Reliability prediction of electronic boards by analyzing field return data

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ABSTRACT: In this study, we perform field return data analysis of electronic boards. We cooperate with one of the Europe's largest manufacturers and use their well-maintained data with over 1000 electronic board failures. We follow two steps that are filtering the return data and modeling the filtered data with probabilistic distribution functions. In the first step of filtering we propose a new technique to eliminate improper data, correlated to incomplete and poorly collected data, from the whole field return data. In the second step of modeling, we use the filtered data to develop our reliability model. Rather than conventionally using a single distribution for all service times that does not accurately model the substantial changes of the electronic boards reliability performance over time, we use different distributions for different service time intervals. In order to determine the distributions we propose a technique that deals with forward and backward time analysis of the data.

1 INTRODUCTION

The rapid developments in electronics, especially in the last decade, have initiated the inception of electronics reliability (O'Connor & Kleyner, 2011). Conventionally used accelerated reliability tests have lost their significance; time consuming and expensive feature of these tests is against the demands of today's very rapid electronic product cycles (Pecht, 2010). This underlines the importance of using the product's field return data for reliability analysis that is relatively cheap and time saving (Kleyner & Sandborn, 2004; Wu, 2012]). In this study, we propose a complete reliability methodology exploiting field return data of electronic boards.

Field return data can be used for variety of purposes that include the prediction of future claims, the estimation of field reliability, and the identification of opportunities for quality and reliability improvement. (O'Connor & Kleyner, 2011). If one assumes that the return data is error free then it is not difficult to claim that it is the most trustworthy data in analyzing reliability of a product compared to accelerated test or simulation based data. However, in reality field return data contains errors corresponding to improper, correlated, incomplete, and poorly collected data that result in misleading reliability predictions. In this study, we first deal with this problem. We propose a systematic approach to eliminate errors from field return data. We call this process of elimination as "filtering".

In the filtering process, we classify errors into two categories: obvious and hidden errors. Obvious errors are the errors that can be easily determined with applying one-by-one data check. Changing data orderings make this process even faster. Examples for such errors are unknown assembly dates, invalid time-to-failure values, and quality related errors. In contrary to the obvious errors, hidden errors and their probable sources cannot be directly determined from the data. Examples for hidden errors are significant changes in product manufacturing process, data loss, and inappropriate data recording in services. Hidden errors are fatal and overwhelm obvious errors in terms the number of occurrences. This obligates us to eliminate hidden errors before starting statistical analysis. In this work, we propose a new systematic approach to determine and eliminate both obvious and hidden errors. After eliminating the errors, now we have "filtered data" that is accurate and ready to be used in our statistical modeling.

In statistical modeling, the hazard rate of an industrial product is an important parameter especially for companies which have high volume products in the field. Additionally, hazard rate functions can directly be used for warranty forecasting. In this study, we mainly construct our model on hazard rate functions. In the literature it is well accepted to assume that the hazard rate function of a product shows a bathtub characteristic. In general hazard rate models depict an entire bathtub curve as a combine of two Weibull distributions for early failure and wear out periods (Dhillon, 1999; Kececioglu, 2002). This is illustrated in Figure 1. Although the models using all regions of the bathtub curve are theoretically correct, they are not practically applicable to some industrial product groups with relatively long lives (Kleyner & Sandborn, 2004). Electronic boards, studied in this work, fall into these product groups. Electronic boards are expected to work at least 10-15 years with a warranty period of at most 5 years. This is illustrated in Figure 1.

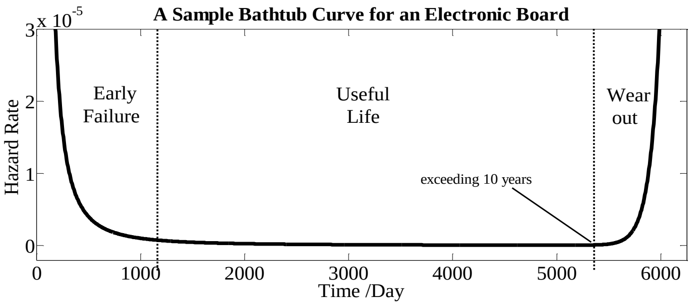

Figure 1. *A bathtub curve* - hazard rate function over time.

