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Reliability modeling for electronic products

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Abstract

This paper presents a reliability model for an electronic product using warranty data. Warranty data are obtained through customer complaints about flaws in products within the warranty period. There are some inherent difficulties in using warranty data to estimate the reliability of products, such as lack of failure data within the warranty period, the presence of high censored data and the presence of more than one failure mode acting on the same component. Thus, early and wear-out failures can exist together in the same product, hindering the association of a probability distribution to collected field data. Yet it is difficult to observe failures due to wear within the warranty period, since this failure mode occurs late in the product life cycle. We gather opinion from the experts as an attempt to retrieve the failure to wear information that occurs after the warranty period. Thus, this paper presents two sources of information for reliability modeling, the first one consists in the failure data collected in the field within the warranty period to model the early failure modes, the second one consists in the opinion of experts on wear-out failure to retrieve the information for the post-warranty period, so a more realistic modeling of product reliability became possible. In this paper, a real numerical example is conducted to illustrate the difficulties of working with warranty data and it is proposed a solution to the reliability modeling of an electronic product. The methodology used is an axiomatic descriptive modeling type that proved to be successful in this kind of problem. As a result, this paper presents the parameters estimation for the probability distribution that fits the data analyzed.

Keywords: Warranty Data, Customer Complaints, Failure Modes

1 Introduction

The reliability study has gained importance due to the increasing need to have products that meet customer quality requirements. Customers require assurances that the product purchased will not fail and it will meet your expectations for a certain period of time.

Companies are increasingly offering extended warranties to its customers as a way to convince them that the product purchased will meet your expectations. However, a longer warranty period means an increased cost and a decreased profit for companies.

Thus, the development of a reliable product that will not easily fail when exposed to the use has become a competitive factor for most companies. In an attempt to determine the product´s reliability some companies maintain a structured failure related database. Such failures can be studied and can generate knowledge for increase products reliability in the future. The determination of product´s failure profile however, is not easy.

The correct failure registration assumes that any failure is reported and recorded by the supplier, which does not occur mostly, in practice. Customers tend to fail in communicate product´s failure to the supplier when the products are no longer within the warranty period. This way, there is a lack of reliable information to determine product reliability beyond this period.

Because of this, many companies use only the data collected within the warranty period but to determine the product´s reliability using only warranty data has some limitations. First, a very small percentage of products fail in the first year of the lifecycle. These failures are usually due to mounting process and generally do not represent the total product´s failure profile.

Warranty data generally do not consider failures due to component wear. These failures usually occur in another phase of the product´s lifecycle and are not represented in the data collected under warranty. The presence of more than one failure mode acting in a same product is frequent and the predominant failure mode often depends on product´s lifecycle phase.

The determination of failure´s profile becomes unreliable due to the high censorship of the data. As a way to retrieve the information lost in the post warranty period, expert´s opinion on product failures are used. Thus, determining the failure´s profile will no longer use only one source of information, but two: failure data observed in warranty period and failure data generated by expert opinion. The combination of these two general information may generate a more reliable failure profile for the product under study.

To model the reliability data in this paper, the axiomatic descriptive modeling type proposed by Bertrand and Fransoo (2002) was used. In this method, the focus is on the modeling phase itself not worrying too much in the model solving and the implementation of the solution. The paper finishes in the moment that a good and fitting model is found.

This article aims to extensively discuss the difficulties of working with warranty data and propose a solution for determining the total product´s failure profile based on the use of expert´s opinion.

2 Literature Review

The reliability study is relatively recent, but has gained importance over the past fifty years. The issue found its way both in the equipment´s maintenance in an attempt to prevent undesirable gaps in the production process, and in the product´s failure prevention, reducing customer dissatisfaction and possible losses that it creates.

When it comes to the application of reliability in equipment, we can emphasize the practice of Reliability Centered Maintenance (RCM) which basically consists of an analysis of potential failures of components followed by a quantitative analysis of the failure´s risks in each component. (SELVIK e AVEN, 2011).

In an equipment structure, many components are considered critical and require more attention because they suffer the action of wear over time. An alternative to study the reliability of these components is to use degradation methods. Freitas, Toledo, Colosimo and Pires (2009) claim that degradation experiments aim to investigate the mean lifetime and thus predict the reliability of components that generally do not fail in accelerated life tests.

