

Minimization of Life Cycle Costs Through Optimization of the Validation Program – A Test Sample Size and Warranty Cost Approach

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SUMMARY & CONCLUSIONS

This paper presents a method for calculating desired reliability demonstration for a product validation process, based on life cycle cost minimization. The paper is written in the context of a high-volume production industry and has a specific application to automotive electronics. The proposed method suggests a way to optimize the target reliability based on minimization of the sum of validation cost and expected reliability-related warranty returns by analytically linking the product validation cost with the expected warranty. Validation cost can be related to a test sample size required for demonstration of a specified reliability with a pre-determined confidence level. Test sample size is in turn often linked to reliability demonstration in environmental tests targeted at durability, such as vibration, high-temperature endurance, and temperature cycling.

Higher reliability is expected to reduce the cost of warranty returns, but at the same time to drive up the cost of product development. Thus an optimal solution is possible by finding a target reliability corresponding to the lowest value of the total expected life cycle cost. The methodology in this paper is developed and demonstrated using applications from automotive electronics industry with a case study based on data obtained from the real life warranty databases

1. INTRODUCTION

Many of the product life cycle accounting models presented in the literature (e.g., [1]) consider the overall cost of the design cycle, but often ignore the specific components of product validation cost¹. This paper presents an analysis of life cycle cost from the viewpoint of a reliability organization and suggests ways to optimize the validation procedures with the controls available to a reliability engineer as oppose to product designer. The control variables considered herein are part of the cost structure of an environmental test laboratory as well as the effect of reliability specifications pursued by

reliability professionals as an ultimate goal of a product validation process.

Reliability demonstration is one of the “controls” available to a reliability engineer (also referred here as validation engineer) whose main function in this process is to detect a potential nonconformance to the specification of the product and to communicate this information to a design engineer. Knowledge about the cost of an application-specific validation program can be a very important piece of information during a quoting process, where a validation engineer is expected to estimate validation cost based on the reliability requirements presented by the customer.

1.1 Nomenclature & Notation

- R = reliability
- R_0 = target reliability demonstration
- C = confidence level
- N = test sample size
- n = number of units produced
- λ = failure rate
- α_b = per unit cost to the customer (customer’s price)
- α_d = design cost of the total program
- α_{pv} = cost of product validation for the program
- α_m = manufacturing cost on a per unit basis
- α_w = cost of warranty on a per unit basis
- P' = seller’s profit
- θ = vector of design parameters
- n_f = number of failed units subjected to warranty repair within the warranty period
- OEM = Original Equipment Manufacturer
- $\underline{W} = \{T_0, M_0\}$ = two-dimensional warranty [2] where T_0 is the warranty time limit (typically 36 months) and M_0 is the warranty mileage limit (typically 36,000 miles).

¹ Validation cost usually includes engineering and capital expenses associated with full-scale environmental, mechanical, electrical, and other types of testing at various stages of product development.

1.2 Test Sample Size

Test sample size has always been an important part of the reliability requirements presented by OEMs to their suppliers. The goal of testing a number of test samples is to reflect the variation in the product design and to draw conclusions about the demonstrated reliability and the confidence level associated with it. The choice of a test sample size is usually dictated by a variety of factors. On one hand, the larger the sample size the better the chances of discovering design-related failure, which could be related to a specific design parameter being outside of its specification. On the other hand, a large sample size would negatively effect the overall cost of the validation program, since each test sample carries the expense of producing, testing, recording, storing, and other costs associated with environmental and functional testing.

Statistical experiments are generally performed to learn more about unknown parameters characterizing the product of interest. In reliability demonstration testing the unknown parameter is the product reliability R and an attribute reliability experiment is performed to learn more about its magnitude. The experiment consists of observing N successes out of N reliability test trials. A peculiar feature of the product specification is that most often 100% success rate is required, failing which would necessitate certain corrective actions.

