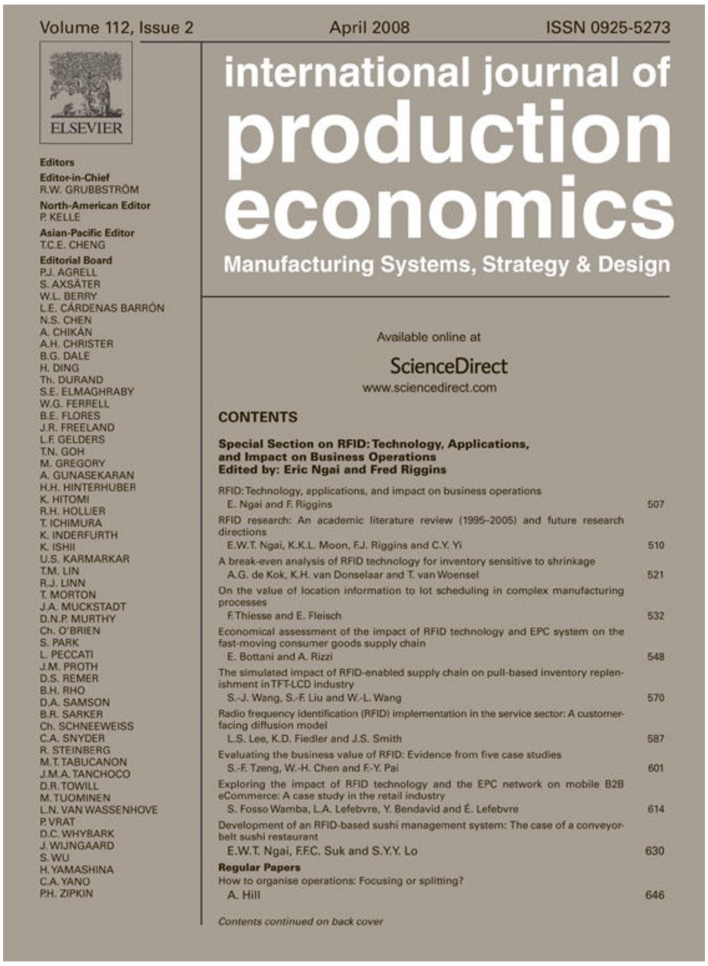

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Minimizing life cycle cost by managing product reliability via validation plan and warranty return cost

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Abstract

This paper presents a quantitative solution that minimizes the life cycle cost of a product by developing an optimal product validation plan. Dependability constitutes an integral view of a product's reliability, availability, maintainability, quality, and safety. The methodology developed in this paper incorporates several dependability-related activities into a comprehensive probabilistic cost model that enables minimization of the product's life cycle cost. The model utilizes the inverse relationship between the cost of product validation activities and the expected cost of repair and warranty returns. The model emphasizes the test duration and sample size for the environmental qualification tests performed in a product validation program. The overall stochastic cost model and its minimization are done with Monte Carlo simulation in order to account for uncertainties in model parameters. The model is demonstrated on an automotive electronics application. The results of this work provide application-specific optimal product validation plans and evaluate the efficiency of a product validation program from a life cycle cost point of view with an emphasis on the cost of validation and product warranties.

Keywords: Warranty; Reliability; Life cycle cost; Validation; Automotive

1. Introduction

Life cycle cost (LCC) analysis is a tool that produces important metrics for choosing the most cost-effective approach from a series of alternatives. LCC generally refers all the costs associated with a product throughout the product's life. The exact content of LCC varies depending on the horizon of the interested party; however, generally LCC includes conceptual/preliminary design costs, detailed design and development costs, production and/or construction costs, and product use/support/phase-out/disposal costs (Fabrycky and Blanchard, 1991). In this paper, LCC is used to refer to the combination of design, validation, manufacturing, and warranty costs. One important contributor to LCC for many types of products is the cost of product failure. The product characteristics associated with a product's potential failures or malfunctions are often summarized by the term Dependability, which constitutes an integral view of product's reliability, availability, maintainability,

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quality, and safety (Fernández, 2001). This paper focuses on two major quantifiable dependability contributions: reliability and quality.

To assure uninterrupted performance during a system's mission life, product testing and validation is conducted as an important part of the development cycle. Product validation activities normally include reliability analysis and testing (both functional and environmental), which are intended to prove that the design satisfies specified quality and reliability requirements. From a supplier's viewpoint, the cost of product validation activities is a significant variable in the overall cost model. Product development activities associated with dependability are presented in Fig. 1.

Clearly product validation activities have a direct impact on the expected warranty cost, although in many industries the issue of product validation cost and its impact on the development program are not given sufficient attention especially in the early stages of product planning.

Traditionally, in the initial phase of the business cycle during product quoting, the costs of product development and validation are treated as a one-time expense, and usually not treated in conjunction with the rest of the product's non-recurring costs. This often leads to a customer's insistence on the highest possible reliability without proper consideration for the costs involved in the process. As an example, in the mid-1990s, one of the major automotive manufacturers was on a quest to improve quality and reduce warranty claims. They decided to approach the problem exclusively from the product validation process. The product validation organization calculated the number of test samples and finds that for a required reliability of 0.90 with a confidence level of 90%, the number of test samples required is 22 (see Appendix A for a discussion of sample size calculations). If the reliability requirement is raised to 0.99, the number of required test samples becomes 229. As the reliability approaches 1.0 (100%), the number of test samples required approaches infinity. Obviously, the suppliers want to minimize validation testing in order to save money, while the customer often assumes that more testing by the supplier will solve all warranty problems—in this case the customer desired increasing reliability targets without an accurate understanding of the economic benefits (or lack thereof).

Product warranty is a significant contributor to the post-manufacturing portion of the LCC. For example, according to Nasser et al. (2002), on average General Motors spends approximately $3.5 billion per year (roughly 22.5 million warranty claims) paying dealerships to repair failed parts under warranty. Original Equipment Manufacturers (OEMs), the brand name of the product, often penalize their suppliers based on their cost of warranty by passing to the suppliers all or part of their warranty cost (Balachandran and Radhakrishnan, 2005). Based on these considerations, suppliers must make decisions at the beginning of a product development cycle regarding how much should be spent on product validation and estimate the effect of that spending on the expected warranty cost. Project managers often need to focus their activities on the dependability-related variables of LCC analysis, since these are the inputs that can be affected during the development process.