The use of degradation data to predict reliability has several advantages over the use of traditional failure data as it allows reliability analysis of very robust systems, where failures occur rarely, and in cases where a high time to failure would be a limitation in a tradition failure data analysis (MEEKER, DOGANAKSOY and HAHN, 2001).

Obviously, is not always possible make use of degradation data. In Products, processes or equipment where the failure is instantaneous, the wear data tend not to be significant for prediction of system reliability. In those cases where the cause of failure is usually an external cause, as a condition of strain or stress over which the equipment is designed, one should make use of traditional data failed to reach any conclusion about the reliability system

Several researchers (TORRES e RUIZ, 2007; ZHOU, XI, e LEE, 2007; JOSEPH e YU, 2006) have worked in the reliability study based on degradation data.

When it comes to products, the study of reliability can be divided into studies aimed at developing and launching new products or for warranty data analysis for products that are already consolidated in their respective niches. The challenge of the product development process is to determine the reliability of the product before it is released to the market. In many cases, where a product failure threatens human´s lives, this aspect is mandatory.

According to Yadav *et al.* (2003) there are several sources to access product´s reliability during its development phase. Information from experiments, robustness tests, analysis of failure modes and even experts opinions should be considered to improve the under development product´s reliability. The same author points out that traditional models to reliability prediction are not flexible enough to integrate the different information sources.

As an alternative solution to determine the reliability of the product in the early stages of its development Lindley (2000) proposes a theory of subjective probability analysis to handle data that can often be vague in the early stages of development. Yadav *et al. (2003)* propose the use of fuzzy logic as a solution for the problem.

In the lasts stages of the development process, the information becomes less subjective, and exists in greater quantity. When the product is fully designed, arises the opportunity to conduct tests in the product before releasing it effectively in the market.

Fard and Li (2009) and Hussain and Murthy (2003) studied the modeling of product´s reliability based on accelerated life tests, performed before its release. Fard and Li (2009) state that the main objective of the accelerated life tests is to accelerate the time to failure of a product making it possible to predict, before the market launch, the warranty period which minimizes costs and optimizes customer satisfaction.

While maintaining that the best time to improve the product´s reliability is in its development phase, due to high costs of working a product that is already on the market, Cui and Khan (2008) proposed a method to study and estimate the reliability after product launch. In the same direction, Ion *et al.* (2007) and Thomas and Richard (2006) propose the analysis of warranty data for modeling reliability.

Warranty data is, in fact, failure data from products that are still on the warranty period. Product´s reliability, therefore, can be obtained through the number of failures during a predetermined period of time. Field data are mainly generated from technical assistance´s reports of products under warranty. The reliability of data collection depends largely on the assumption that the vast majority of clients injured by a product failure trigger the technical assistance sector. This behavior, however, is usually observed only for products that are within the warranty period.

Marcorin and Abackerli (2006) present a pack of difficulties in working with field data using traditional reliability models. According to these authors, field data are highly censored turning the data volume often insufficient for an appropriate analysis. The same authors propose the use of bootstrap resampling method to minimize these problems and generate, from a small set of data, sufficient data for analysis.

In an extreme situation, with the occurrence of zero defects during the warranty period becomes impossible to use a resampling method. For these cases, Jiang *et al.* (2010) presents a modified maximum likelihood method adapted to reliability without the use of failure data.

Another positive aspect of using the resampling method is the fact that, after resampling, the data can be considered normal, facilitating the adequacy of the mathematical model to the data (MARCORIN & ABACKERLI, 2006).

Often, for field data, it is impossible to determine a probability distribution that really fits the data. Failure data may follow different probability distributions, the most common in reliability are the weibull distribution, the lognormal, gamma and exponential. The identification of the probability distribution that fits the field data is important because it is through it that one can extrapolate the data and make predictions about the behavior of the product´s reliability.

There are parametric and non-parametric distributions. The basic difference between them is that the first requires you to assume a specific distribution, *e.g*, Weibull, for the estimation of parameters. The second does not require this assumption, and is most suitable when you do not know or is not possible to identify the prior distribution.