In this study, we propose a model regarding early failure and useful life periods of electronic boards. Our model is based on Exponential and Weibull distributions among many other distribution options regarding the optimum curve fitting. Rather than conventionally using a single distribution for all time-to-failures that does not accurately model the substantial changes of the board's reliability performance over time, we use different distributions for different service time intervals. For this purpose we propose a new technique that deals with forward and backward time analysis of the data. In the fitting process we use "rank regression" and "maximum likelihood" methods.

The data used in this study (filtering and modeling analysis) contains assembly and return dates for each warranty call. Warranty period of the board is three years. The maintenance policy for electronic boards under this study is to replace the board with a new one in any suspected case such as stopping from time to time or breaking down entirely in the field. Therefore the analyzed data has no record of repaired boards. Throughout our analysis we benefit from Weibull++ by ReliaSoft Corporation.

The structure of this paper is as follows. In Section 2-Filtering, we describe the filtering procedure of field return data. In Section 3-Modeling, we work with the filtered data to develop our statistical model. Finally, Section 4 reports the conclusion of the work.

2 FILTERING

In order to guarantee accuracy of the analysis and eliminate errors, field return data must be filtered. For this purpose, we use a step by step procedure. In the first step, we filter obvious errors from the whole data. We filter data having unknown assembly date, data with quality failure records that result in zero time to failure (TTF), and data with negative TTF or unreasonable TTF.

In the second step which is the main target of this section we are dedicated to find and eliminate hidden errors. As it is mentioned before, obvious errors can be easily found by applying one-by-one data check. But, we cannot find hidden errors as direct as we find obvious errors. Here, a systematic approach is needed. By using Weibull++ ReliaSoft Corporation software we survey the consistency of the data and systematically investigate if there are hidden errors or not. We use 2 parameter Weibull distribution for our analysis because of being mathematically more tractable than other distributions (Reliasoft, 2014 ; Babington et al. 2007). Also using Weibull distribution to model reliability has long been approved in the literature. Maximum likelihood method (MLE) is selected for parameter estimation since regression methods generally work best for large data sets (O'Connor & Kleyner, 2011). In analysis, we deal with six month assembly time intervals. Selecting 6 month intervals is quite reasonable because we have 54 month return data.

The proposed methodology targeting hidden errors is as follows. We first perform forward analysis for 1-6, 1-12, 1-18, 1-24, 1-30, 1-36, 1-42, 1-48 and 1-54 month time intervals. This is illustrated in Figure 2. For example, 1-6 time interval represents products assembled in the first six months. Similarly, 1-42 time interval represents the whole data excluding the ones assembled in the last six months. In forward analysis we expand time window from left to right where the left edge is fixed. We then perform backward analysis for time intervals of 48-54, 42-54, 36-54,,,,,,12-54, and 1-54. This is illustrated in Figure 3. Here, we expand time window from right to left where the right edge is fixed. Finally we perform analysis for seperate 6 month time intervals of 1-6, 7-12, 13-18, 19-24, 25-30, 31-36, 37-42, 43-48, 49-54. This is illustrated in Figure 4. Note that X-axes in figures represent assembly times (not TTF). As a result, using parameters of Weibull distributions of these three analysis, we filter improper time intervals corresponding to hidden errors.

We develop our filtering systematic mainly on a Weibull parameter β that explains the hazard rate function's behavior. If β <1, it indicates a decreasing hazard rate and is usually associated with the early failure region. If β≈1, it means a constant hazard rate and is usually associated with the useful life region. If β >1, it indicates an increasing hazard rate and is usually associated with the wear out region, corresponding to the end life of the product. As a reminder, the early failure, useful life, and wear out regions are illustrated n Figure 1. As follows we investigate Figure 2, Figure 3, and Figure 4 in details regarding β values.