Fig. 2 shows a qualitative diagram of the relationship between the pursued reliability and the total cost. The higher the pursued reliability of the product, the higher the product development cost (the ascending curve). At the same time the higher the achieved dependability of the product, the lower the cost of the associated warranty and service (the descending curve). Relationships similar to Fig. 2 have been referred to as 'contractor's cost vs. reliability' (Blischke and Murthy, 1994) and 'dependability vs. non-dependability cost' (Fernández, 2001).

The sum of those two costs in Fig. 2 resembles a U-shaped curve with a minimum at the lowest sum of product validation and warranty cost, thus minimizing the contribution to total LCC. Unlike

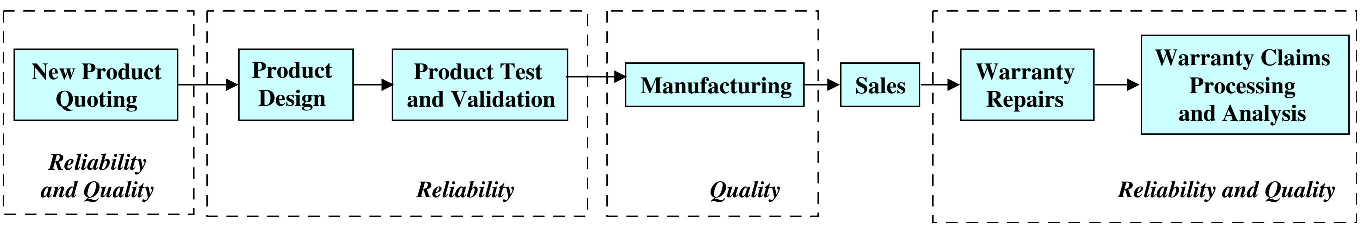

Fig. 1. A product development process involving dependability-related activities.

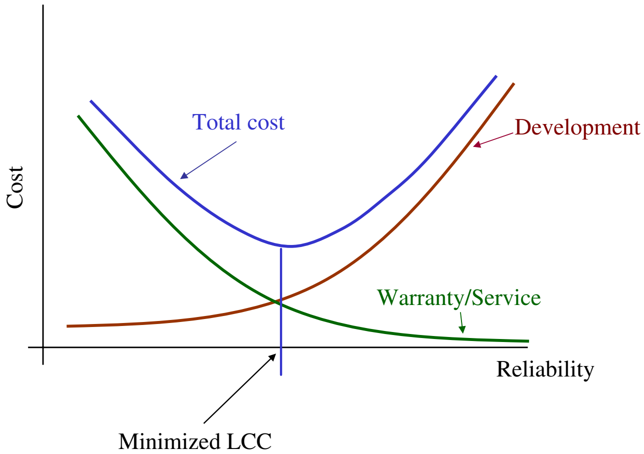

Fig. 2. Theoretical product development cost versus reliability curve.

validation cost, the cost of warranty is not known upfront and involves a process of modeling and forecasting discussed in detail later in this paper.

Validation activities are defined as the formal process of confirming through environmental testing, analyses, inspections, and other engineering activities that product reliability requirements are met. Validation potentially improves the product's quality (this assumes that problems discovered during validation are fed back into the development process) and validation also improves the reliability prediction for the product thereby making the warranty cost forecast more accurate. However, validation can be a significant expense that must be traded off against the value gained. Accurate modeling of the validation costs (and their relation to the reliability and its associated confidence level) coupled with warranty cost modeling enables the customer to optimize the reliability targets based on LCC minimization.

In this paper, we develop a life cycle model that incorporates several key elements of dependability to enable the study of a set of strategic choices facing engineers and project managers as they develop the best product development flow in order to minimize the total expenses associated with product failures.

1.1. Modeling nomenclature

α_d design cost of the project
α_e cost of equipping one test sample
α_m manufacturing cost on a per unit basis
α_{mnt} cost of monitoring one test sample during validation
α_p cost of producing one test sample
α_{parts} cost of the spare parts per repair—random function $f_2(x;\ \gamma_2)$
α_{PM} average cost of preventive maintenance
α_{pv} total cost of product validation
α_W warranty cost per unit per repair
β Weibull slope of the failures observed before the time point t_S
β_T historical Weibull slope for primary failure mode.
C confidence level
D depreciation of test chamber
$Dc(N, t_T)$ dependability reliability cost function
$F(t)$ cumulative distribution function for the first time to failure
$F_{Forecast}(t_{ML})$ expected percent of cumulative failures obtained using the warranty forecast model extended to the mission life t_{ML}
$\underline{\theta}$ vector of design parameters
K test equipment capacity
k number of recorded failures
L number of service lives the product is tested for
M maintenance cost
$MTBF_{EQ}$ Mean Time Between Failures of the test equipment (repairable system)—random function $f_1(t;\ \gamma_1)$
N test sample size
n total production volume
n_f number of parts expected to fail during the warranty period
N_{PM} number of preventive maintenances per year
n_{sold} number of units sold, which approximates the total number of manufactured units
O' overhead expenses (management, certain fixed costs, etc.)
Q_{Corr} correction factor, a random variable obtained from the ratio of predicted reliability and demonstrated reliability approximated from the similar products.
R reliability of the product
$R(t)$ reliability function
$R_{Demo}(t_{ML})$ a demonstrated reliability at the end of a mission life (see Appendix A for details)
$R_{Forecast}(t_{ML})$ predictive model reliability
t time
t_{Bogey} test duration (one mission life)
t_{ML} product mission life (e.g., 10 years, 100,000 miles, etc.)

t_{repair} duration of repair—random function $f_3(t; \gamma_3)$
t_{S} hazard rate stabilization point
t_{T} test duration
T_{W} warranty period (e.g., 2 years, 36 months, etc.)
Y additional equipment expenses
$\underline{W}$ warranty terms (can be one- or two-dimensional)
W_{C} total warranty cost for a renewable process
$\Lambda(t)$ cumulative failure intensity function (number of replacements per unit)
γ_i vector of statistical parameters. These parameters can be obtained from statistical analysis of the repair and failure data of a particular test facility
η Weibull scale parameter of the failures observed before the time point t_{S}
$\varphi_{\mathrm{repair}}$ repair labor rate
φ_{T} hourly labor rate of performing the test
ξ_i vector of statistical distribution parameters for the warranty prediction model
$\lceil\,\rceil$ ceiling function, indicating rounding up to the next integer