Besides the data volume limitation, there is a second limitation that may prevent or hinder assertive conclusions about the data. Often there are gaps in the systematic collection of data which often generates reports with missing data. A classic example is the lack of time to failure in some reports.

The time to failure (TTF) can be defined as the difference between the instant of failure occurrence and time in which the product went into operation. Coit and Jin (2000) propose a model to estimate distribution´s parameters where there are missing data.

The use of field data though, has benefits that are worth mentioning. In laboratory tests they usually try to simulate some product´s operational conditions In even the most accurate of the laboratories there is always an error that involves the difference between the actual conditions with the simulated conditions.

Moreover, when controlling the conditions within laboratories, it is possible to determine the influence of a particular factor over product´s TTF. Under real conditions, what happens is the presence of several failure modes (caused by variation of several factors simultaneously) that follow different probability distributions. In most studies involving field data, the assumption made is that there is only one mode of failure or that the distributions of all failure modes are the same, which is not always consistent with reality.

Rand and Linn (2010) presented a study that proves the difference in results when it mistakenly assumes a single failure mode. The authors state that the assumption that field data follows a single distribution with a single failure mode should not be done. Santos (2008) applies a model to predict the reliability considering three failure modes.

What happens when using warranty data is that the short period of analysis does not allow the occurrence of the main failure modes that include, for example, component wear. Wear, in mechanical components, or in products where the main failure mode is fatigue of the components are only observed after a few years in the product´s lifecycle, in its final stage where the failure rate tends to grow. Then, how to model the product´s reliability using only warranty data? It would be a reliability estimation that would not include at least one of the principal failure modes leading to a mistaken estimation of product´s reliability.

Santos (2008), presents an alternative solution to access the information of failure due wear which is not evident during the warranty period. The author combines the information obtained during the warranty period with information collected from experts through a directed questionnaire.

Table 1 lists the main authors discussed in this section and where these authors are applying the concepts of reliability.

Table 1 – Main authors cited in this paper

Author	RCM	Degradation Data	Product Development	Accelerated Life Tests	Warranty Data
BERTLING, ALLAN, and ERIKSSON, 2005	X				
COIT and JIN, 2000					X
CUI and KHAN, 2008					X
ENDRENYI, *et al*., 2001	X				
FONSECA and KNAPP, 2000	X				
FREITAS, TOLEDO, COLOSÍMO and PIRES, 2009		X			
HUSSAIN and MURTHY, 2003				X	
ION *et al*., 2007					X
JIANG *et al*., 2010					X
JOSEPH and YU, 2006		X			
LINDLEY, 2000			X		
MARCORIN and ABACKERLI, 2006					X
MARQUEZ, SCHMID and COLLADO, 2003	X				
MEEKER, DOGANAKSOY and HAHN, 2001		X			
RAND and LINN, 2010					X
SANTOS, 2008					X
SELVIK and AVEN, 2011	X				
THOMAS and RICHARD, 2006					X
TORRES and RUIZ, 2007		X			
YADAV et al. , 2003			X		
ZHOU, XI, and LEE, 2007		X			

3 Proposed Model

The model proposed by Santos (2008) has the main purpose to overcome some of the difficulties presented in section 2 about the use of warranty data for modeling product´s reliability. The various failure modes are considered concurrent and, therefore, the mathematical formulation becomes complex and creates the necessity to adopt several assumptions. In this article the failure modes are considered independent, which limit the model presented here.

4 - Follow up experiment

An electronics company produced 648 pieces in 2010. Each of the products was followed during the period of one year that represents the warranty period provided by the company. Table 2 shows the failure data, in weeks, observed during the warranty period for the studied product.

3	3	4	4	4	4	5	5	7	9	9
9	10	10	10	11	12	14	15	15	16	18
21	21	23	30	32	36	38	39	45	47	52

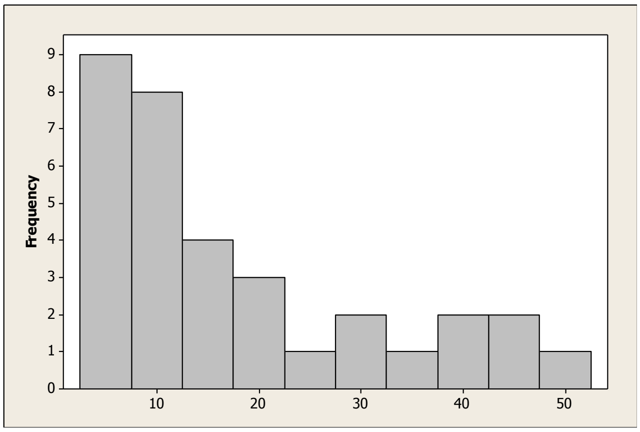
Table 2 – Warranty Period Failure Data (weeks)