In most common reliability trials, the success rate, albeit usually high, is random. Techniques commonly utilized to calculate sample sizes for reliability demonstration of a product when a 100% success rate is required are generally referred to as Success Run Formulae derived from the binomial distribution (see for example [3]):

$$C = 1 - R^N \Rightarrow N = \frac{\ln(1-C)}{\ln R} \quad (1)$$

One of the features of success run equation (1) is that as the reliability R approaches 1.0, test sample size quickly approaches infinity, which limits the usefulness of the Success Run approach in cases where high reliability demonstration (e.g., $R > 99\%$) is required.

2. PRODUCT DEVELOPMENT COST VERSUS RELIABILITY

The conventional approach to minimizing the life cycle cost is illustrated in Figure 1, which depicts the growing product development cost with the increase in reliability and decrease in warranty/service cost with rising reliability. The domain where the total cost, which is equal to the sum of the cost of product development and the warranty/service costs reaches its minimum would indicate the optimum target reliability of the program.

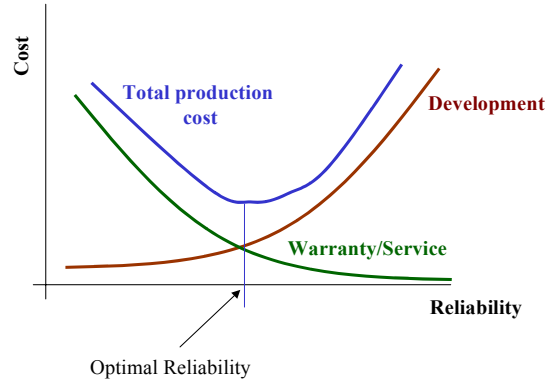


Figure 1. Theoretical 'Product Development Cost versus Reliability' Curve.

Needless to say that the relationship depicted by Figure 1 is very generic in nature and does not reflect the specifics of a real program, which obviously can vary significantly from situation to situation. In cases where reliability demonstration is governed by Success Run testing that is represented by equation (1), the cost of product validation grows exponentially with the increase of a test sample size. Since each sample adds cost to a validation program, at some point its cost would outweigh the benefits of further reduction in expected warranty cost. Thus the high reliability requirements often required by automotive customers are not always economically justifiable in the cases where sample size is based on Success Run reliability testing.

3. TOTAL PRODUCT COST

In general terms, the cost model for a mass production automotive components can be described by the relation below:

$$\text{Buyer's Cost} = \text{Design Cost} + \text{Validation Cost} + \text{Manufacturing Cost} + \text{Warranty Cost} + \text{Seller's Profit} \quad (2)$$

Using the nomenclature defined in Section 1.1 of this paper, equation (2) can be presented in form:

$$n\alpha_b(\theta, W) = \alpha_d(\theta, W) + \alpha_{pv}(\theta, W) + n\alpha_m(\theta) + n_f(\theta, W)\alpha_w(\theta, W) + P \quad (3)$$

Equation (3) assumes that the number of manufactured units, n approximates the number of units sold, which is usually true for high-volume products. Equation (3) can also be regrouped the following way:

$$n\alpha_b(\theta, W) - \alpha_d(\theta, W) - n\alpha_m(\theta) - P = \alpha_{pv}(\theta, W) + n_f(\theta, W)\alpha_w(\theta, W) \quad (4)$$

On the left-hand side of equation (4), the cost of design α_d represents the value that is most difficult to estimate, since it often involves engineering time, prototype fabrication, testing, training, overhead, and many other factors. However most of α_d is estimated prior to the beginning of the new product quoting process, often during the product specification phase. The cost of product development that is included in product quotes is usually based on forecasting approaches, such as analogy models, expert judgment, prototype models, top-down calculations, and others (see for example [4], [5]). Thus, in our first order approach, we will associate α_d with the value, based on historical development cost of similar product lines and assume it is not significantly affected by product validation activities and therefore will be considered as constant relative to test sample size. Other left-hand side components of (4) also will not be noticeably affected by the test sample size.