2. Life cycle cost analysis and its dependability-related variables

Eqs. (1) and (2) show the components of the supplier's cost for products in general and automotive products in particular (Kleyner et al., 2004).[1]

$$\mathrm{LCC} = \mathrm{Design\ cost} + \mathrm{Validation\ cost} + \mathrm{Manufacturing\ cost} + \mathrm{Warranty\ cost} + \mathrm{Overhead}. \tag{1}$$

Writing Eq. (1) more explicitly produces

$$\mathrm{LCC} = \alpha_{\mathrm{d}}(\underline{\theta}, \underline{W}) + \alpha_{\mathrm{pv}}(\underline{\theta}) + n\alpha_{\mathrm{m}}(\underline{\theta}) + n_{\mathrm{f}}(\underline{\theta}, \underline{W})\alpha_{\mathrm{W}}(\underline{\theta}) + O'. \tag{2}$$

The cost of product development that is included in product quotes is usually based on forecasting methods, such as analogy models, expert judgment, prototype models, top-down calculations, and others (Bashir and Thompson, 2001). Thus, α_{d}, which is based on historical development cost of similar product lines, is assumed to be independent of product dependability factors. The basis to support this supposition is discussed in the next paragraph.

In today's competitive environment a fixed budget is often allocated for design and development. Many companies do not allocate budgets for redesign, since redesign will make the company non-competitive, therefore when redesigns happen they are dealt with on an emergency basis and usually funded from profits. A similar view is taken with product recalls; they are also an emergency activity funded from profits. Small redesign expenses relative to the expected product revenue are included in the model and the large redesign expenses are not since there is no accurate way to account for them. The majority of the design changes resulting from failures during validation are assumed to be relatively minor. For example, in the automotive electronics industry, changes may include circuit board re-mounting, component derating/uprating, enclosure redesign, seal change, connector type change, etc. Also at the product validation stage, the design changes are relatively inexpensive. Therefore we model the reliability (validation and warranty) portion of the LCC as

$$\mathrm{Reliability\ cost} = \alpha_{\mathrm{pv}}(\underline{\theta}) + n_{\mathrm{f}}(\underline{\theta}, \underline{W})\alpha_{\mathrm{W}}(\underline{\theta}). \tag{3}$$

Eq. (3) is consistent with the reliability cost model depicted in Fig. 2, where $\alpha_{\mathrm{pv}}(\underline{\theta})$ is the ascending part of the curve and $n_{\mathrm{f}}(\underline{\theta}, \underline{W})\alpha_{\mathrm{W}}(\underline{\theta})$ represents the descending portion, which will be described in more detail in Section 4 of this paper.

3. Model formulation

Fig. 3 provides the general outline of the LCC model. The process starts with the product definition and then splits into the parts representing the ascending and descending curves of Fig. 2. The two key blocks corresponding to the ascending curve include the cost of ownership (COO) of the test equipment required to conduct particular environmental tests and the contribution of the sample size cost. The descending curve deals solely with the expenses related to future product failures, such as warranty and service costs. After all the key inputs are estimated, the LCC value is simulated, which is followed by the minimization process. The five key input blocks of Fig. 3 will be addressed in the subsections that follow.

[1]Eq. (1) models the buyer's perspective on LCC necessary for the purposes of this paper. Eq. (1) is not the only way to express LCC. Other formulations exist that focus on different contributions to the LCC and/or are expressed to satisfy other views of the problem, e.g., Fabrycky and Blanchard (1991).

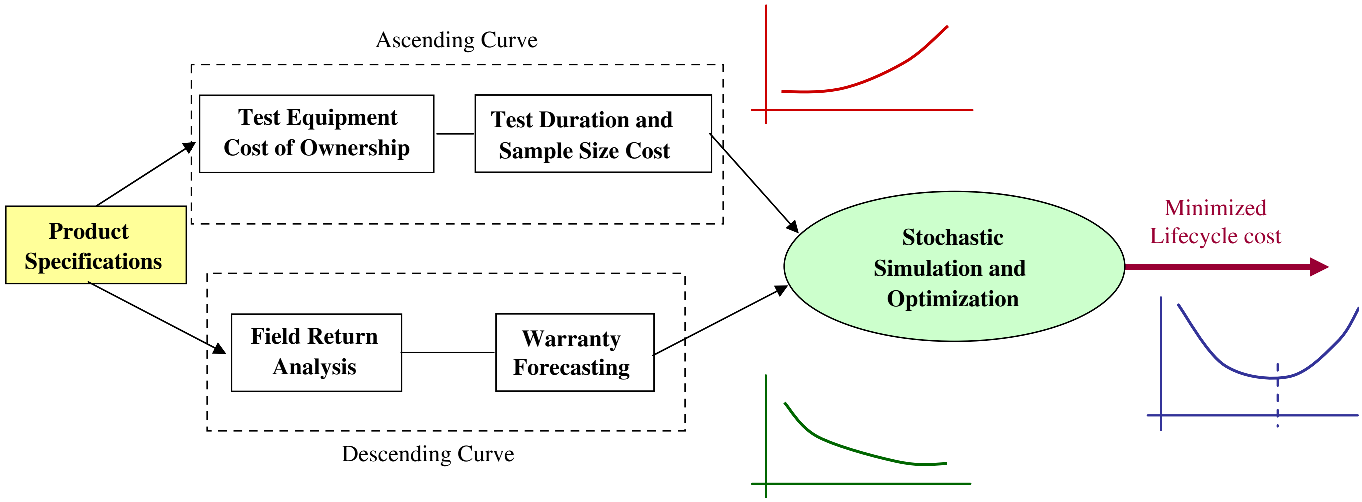

Fig. 3. Block diagram of the LCC methodology flow.

3.1. Product specifications

Typically, the first step in product development includes some form of product definition, which requires a wide variety of information including product specifications, functionality, usage, and others attributes. The majority of the products designed to be used by consumers in the real world are validated using a series of environmental tests such as those discussed in Lewis (2000). Reliability requirements usually cover a wide variety of environmental tests including temperature, humidity, vibration, mechanical shock, dust, electrical overloads, and many others. Other relevant specifications often include warranty terms and other contractual obligations concerning product service and repair.

3.2. Test equipment cost of ownership (COO)

Test and validation of the product is an integral part of the product development cost. In some industries, including consumer and automotive electronics, the cost of product validation can easily reach millions of dollars depending on the type of the product, its geometry, technology, functional requirements, reliability specifications, and other parameters.