The modeling such data is quite simple and may be conducted through any statistic software. In this article it is used the software Minitab to conduct statistical analysis of warranty data. Can be observed that only 5% of products failed within 1 year., 33 products in a total of 648 produced.

The graph 1 presented below shows the failure distribution in time. There is a higher failure occurrence in the first weeks of product´s use with relative reduction of failure occurrence as time advances. This distribution is characteristic in electronic products in which assembly failures are easily evidenced in early stages of product´s lifecycle, especially in products where the Burn-in test is not accomplished.

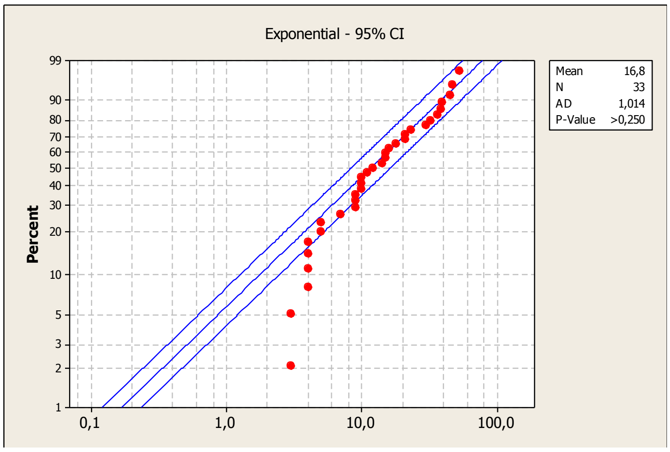
For this type of failure in electronic products, an exponential distribution can usually be fitted in warranty data. An adherence test was conducted for the exponential distribution with parameter lambda equal to 0.059, which leads us to a mean time to failure of 16.8 weeks as seen in graph 2. An hypothesis test was conducted as well to test the hypothesis that the data actually follows the chosen exponential distribution, the P-value for this test was higher than 0.25 which brings us to accept the assumption that the distribution is truly exponential with the parameter found.

Many reliability analysis admit the distribution found by the warranty data analyses as the model that describes product´s failure profile within all its lifecycle. Most often, it is not true, because once the product is not within the warranty period, other failure modes appear and modify the ideal model for the data set.



Graph 1 – Warranty Period Failure Histogram

In other words, one can ensure that the exponential distribution found is the best model to describe warranty data, which represent only 5% of total products, but not contains the data information outside that period, approximately 95 %, ignoring the failure modes of wear. Therefore, after the warranty period, it is necessary to determine other model to describe the product´s behavior. The problem is that in most cases the failure data outside the warranty period are not reliable. To solve this problem is proposed the use of expert opinion to model failures after the warranty period.



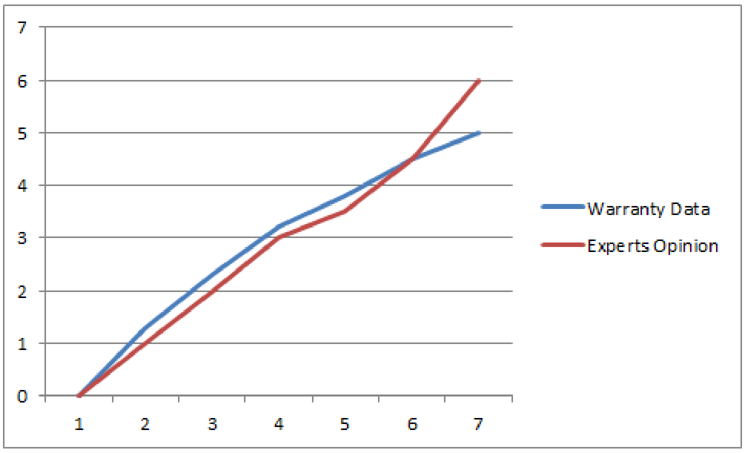
Graph 2 – Exponencial Fitting

Experts are trained technical staff, who has deep knowledge about the studied product. The data collection methodology used was a direct questionnaire given to ten experts. The applied questionnaire is rather extensive and can be found in Santos (2008). The mean responses obtained by the experts about the cumulative percentage of failures are presented in table 3.