Now let's take a look at the terms on the right-hand side of equation (4). We assume that validation procedures will be similar across products with similar application conditions, which for automotive electronics is largely dictated by product location in a vehicle. The requirement of reliability and associated confidence level submitted by the end-use customers are linked to reliability demonstration procedures, which are in turn related to a sample size. Thus, the main factor, affecting the variable cost of product validation will again be the test sample size,

$$\alpha_{pv}(\theta) \cong \alpha_{pv}(N) \quad (5)$$

At the same time, the number of units, n_f , expected to fail due to design-related problems will be proportional to unreliability, $(1-R)$ of the product and thus partially dependent on validation procedures. In fact, assuming that the demonstrated reliability would be reflected in product performance in the field, n_f will also become dependent on demonstrated reliability and thus the test sample size: $n_f = n_f(N)$

Thus equation (4) will take form:

$$n\alpha_b(\theta, W) - \alpha_d(\theta, W) - n\alpha_m(\theta) - P' = \alpha_{pv}(N) + n_f(N)\alpha_w(W) \quad (6)$$

The left-hand side of this equation is primarily determined during the new product quoting process and is often based on previous cost data as well as competitive pressures. Therefore, we assume, to first order, that the left-hand terms of the equation (6) cannot be significantly affected by product validation efforts. Thus the right-hand side of the equation (6) would be used to optimize the life cycle cost if only the variable cost of validation can be controlled as shown in equation (7),

$$\text{Validation Controllable Cost} = \alpha_{pv}(N) + n_f(N)\alpha_w(W) \quad (7)$$

In automotive electronics applications the biggest share of validation expense comes from environmental testing and power-temperature cycling in particular. Environmental testing will remain largely, but not exclusively in the focus of this analysis.

The portion $\alpha_{pv}(N) + n_f(N)\alpha_w(W)$ of equation (7) can be illustrated by the classical *reliability-cost* model (see Figure 1), where it can be optimized based on the inverse relationship between target reliability and expected warranty cost. However, most of the models presented in the literature (e.g., [2], [4]), typically lack specifics due to unavailability of the real cost data. In the example section of this paper we will specify the part of development cost, which is controlled by a reliability engineer.

4. THE WARRANTY-RELIABILITY CONNECTION

In equation (7) the term $\alpha_{pv}(N)$ would represent the ascending curve in Figure 1. The cost of validation typically increases with increases in reliability requirements. The descending curve called "Warranty/Service" is directly linked to the term $n_f(N)\alpha_w(W)$ and depends on n_f , since the cost of warranty repair α_w is typically the function of the type of product (radio, engine control system, air control, etc.), rather than the overall reliability of the product. Thus the total cost on the right hand side of equation (6) is represented by the sum of the Development and Warranty/Service curves as shown on the "Total Production Cost" curve in Figure 1. The inverse relationship between the cost of reliability and the cost of warranty will be the basis for optimizing the sample size and test duration in order to minimize the life cycle cost of the product.

A simplified equation to find a number of failed units would take the form:

$$n_f = n[1 - R(\text{Warranty Period})] \quad (8)$$

The majority of the failures reported in warranty return databases fall under one of the following five categories: initial performance and quality, manufacturing or assembly generated defects, service damage or misdiagnosis, customer misuse, and design/reliability related failures; typically only the last category can be addressed by product validation activities. The rest of the failure categories are assumed to be independent failures from design/reliability problems and generally cannot be screened by the product validation procedures.

It is extremely difficult to make a projection of product failures to the end of the expected life for automotive electronics due to a general lack of warranty data beyond a five-year time span. However based on existing knowledge and experience with automotive warranty, the following assumptions can be made:

- a. After the “infant mortality” phase, which usually lasts for approximately a year [8] for automotive electronics, the product enters the phase of relatively constant failure rates
- b. Assuming the product is designed properly, its wear-out phase begins after its expected life, thus the failure rate stays approximately constant throughout the product’s expected life
- c. At the end of the expected life the product will meet a demonstrated reliability $R_0 = R(\text{Expected Life})$. This is expected to be true for the design-related portion of the total failures

Thus, assuming a constant rate of failures, the reliability-warranty relationship can be represented as:

$$R(\text{Warranty period}) = \left[R(\text{Expected Life}) \right]^{\left(\frac{\text{Warranty period}}{\text{Expected life}} \right)} = R_0^{\left(\frac{\text{Warranty period}}{\text{Expected life}} \right)} \quad (9)$$

This relationship would provide a necessary link for calculation of Validation Controllable cost in equation (7).