The primary test and validation cost contributors are test equipment COO, labor cost, test sample population attributed costs, floor space, laboratory overheads, and other miscellaneous expenses. The general COO concept relates to the total cost of acquiring, installing, using, maintaining, changing, upgrading, and disposing of a piece of equipment over its predicted useful lifespan. The major concepts of COO as it is applied to manufacturing are discussed in LaFrance and Westrate (1993) and Dance et al. (1996).

3.3. Test duration and sample size cost

Test sample size also has a large effect on the cost of product validation. Each test sample carries the following costs associated with the sample population:

- Cost of producing a test sample.
- Cost of equipping each test sample. In the electronic industry this would include harnesses, cables, test fixtures, connectors, etc.
- Cost of monitoring each sample during the test. For example, in the electronics industry this includes the labor cost associated with: (a) designing and building the load boards that simulate the inputs to the electronic units, (b) connecting and running the load boards, (c) recording the data, and (d) visual and other types of inspection.

Considering that some tests may run for weeks or even months, these expenses can be significant. The mathematical aspects of calculating test sample size are presented in Appendix A. It is also important to note that an increase in sample size sometimes causes the growth of the equipment-related costs as a step-function due to the discrete nature of the equipment capacity. For example, if the capacity of a testing chamber is 25 units of a particular geometric size, then a test sample of 26 units would require two chambers if simultaneous testing is desired.

Calculation of product validation cost includes both the COO of test equipment and the expenses associated with each test sample size. Capital and depreciation cost (D), which includes acquisition, installation, and cost of scraping, spread over the useful life of the equipment. Maintenance cost (M), includes both scheduled and unscheduled maintenance, plus indirect maintenance cost. Indirect maintenance includes technician training, lost revenue due to the equipment idle time, etc. Miscellaneous costs (Y) include energy cost, floor space, upgrades, insurance, etc. Therefore, the total cost of product validation per test can be represented by

$$\alpha_{\mathrm{pv}} = t_{\mathrm{T}}\left(\varphi_{\mathrm{T}} + \frac{(M+D+Y)}{365 \times 24}\right)\left\lceil \frac{N}{K} \right\rceil + N(\alpha_{\mathrm{p}} + \alpha_{\mathrm{e}} + \alpha_{\mathrm{mnt}}). \tag{4}$$

In many cases it is economically advantageous to run the environmental tests beyond the bogey life t_{Bogey}, which is in test time terms equivalent to one mission life. This is often done to reduce the test sample size while demonstrating the same target reliability (see Appendix A). In these cases the life test ratio L given by Eq. (5) is widely used in the validation cost calculations in lieu of t_{T}.

$$L = \frac{t_{\mathrm{T}}}{t_{\mathrm{Bogey}}}. \tag{5}$$

Maintenance cost per year, including both corrective and preventive maintenance can be calculated as the total cost of parts and labor multiplied by the number of maintenance actions per year (Kececioglu, 2002). Therefore the yearly maintenance can be represented by the following equation:

$$M = \frac{365 \text{ days}}{\mathrm{MTBF}_{\mathrm{EQ}}}(t_{\mathrm{repair}}\varphi_{\mathrm{repair}} + \alpha_{\mathrm{parts}}) + N_{\mathrm{PM}}\alpha_{\mathrm{PM}}. \tag{6}$$

The presence of a random vector γ_i reflects the uncertainty associated with equipment maintenance information. The cost of corrective maintenance is not known in advance and can only be estimated based on the prior history or expected reliability of the equipment. In a commercial environmental testing laboratory, the maintenance cost can be a major source of uncertainty due to incomplete or missing maintenance records, long storage times in inventory for spare parts and other maintenance materials. These effects impact the parameter M (maintenance cost per year) in Eq. (4) and are reflected in the statistical parameters γ_i. To determine M, a case study was performed based on data from an automotive validation test laboratory and its results were utilized in the automotive example in Section 4 of this paper. In the example, maintenance data were available only for the last 4 years of operation and all the missing records were related to the past 20 years, effectively making it a left-censored with univariate missing data. It is beyond the scope of this paper to provide details for those calculations; however, a summary of the result is discussed in the example.

3.4. Field return analysis and warranty forecasting

This section discusses Fig. 3 blocks responsible for the descending portion of the curve in Fig. 2. Warranty and its associated costs are another significant contributor to the LCC. At present, it is difficult for a product developer to have a clear indication of predicted warranty cost when products are at the conceptual design level (Nasser et al., 2002); however, the ability to estimate the warranty cost with a known uncertainty would provide a distinct engineering and business advantage. A forecast of a product warranty often becomes an important input in the decision-making process associated with awarding automotive component business. There exists a multitude of warranty cost models, many of which are reviewed in Murthy and Djamaludin (2002).

Most companies maintain some form of warranty reporting system, in which they collect and analyze field and test failures. This type of information is used for the prediction of future field failures and their expected warranty costs as well as for guiding design improvements of the current products. Root cause analysis of automotive electronics warranty problems at Delphi Corporation shows that the range of warranty claims contains a large mix of different types of problems including: (a) initial performance or quality, (b) manufacturing or assembly related, (c) design-related failure or unacceptable performance degradation due to applied stresses (environment, usage, shipping, etc.), (d) service damage and misdiagnosis, (e) software-related problems, and (f) others.

The process of warranty forecasting starts with product specifications, where the main design characteristics of the product should be defined. Based on the knowledge of the geometry, utilized technology, applications, and other parameters we can determine the products that are similar to the product under development. The warranty numbers for the similar products can be analyzed for failure rates, trends, statistical distributions, and other properties. These data can be utilized for the warranty analysis and prediction.

For free replacement non-renewable warranty policies, which are very common in the industry, the expected total warranty cost can be estimated as a number of units expected to fail multiplied by the average cost of repair. Assuming that the number of failed units can be approximated by the number of units sold multiplied by the cumulative percent failed, the total warranty cost W_C for a renewable process can be represented as

$$W_C = \Lambda(T_W)\alpha_W n_{sold}, \tag{7}$$

where $\Lambda(t)$ represents the number of replacements per unit (see Kaminsky and Krivtsov, 2000), which, according to Rigdon and Basu (2000), is governed by the fundamental renewal equation given in (8):

$$\Lambda(t) = F(t) + \int_0^t \Lambda(t-\tau)\,\mathrm{d}F(\tau). \tag{8}$$

However, it is not uncommon in the supplier industry to model the replacements per unit by the cumulative distribution function $F(t)$, which is easier to model than $\Lambda(t)$, see for example Lu (1998) or Majeske (2003). This approximation is suitable for non-repairable systems and the systems with a low number of the repeat failures. An analysis of several automotive electronics products at one of the Delphi remanufacturing centers showed the number of parts with repeat failures is below 5% and for some product lines well under 1%. Therefore, this approach will be utilized in the case study discussed in Section 4.