t (weeks)	Accumulated Failure (%)
1	0
5	1
10	2
20	3
30	3,5
40	4,5
52	6
78	11
104	25
130	37
156	48
182	58
208	68
234	76
260	83
286	88
312	93
338	97
364	100

Table 3 – Accumulated Failure from Experts

The first analysis to be done is a comparison between expert´s opinion and the failure data previously collected within the first year of use. Graph 3 shows us the two curves.

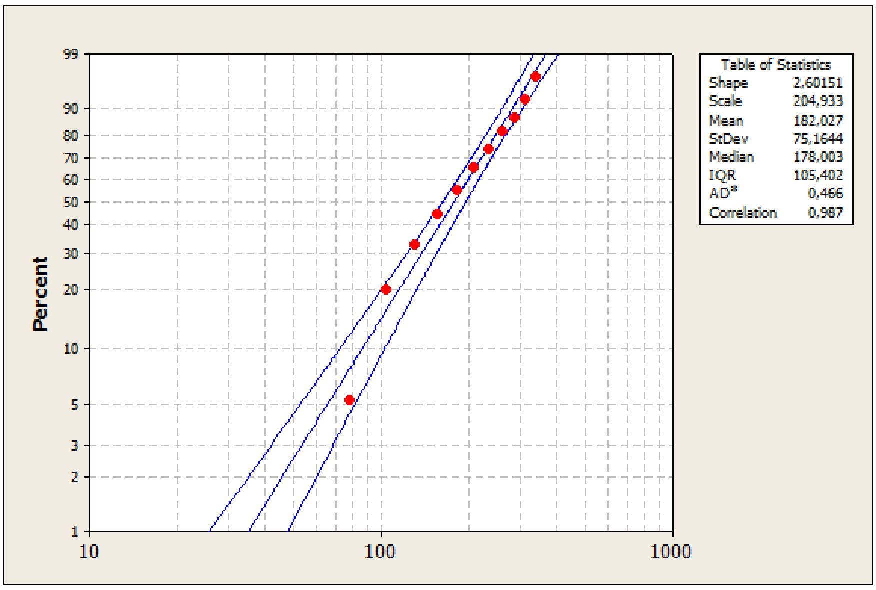


Graph 3 – Comparison between collected data and expert’s opinion

Comparison of the two data sets showed consistency in the expert´s opinion. To perform this analysis, two empirical distributions of cumulative failure percentage was generated based on the data collected and the answers from experts. A paired-t test was conducted to test the hypothesis that the two data sets are statistically equal. The resulting p-value was 0.94, higher than the 5% significance level adopted for the test.

As expert´s opinion was validated, the next step is to derive, through it, a probability density function of failure for the product after the warranty period. This probability distribution will represent the 95% of products missing, where failures were not observed within the first year. This can also be accomplished through the issue of the questionnaire from Santos (2008).

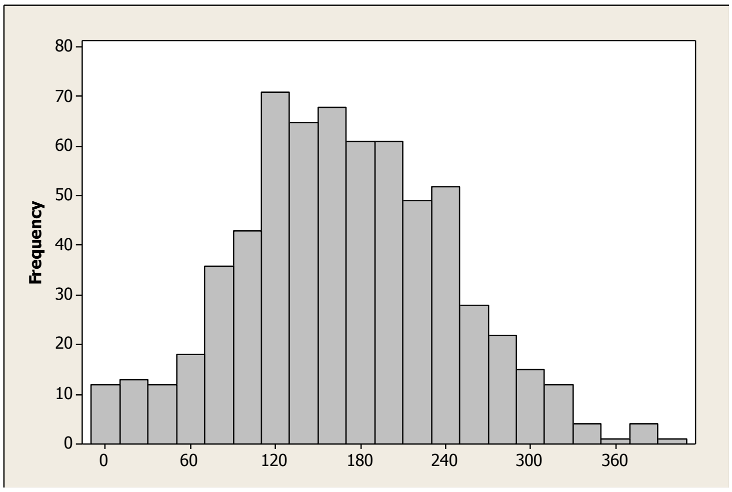
Through the cumulative probability density function one can derive the probability density function. As it is data whose dominant failure mode is wear, it was assumed a priori a Weibull distribution to describe the data. The shape and scale parameters found for the Weibull distribution previously assumed were 2.6 and 204.93 respectively as can be seen in graph 4.