5. ANALYSIS OF WARRANTY AND SERVICE COST

The cost of warranty is typically reported in most automotive databases and usually is a part of a warranty accounting system. There are two common ways the automotive dealerships calculate and report the cost of repaired items. In the cases where the unit is replaced by a reworked part, its cost is calculated at some fixed rate associated with parts repair, which is normally much lower than the cost of the new part. In the cases where the remanufactured part is not available, the cost of a new part is often calculated at a market price, which is usually higher than the actual cost of the part to the supplier or a dealer. The numbers reported have very wide ranges in dollar amount per repair, thus the best way to approach this kind of cost analysis is to perform a best-fit statistical distribution analysis of the total cost per repair on the previous year or similar models. Experience shows that most of those costs are distributed according to a lognormal statistical distribution. When the confidence bounds of the solution are of interest, statistical modeling techniques such as Monte Carlo are appropriate for optimization.

In many cases automotive suppliers rework the failed units and then reuse them as replacement parts. For simplicity we will only consider here the cases with reworked parts, where the cost of warranty and service is usually known in advance and equals to the cost of the remanufactured unit plus the labor, making them easy to include in the overall cost analysis without additional statistical simulation.

Validation controllable cost (7) can be further transformed to the equation below:

$$\text{Validation Controllable Cost} = \alpha_{pv}(N) + \alpha_w(W)[1 - R(\text{Warranty})] \quad (10)$$

In the cases where automotive dealerships replace failed parts with reworked units, warranty cost α_w can be determined relatively easily as a combination of replacement unit and labor. There are various ways of linking expected reliability and the cost of the product. For example [9] assumes the known relationship between the product’s cost and its expected failure rate λ . Here we suggest establishing this link through demonstrated reliability, confidence level, and cost associated with the required test sample size. Substituting from equations (1) and (9), we can rewrite (10) as:

$$\text{Validation Controllable Cost} = \alpha_{pv}(N) + \alpha_w \left[1 - \left((1-C)^{\frac{1}{N}} \right)^{\frac{\text{Warranty Period}}{\text{Expected Life}}} \right] \quad (11)$$

If a warranty cost α_w can be calculated as an independent variable from the data on repair or remanufacturing cost of similar units, equation (11) can be optimized by the choice of a single variable N .

6. EXAMPLE ANALYSIS

The data below is based on product validation cost and warranty returns of radio and CD playback systems, supplied to several automotive manufacturers. The cost values and reliability numbers in this example were altered due to proprietary nature of this data. In the example presented in this section we calculate the optimal target reliability with a confidence level of $C = 90\%$ for the CD playback radio with the expected life of 15 years and warranty period of 3 years.

Product Validation Costs:

Maintenance and depreciation of the test equipment (primarily test chambers),

M+D = \$40,000/year

Test unit manufacturing cost, $\alpha_u = \$1500/\text{test unit}$

Equipment and harnesses $E_h = \$120/\text{test unit}$

Labor cost associated with performing of the testing: $\alpha_T = \$40/\text{hour}$

Test duration: $L_{\text{test}} = 1200 \text{ hours/unit}$

Chamber capacity: $K=25 \text{ units}$.

Expected number of production units $n = 200,000$.

In the case where required sample size exceeds the chamber capacity, a new chamber is required, increasing the

validation cost in a step function manner. Thus the number of required chambers will equal to $2^2 \left\lceil \frac{N}{K} \right\rceil$.