Most of the time, warranty reporting systems and product validation activities deal with different time horizons. Product validation is normally intended to simulate the product mission life t_{ML}, which can be 10–15 years in the automotive industry. However, warranty usually deals with shorter time intervals, therefore the current warranty reporting system does not normally provide enough information to evaluate the failure rates corresponding to the product mission life.

Therefore, the best way to link this model with reliability at the end of the mission life $R(t_{ML})$ is to relate the projected numbers to the target reliabilities demonstrated during product validation. This can be accomplished by using a correction factor Q_{Corr}, linking the predictive model $R_{Forecast}(t_{ML})$ with demonstrated reliability:

$$R_{Forecast}(t_{ML}|\xi_i) = Q_{Corr} R_{Demo}(t_{ML}|\xi_i). \tag{9}$$

Q_{Corr} in this case is a random variable specific to a particular product or a product family. Therefore the calculation of Q_{Corr} can be based on the history for the similar products or early filed return data for the existing product. In general, terms Q_{Corr} reflects how well the reliability forecasting model correlates with the demonstrated reliability obtained during validation testing. The forecasted reliability value can be obtained using a variety of the available forecasting techniques (see for example Attardi et al., 2005; Lu, 1998 or Kleyner and Sandborn, 2005) and in many cases is dependent on a series of statistical distribution parameters ξ_i utilized in the prediction model.

Since reliability demonstration values obtained during product development cycle depend on a test sample size and test duration (see the case study in Section 4 and Appendix A), the statistical distribution parameters ξ_i will depend on validation parameters N and t_T as well as on Q_{Corr}:

$$\xi_i = \xi_i(N, t_T, Q_{Corr}). \tag{10}$$

Eq. (9) shows that the demonstrated reliability would be reflected in product performance in the field with the forecasted number of warranty claims becoming a function of demonstrated reliability and therefore of the test sample size and test duration.

3.5. Stochastic simulation and optimization

Based on Eqs. (4), (6), (9) and (10), the reliability cost given in Eq. (3) will be a function of test sample size N and test duration t_T in addition to other parameters. Therefore the target of the optimization is the reliability cost function $Dc(N, t_T)$:

$$Dc(N, t_T) = \alpha_{pv}(N, t_T) + n_f(N, t_T)\alpha_W. \tag{11}$$

In the case of extended life testing given in Eq. (5), t_T will be replaced by L in Eq. (11). Being a superposition of the ascending and descending curves, Fig. 2, the objective function will have a minima point, which is not an extreme. Achieving that point by managing dependability variables will provide the desired target value for the LCC.

The formulation thus far has not assumed specific functional forms for the various distributions that appear in the model. Section 4 applies the model to an automotive electronics case by assuming specific distributions for the input parameters and performing a stochastic simulation.

4. Case study

The automotive electronics case study presented in this section illustrates the methodology developed in this paper. This case study contains many similarities to the operation of the design, validation, and quality functional areas in the Electronics & Safety Division of Delphi Corporation. The actual values in this example have been modified to protect the proprietary nature of the data. This case study considers an automotive radio with CD player designed for a mission life of $t_{\mathrm{ML}} = 10$ years, with a total production volume of 500,000 units, sold to the automotive OEM for \$150 each.

Validation cost in this case can be estimated by applying Eqs. (4) and (6) using the input parameters presented in Table 1, which comprises the ascending portion of the curve in Fig. 2.

As mentioned in Section 3.4, the analysis of the descending portion of the cost curve utilizes warranty prediction activities. Based on the fact that a typical automotive part is designed for a mission life of 10–15 years it would not be expected to see wear-out failures during either the warranty or even extended warranty period of 3–7 years, which is confirmed by the analysis of the failure rates during the extended warranty, Fig. 4.

The data suggest that in the majority of cases the warranty failure model is sufficiently represented by the combination of the infant mortality and useful life phases of bathtub curve. A detailed study of the existing warranty of various product lines of automotive parts performed at Delphi Electronics & Safety showed a clear trend of diminishing failure rate for the first 8–18 months followed by a flattening of the failure rate curve for the remainder of the time period where warranty and extended warranty data were available as shown in Fig. 4.

Taking this into account, the choice of the expected failure probability function was based on the model in Eq. (12) presented in Kleyner and Sandborn (2005):

$$F_{\mathrm{Forecast}}(t|\beta,\eta,t_{\mathrm{S}}) = 1 - \mathrm{e}^{-(1+(\beta(t-t_{\mathrm{S}})/t_{\mathrm{S}}))(t_{\mathrm{S}}/\eta)^{\beta}}, \quad t \geqslant t_{\mathrm{S}}. \tag{12}$$

Therefore, Eq. (9) can be presented as

$$1 - F_{\mathrm{Forecast}}(t_{\mathrm{ML}}|\beta,\eta,t_{\mathrm{S}}) = Q_{\mathrm{Corr}} R_{\mathrm{Demo}}(t_{\mathrm{ML}}). \tag{13}$$

The common technique of calculating the demonstrated product reliability is presented in Appendix A, where $R_{\mathrm{Demo}}(t_{\mathrm{ML}}) = R$. Therefore substituting Eq. (18) into Eq. (9) would produce

$$Q_{\mathrm{Corr}} = \frac{1 - F(t_{\mathrm{ML}}|\beta,\eta,t_{\mathrm{S}})}{(1-C)^{1/NL^{\beta}}}. \tag{14}$$

Time t_{S} is a change point, the coordinate where the pattern of data changes requires a different data-fitting model. Each of the parameters, β, η, t_{S} is a random variable and could be represented by a statistical distribution obtained from the warranty history of the product.