Graph 4 – Fitted Weibull Distribution

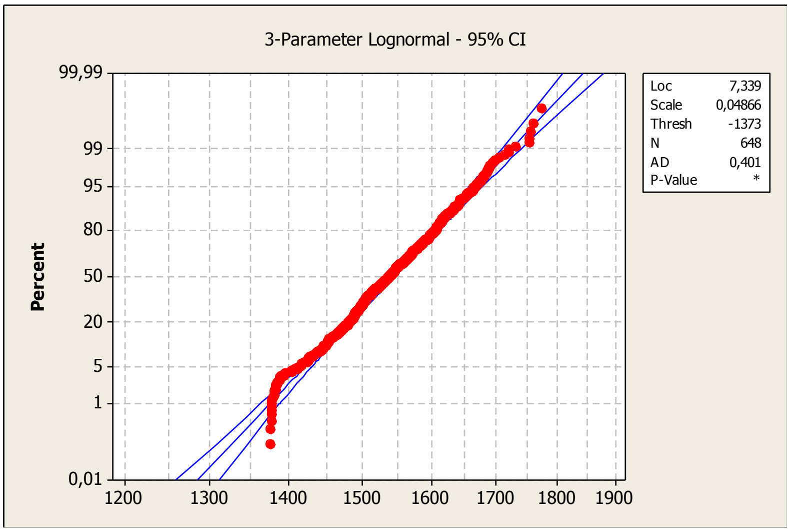
From these data it was possible to establish the full failure profile for the studied product, this profile can be seen in graph 5.

It is easy to note the difference between the graph 1 that represents the failure profile considering only warranty data and graph 5, which represents the full failure profile using expert's opinion to retrieve the post warranty period information.



Graph 5 – Total Period Failure Histogram

The next step is to set a single probability distribution for the data represented in graph 5. Comparing the data against various probability distributions, it was decided to consider the lognormal distribution with parameters of location, scale and threshold respectively equal to 7.34, 0.0049 and -1373. As can be seen in graph 6, the distribution has a good fit with the data.



Graph 6 – Fitted 3 Parameter Lognormal Distribution

4 Conclusion

The proposed methodology has been successful in using warranty data in conjunction with failure data generated by expert´s opinion to determine the product´s failure profile. It shows a drastic change from the failure profile found using only warranty data and the failure profile found by using the data generated by expert´s opinion. This occurs due the occurrence of a failure mode that had not been occurred in the first year of product´s lifecycle.

The use of expert´s opinion may seem at first, subjective, but there are methods such as Delphi method that, when applied to questionnaires, can improve the reliability of the information gathered.

Also, to have access to real failure information even after the one year warranty period, other strategies can be used. Offer special warranties, which last longer only for a specific group of clients can be a source of information to validate the failure data generated by expert´s opinion.

In this paper, we considered only two dominant failure modes, one, due to assembly failures, in the early stages of product lifecycle, and the other, due to wear, in the last stages. There are works as Santos (2008) who also consider a third failure mode called random failures, which should have its dominance in the middle period of the product´s lifecycle.

After modeling the product´s reliability, a detailed study about the failures causes should be conducted in order to improve the product´s reliability or to generate more robust and reliable products in the future. After this study, a new model may be developed in order to compare the product´s performance before and after improvement. What often happens is that with the advancement of technology products have had their lifecycles decreased and, therefore, there are not enough time for long failure data analysis

The modeling of electronics and high technology products has advanced to be made before launching the product on the market through accelerated life test and using other modeling methods, but companies in this industry should still keep records of field failures for monitoring the product´s reliability after its delivery to the client. For this reason, there will always be the need to model reliability through data collected in the field.

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