The simplified validation cost model can be represented by the equation:

$$\alpha_{pv} = L_{test} \left(\alpha_T + \frac{(M + D)L_{test}}{365 \times 24} \right) \left\lceil \frac{N}{K} \right\rceil + N(\alpha_u + E_h) \quad (12)$$

Warranty cost per unit is equal to the cost to remanufacture one unit \$30 plus the average labor cost of \$60, thus, $\alpha_w = \$90$.

The simplified form of the expected warranty cost would come from equation (11) in the form:

$$Warranty\ Cost = \alpha_w n \left[1 - \left((1 - C)^{\frac{1}{N}} \right)^{\frac{3\ years}{15\ years}} \right] \quad (13)$$

The analysis of the total cost (sum of the equations (12) and (13) and its function of test sample size N is presented in Figure 2. The analysis shows that the minimum cost is obtained at a reliability value of $R = 91\%$, which corresponds to 25 test samples.

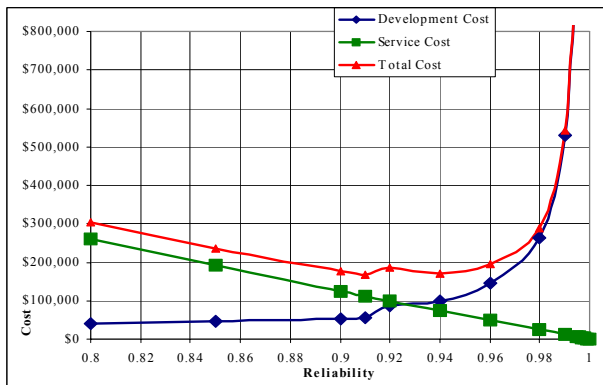


Figure 2. CD Radio cost optimization chart ($C = 90\%$)

Comparing those results with the occasionally used requirement of $R = 99\%$ with $C = 90\%$ would show the expected cost benefit of the proposed method in the amount of approximately \$375,000.

$2^2 \left\lceil \right\rceil$ is a ceiling function, indicating rounding to the next highest integer

Clearly, the cost model presented by equations (12) and (13) is somewhat simplified, however it is of value as a first step approach to a cost optimization process. The cost elements in this model may be further broken down into many additional cost factors and/or new cost factors can be introduced.

7. ADDITIONAL CONSIDERATIONS

Undoubtedly, the complete life cycle cost modeling of the product is a highly complex process and considerably more cost of ownership detail could be incorporated to obtain more accurate solutions, however the presented approach focuses on the controls available specifically to a validation engineer. Many of the cost model inputs are usually random variables and the final optimization of the cost model is an interaction of a variety of random factors. Thus the use of statistical modeling tools, such as Monte Carlo simulation or response surface models (RSM) would help to evaluate the uncertainties and confidence bounds of the optimized solution.

This type of analysis demonstrates that product validation efforts to demonstrate high reliability (e.g., $R \geq 0.99$) through success testing are rarely justified economically and offer little return value in warranty and service cost reduction. If high reliability demonstration is required by the product specifications, alternative methods should be considered, i.e., modeling and simulation, reliability prediction, Bayesian analysis, probabilistic design, step-stress programs, etc.

Whenever possible, the optimum reliability should be estimated in the early development stages of the program and be included in the technical specifications of the product. It is important to pursue optimum reliability during the program development in order to avoid excessive program expenses.

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Andre Kleyner has 18 years of experience as a mechanical engineer specializing in reliability of mechanical and electronic systems designed to operate in severe environments. He received his MS degree in Mechanical Engineering from St. Petersburg Polytechnic Institute in Russia, and MBA from Ball State University. Andre Kleyner is currently employed by Delphi Delco Electronics as a Product Validation Architect. He is a member of ASQ, and a Certified Reliability Engineer.

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Joe Boyle has 27 years of experience as an electrical engineer, 11 of those years specializing in reliability of mechanical and electronic systems designed to operate in severe environments. Joe Boyle received his BS degree in Electrical Engineering from Pennsylvania State University, MS degree in Electrical Engineering from Purdue University, and MBA from Ball State University. He is currently a Product Validation Manager with Delphi Delco Electronics and a Registered Professional Engineer.