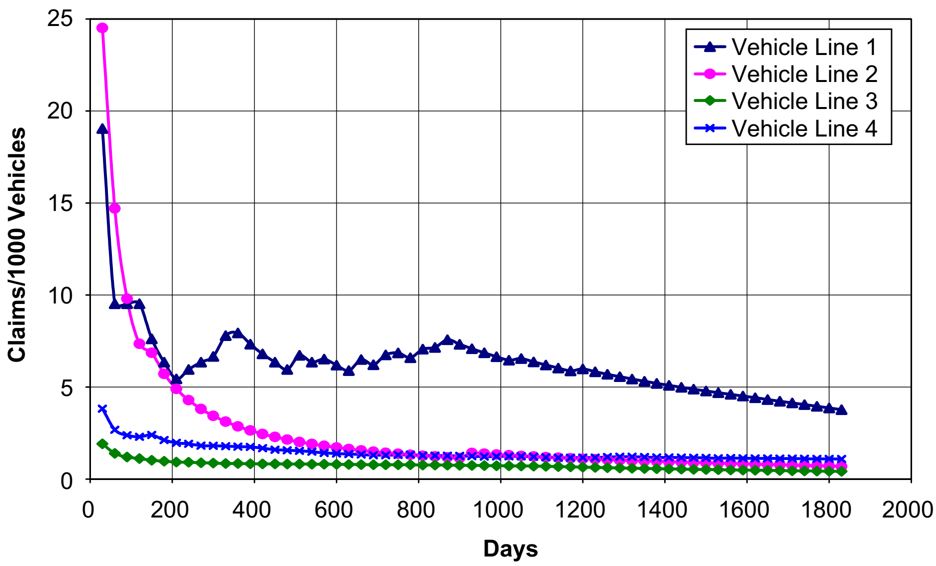

Fig. 4. Extended warranty charts compiled from Delphi Corporation's 5-year warranty data (modified for the reason of propriety).

Solving Eqs. (9), (10), and (12) for distribution parameters would provide the functional relationship between the distribution parameters in Eq. (12) as

$$\eta = \frac{t_S}{[-\ln[Q_{Corr} R_{Demo}(t_{ML})]/1 + \beta(t_{ML} - t_S)/t_S]^{1/\beta}}. \tag{15}$$

The choice of the modeling parameters β, η, and t_S is based the product family and is typically obtained from the prior warranty history for the family of products with the similar features. The example can be an XM-satellite automotive radio with six CD changer and cassette player. Eq. (15) links the scale parameter in the warranty model in Eq. (12), η with the validation target reliability R_{Demo}. It has been noticed from the warranty data analysis that η fluctuates significantly more than the shape parameter β. The shape of the warranty distribution remains reasonably consistent within the same product line, where the scale parameter η is more volatile due to the fact that it is directly linked with the expected life of the failed part. Product-specific variable Q_{Corr} in Eq. (15) was generated as one of the random inputs for Monte Carlo simulation.

The dependability-related portion of the LCC plays the role of the objective function in the optimization procedure. A direct search for the variables C, R_{Demo}, and L was used to minimize the objective function. Note that C, R_{Demo} are directly linked to the test sample size N, and L is to test duration t_T, which makes it consistent with both Eqs. (12) and (14).

The random input variables simulated as probability distributions are marked "(random)" in the first column of Tables 1 and 2. The random inputs used for this model were obtained from the analysis of the existing automotive data. Goodness of fit of the existing data was used to determine the distribution that best describes the analyzed data.

As expected, some of the inputs to this stochastic simulation model were correlated. The analysis indicates that the cost of the equipment spare parts and the duration of their corrective maintenance had the correlation factor $r = +0.4$ (see Fig. 5) and were simulated as such. Similarly, the data analysis showed some positive correlation between β and t_S. Based on the available data the correlation between β and t_S was modeled with the correlation factor $r = +0.2$.

Table 1
Model inputs for the cost of product validation

Input	Symbol, units	Value
Confidence level (search variable)	C	80–90%
Target reliability (search variable)	R_{Demo}	0.80–1.0
Number of lives tested (search variable)	L	1.0–2.0
Depreciation of test chamber	D, \$/year	25,000
Additional equipment expenses	Y, \$/year	10,000
Hourly labor rate for equipment maintenance	φ_{repair}, \$/h	35.00
Hourly labor rate for product testing	φ_T, \$/h	30.00
Cost: spare parts (random)	α_{parts}, \$/year/chamber	836.21
Time of maintenance repair (random)	t_{repair}, h	2.30
Maintenance MTBF, χ^2-distr (random)	Days	313.6
Number of preventive maintenances	N_{PM}/year/chamber	2
Cost of each preventive maintenance	α_{PM}, \$/year/chamber	2000
Maintenance cost (random)	M, \$/year/chamber	5067
Test duration (one mission life)	t_{Bogey}, h	800
Chamber capacity, units	K, units	25
Cost of producing one test sample	α_p, \$/unit	2000
Cost of equipping one test sample	α_e, \$/unit	450
Cost of monitoring one test sample	α_{mnt}, \$/unit	500

Table 2
Model inputs for the cost of warranty and service

Input	Symbol	Value
Production volume	n, units	500,000
Mission life	t_{ML}, years	10
Failure rate change point (random)	t_S, days	305.4
Correlation factor: warranty to reliability (random)	Q_{Corr}	0.9
Shape parameter (random)	β	0.780
Scale parameter	η, days	101,953
Cost of one warranty claim (random)	α_W, \$/unit	504.47
Warranty period	T_W, days	1095 (3 years)

4.1. Simulation results

Each simulation was conducted with 10,000 iterations, which was based on the convergence characteristics of the simulation. The process demonstrated 3% convergence with 1000 sample sets; therefore 10,000 appeared to be sufficient.

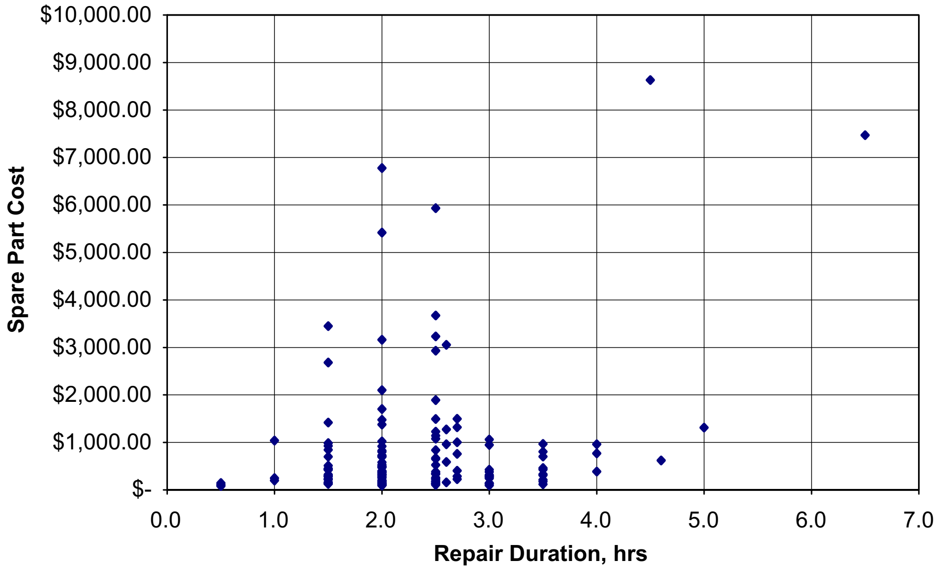

Fig. 5. Correlated inputs: repair duration and spare parts cost.

