Taguchi methods. Firstly, the ideal function that relates the product reliability to its signal input is derived from ALT. Secondly, critical parameters affecting reliability of the product are defined through FMEA. Thirdly, Taguchi methods (signal/noise strategy) are applied to find the optimal combinations of these critical parameters that ensure the optimal function defined in the first stage. This methodology however is mostly suitable for reliability improvement during the development stage of a product and is limited to products whose design is pre-defined and which preliminary underwent ALT. It does not allow the generalization in the context of reliability improvement given any type of control factors. For instance, it cannot be directly applied to efficiently model the reliability of a family of an electronic component.

6 | CONCLUSIONS AND PERSPECTIVES

This work reviews the state-of-the-art of ALT plans based on design of experiments for the purpose of reliability prediction modeling. First of all, a description of the main existing guides for the prediction of the reliability of electronic components is made. This description shows the current limits of the prediction models with respect to the consideration of the failure

mechanisms and that of the various design factors, especially for the newest electronic components. The improvement of these models requires the implementation of accelerated reliability tests taking into account design and stress factors. In a second part, ALT planning methods are reviewed considering one stress, two stresses and several stresses. Experimental designs have been used to optimize the test plan according to an objective function without taking into account the physics of failure except to define the independence of the stresses, allowing the reduction of the number of tests, as in the example of the LHD. In a last part, a literature review of DOE methods, applied to ALTs taking into account design elements, is provided, as well as their challenges.

Although there are various ways which have been used to employ DoE methods for ALTs, literature resources are still introductory and do not thoroughly provide mathematical details on this specific implementation. Besides, in numerous examples, the design factors are the environmental stresses which electronic components are subject to, and the experimental design does not allow for the influence of technological parameters. In fact, the DoE methods are either:

1. Used to define the combinations of environmental factors of the ALT without considering design factors.
2. Applied to assess reliability by evaluating simultaneously levels of design and environmental factors under operating conditions without acceleration.
3. Used to assess the reliability of the product with respect to its design factors while predicting lifetime without studying the impact of these design factors.
4. Applied on ALTs based on the physics of failure but with the aim of finding optimal design parameters in the context of design for reliability or robustness.

A global framework is still missing to provide a reliability model which integrates design and environmental factors such as FIDES. The use of an FMMEA approach can reduce the number of required tests induced by a product DoE matrix. Nonetheless, owing to the contrast between the two approaches, meticulously joining them together throughout all the stages of the methodology is very crucial for an efficient ALT plan in a way that is more consistent with the rapid technological progress of electronics. Promising directions for planning ALTs based on DoE and FMMEA could include:

- Analyzing FMMEA to associate stress factors with design factors that are most vulnerable to it through the failure mechanisms of concern.
- Exploiting Taguchi product array for design factors vs ALT environmental stressors chosen based on FMMEA.
- Using Bayesian methods to incorporate information from FMMEA to improve the designed reliability experiments.

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DATA AVAILABILITY STATEMENT

Data sharing not applicable to this article as no datasets were generated or analysed during the current study.

ORCID

Fatima-Ezahra Indmeskine  <https://orcid.org/0000-0002-3183-4310>

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AUTHOR BIOGRAPHIES

Fatima-Ezahra Indmeskine is currently a PhD candidate in LARIS University of Angers working within the framework of RECOME Project (Reliability of Electronic COmponents for MEDical applications) which is a collaboration between LARIS laboratory of University of Angers, TAME Component a business unit of TRONICO company and SATT Ouest Valorisation. She received, in 2020, an engineering degree from Phelma Grenoble-INP (France) and a joint international Master of Science from Phelma, Politecnico di Torino (Italy) and EPFL (Switzerland) in Micro and Nano Technologies for Integrated Circuits. Her research interests include electronic components reliability, design of experiments, failure analysis, statistical modeling, electronic engineering, physics of semiconductors and material sciences.

Laurent Saintis is an associate professor at University of Angers in the department of Quality, Innovation and Reliability Engineering. He is head of dependability research team of the LARIS lab. He works principally on complex systems modeling for dependability evaluation and reliability testing. Since 2015, he is mainly involved in the design of reliability test plan for electronic medical devices, and is responsible for the RECOME project for the laboratory. His main teaching themes are dependability, maintainability design, reliability assessment and value analysis.

Abdessamad Kobi has a PhD in the field of automatic and electrical engineering from the “Institut National Polytechnique de Lorraine, Nancy France” (1994) and HDR (Habilitation à Diriger les Recherches) from University of Angers (2003) in Optimization and Control the Industrial Processes. He teaches courses in Applied Statistics, SPC, DoE, Six Sigma and Dependability. He is now at the LARIS laboratory of University of Angers and Full Professor at the Polytech Angers, School of Engineering of University of Angers in department Quality-Innovation-Reliability. He is also director of International Master in systems engineering and project management at Polytech Angers/University of Angers. His field of interest includes process diagnosis, statistical process control (SPC), Data Analysis and Lean/Six sigma.