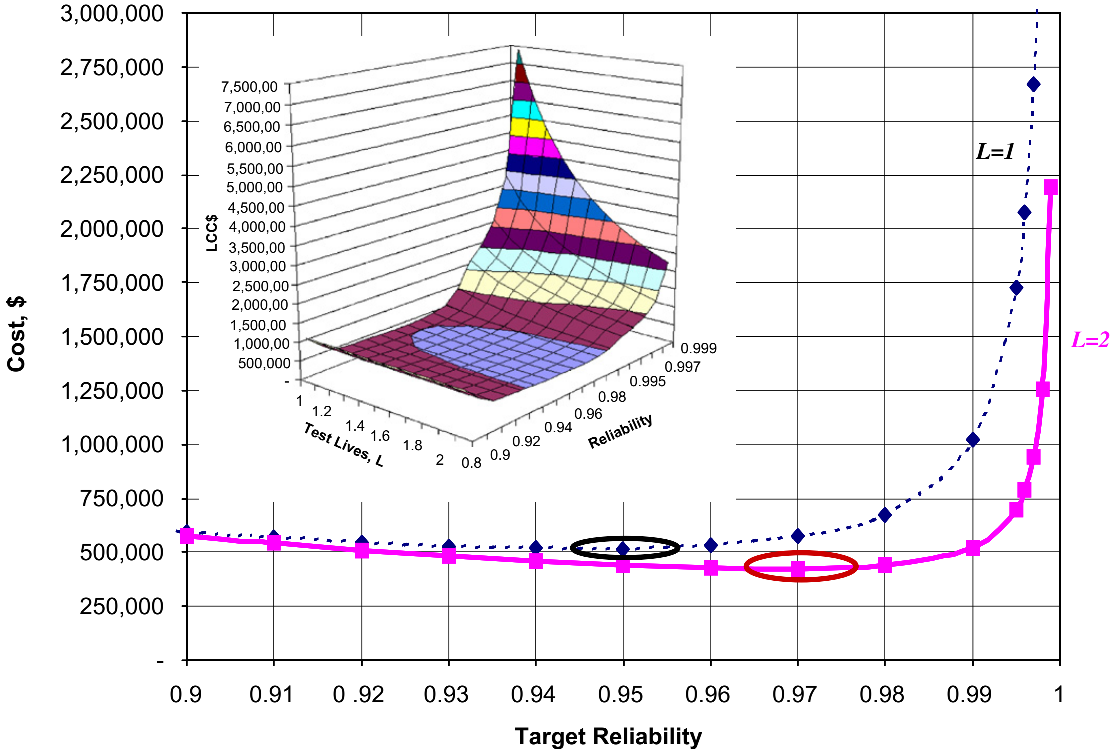

Fig. 6. Case study simulation results.

Fig. 6 shows the results for a standard bogey testing (1 × mission life, $L = 1$) and an extended bogey testing (2 × mission lives, $L = 2$). The entire simulation result Fig. 6 and the results of the simulation along with 2-D slice are provided for $C = 90\%$. The lowest cost data points are circled on the slice chart. The optimal reliabilities R_{Demo} are in the range of R_{Demo} [0.95; 0.98]. The minimum value of LCC was achieved at $C = 90\%$, $R = 0.97$, $L = 2.0$ and equal to \$423,696.

4.2. Uncertainty analysis results

An uncertainty analysis was performed to generate the confidence bounds for the whole LCC optimization curve. Fig. 7 shows the ±25%

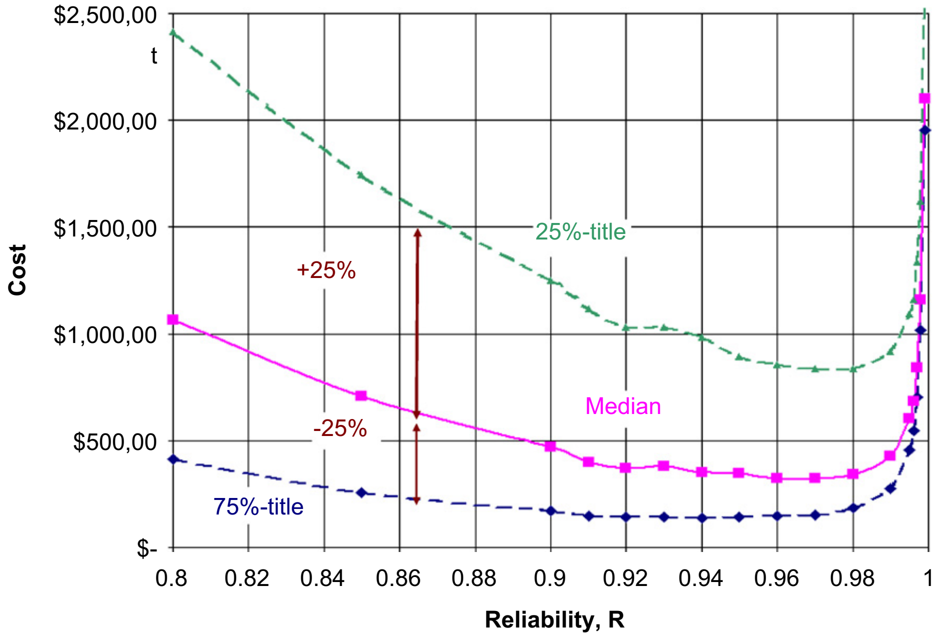

Fig. 7. Results of LCC uncertainty analysis.

confidence bounds of the solution effectively re-creating Fig. 2 with the uncertainty intervals. It was noticed that the confidence bounds are becoming narrower along as R increases demonstrating that the uncertainty of the solution is diminishing with the increasing reliability targets.

This case study demonstrates that the project management activities can be enhanced by the application of dependability principals (specifically reliability and validation) within the product LCC analysis. The LCC of the product can be minimized by properly choosing the product validation program including test sample sizes, test durations, and the choice of appropriate reliability targets. Specifically, this case study showed that the lowest value of LCC can be obtained by pursuing reliability of 97% with 90% confidence, while testing for the duration of two bogey product lives. As can be seen from Fig. 7, this LCC is approximately 30% lower than the cost of pursuing 99% reliability, frequently requested in the industry.

5. Conclusions

The methodology presented in this work can be used to evaluate the efficiency of a product validation program from a life cycle cost point of view with an emphasis on the cost of validation and product warranties. This methodology also provides a basis on which to optimize the environmental test flow during the product validation, therefore affecting the overall life cycle cost of the product. Including product dependability factors into the business model can potentially help to improve the project management by minimizing the life cycle cost of the product. The case study of an automotive electronics product demonstrated that common customer requested reliability targets may not be the most life cycle cost effective requirements.

In this paper, we have not focused on a determination of the "best" numerical optimization approach to solving the problem, no doubt more efficient numerical methods could be brought to bear on this problem. Rather we were interested in demonstrating that an optimum can be found. The emphasis here was made on formulating the methodology and compiling the model with comprehensible inputs and outputs suitable for optimization by most of the available engineering and mathematical methods.

Appendix A. Calculating test sample size and test duration

Reliability demonstration attribute tests intended to prove that reliability of a product is at or above a certain level are often conducted by running a specific number of test samples under conditions simulating the field environment and for a duration equivalent to the mission life. Those tests with two outcomes (pass or fail) are sometimes referred as "test to a bogey". Most of the time, the number of the required test samples are determined by the requested reliability and confidence level and is based on the binomial distribution (Meeker et al., 2004). Therefore, the basic relationship between reliability, confidence level, and the number of test samples can be expressed as

$$C = 1 - \sum_{i=0}^{k} \frac{N!}{i!(N-i)!} R^{n-i}(1-R)^{i}. \qquad (16)$$

Since reliability demonstration is one of the parameters that can be controlled by a project manager during the development process, it is natural to use it as one of the metrics in quantifying the expected reliability of the product. Under the condition of no failures, often referred as Success Run testing with $k = 0$, Eq. (16) can be solved for the test sample size N as

$$N = \frac{\ln(1-C)}{\ln R}. \qquad (17)$$

Based on Eq. (17), the demonstration of reliability R approaching 1.0 requires the sample size N to approach infinity. For example 90% reliability demonstrated with 90% confidence would require 22 test samples, where 99.9% reliability with the same confidence would require the sample size of 2300.

Another factor, which can significantly affect the test sample size, is test duration. A relationship between the test sample size and test duration, often referred as Parametric Binomial or Lipson equality Lipson and Sheth (1973), allows the substitution of test samples for an extended test time and visa versa. This relationship requires the knowledge about the wear-out mechanism for the particular failure mode in form of a Weibull slope β_{T}:

$$C = 1 - R^{NL^{\beta_T}}, \qquad (18)$$

where L is given by Eq. (5). For the case study in this paper, $R = R_{\mathrm{demo}}(t_{\mathrm{ML}})$, reliability demonstrated at the end of the mission life. It is important to note here that Eq. (18) is derived under assumption of Success Run testing, i.e., no failures are experienced during the test.

References

Attardi, L., Guida, M., Pulcini, G., 2005. A mixed-Weibull regression model for the analysis of automotive warranty data. Reliability Engineering and System Safety 87, 265–273.

Balachandran, K.R., Radhakrishnan, S., 2005. Quality implications of warranties in a supply chain. Management Science 51 (8), 1266–1277.

Bashir, H., Thompson, V., 2001. An analogy-based model for estimating design effort. Design Studies 22 (2), 157–167.

Blischke, W., Murthy, D.N.P., 1994. Warranty Cost Analysis. Marcel Dekker, New York.

Dance, D., DiFloria, T., Jimenez, D., 1996. Modeling the cost of ownership of assembly and inspection. IEEE Transactions on Components, Packaging, and Manufacturing Technology—Part C 19 (1), 57–60.

Fabrycky, W., Blanchard, B., 1991. Life-Cycle Cost and Economic Analysis. Prentice-Hall, Upper Saddle River, NJ.

Fernández, A., 2001. Quantification of the dependability. In: Proceedings of ESREL (European Conference on Safety and Reliability). Torino, Italy, pp. 197–204.

Kaminsky, M., Krivtsov, V., 2000. G-renewal process as a model for statistical warranty claim prediction. In: Proceedings of Annual Reliability and Maintainability Symposium, Los Angeles, CA, pp. 276–280.

Kececioglu, D., 2002. Maintainability, Availability, and Operational Readiness Engineering Handbook, Vol. 1. Destech Publications.

Kleyner, A., Sandborn, P., 2005. A warranty forecasting model based on piecewise statistical distribution and stochastic simulation. Reliability Engineering and System Safety 88 (3), 207–214.

Kleyner, A., Sandborn, P., Boyle, J., 2004. Minimization of life cycle costs through optimization of the validation program—A test sample size and warranty cost approach. In: Proceedings of Annual Reliability and Maintainability Symposium, Los Angeles, CA, pp. 553–557.

LaFrance, R., Westrate, S., 1993. Cost of ownership: The suppliers view. Solid State Technology, 33–37.

Lewis, M., 2000. Designing Reliability–Durability Testing for Automotive Electronics—A Commonsense Approach. TEST Engineering and Management, August/September, pp. 14–16.

Lipson, C., Sheth, N., 1973. Statistical Design and Analysis of Engineering Experiments. McGraw-Hill Book Company, New York.

Lu, M-W., 1998. Automotive reliability prediction based on early failure warranty data. Quality and Reliability Engineering International 14, 103–108.

Majeske, K., 2003. A mixture model for automobile warranty data. Reliability Engineering and System Safety 81, 71–77.

Meeker, W., Hahn, G., Dogannaksoy, N., 2004. Planning Life Tests for Reliability Demonstration. Quality Progress. ASQ Publishing (August).

Murthy, D.N.P., Djamaludin, I., 2002. New product warranty: A literature review. International Journal of Production Research 79, 231–260.

Nasser, L., Dey, A., Tryon, R., 2002. Simulation tool for predicting warranty and total ownership cost. SAE Publication 2002-01-0338, SAE World Congress & Exhibition, March.

Rigdon, S., Basu, A., 2000. Statistical Methods for the Reliability of Repairable Systems. Wiley, New York.