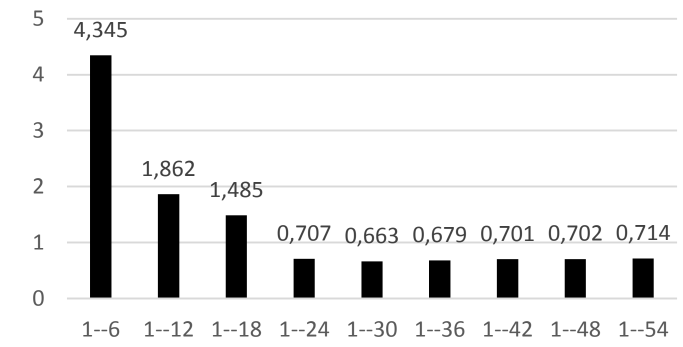

Figure 2. Beta (β) values for forward analysis

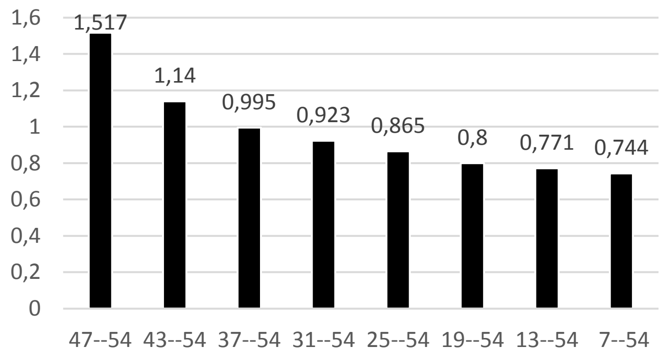

Figure 3. Beta (β) values for backward analysis

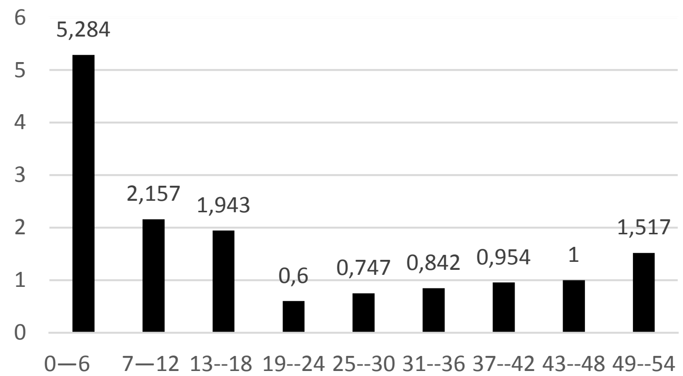

Figure 4. Beta (β) values for analysis of 6-month periods starting from the beginning

Figure 2 shows β parameters of Weibull distributions for the forward analysis. Looking at β values we can derive that there are problems in the first 3 intervals 1-6, 1-12, and 1-18. These β values are greater than one, meaning that we are in the wear out region. This is impossible; the first 18 months of the field return data are suspected. Figure 3 shows β parameters of Weibull distributions for the backward analysis. Again, by looking at the β values we see that the last 6 months have β>1. Here, we cannot come to a conclusion since we have insufficient data (sample size of 10) for the products assembled in the last six months. This low amount of sample size is not enough to perform accurate statistical analysis. Finally, Figure 4 shows β parameters of Weibull distributions for 6 month periods. If we look at β values we can derive that the first 3 intervals 1-6, 7-12, and 13-18 having β>1 are suspected.

In conclusion, we should filter the first 18 months of the field return data corresponding to hidden errors. In other words, the products assembled in the first 18 months have insufficient field return data with hidden errors. Note that if we just performed backward analysis, we would not find any hidden errors. This could also happen for only performing forward or 6-month analysis for a different case. However, with performing backward, forward, and 6-month analysis together, as suggested in this study, we consider all aspects of hidden errors. We have now 36 month field data to be safely used in statistical reliability modeling.

3 MODELING

As we discussed in introduction, the field return data can not be used for analysis of the wear out region since electronic boards get into this region long after their warranties expire. Therefore, we only deal with early failure and useful time periods. We develop our hazard rate function with phases having "Decreasing Failure/Hazard rate (DFR)" and "Constant Failure Rate (CFR)" like those proposed by Yuan et al. (2010) and Chen et al. (1999). Here, DFR and CFR correspond to early failure and useful life regions, respectively. The proposed overall hazard rate function $h_o(t)$ is presented in Equation 1 where $h_1(t)$ = hazard rate function in early failure period, $h_2(t)$ = hazard rate function in useful-life period, t = time (TTF), and τ = change point from DFR to CFR.

$$h_o(t) = \begin{cases} h_1, & t < \tau \\ h_2, & t \geq \tau \end{cases} \qquad (1)$$

Using a piecewise hazard rate function for reliability modeling, as we suggest, is a well-studied subject in the reliability and statistics literature. This includes the determination of τ often called as change point problem. In some sources τ is even called as burn-in time. Studies on parametric change point analysis of nonmonotonic hazard rate functions consider the change point as a parameter and propose statistical estimation methods like MLE and least squares (Yuan & Kuo, 2010; Blischke 2011). Also nonparametric methods were studied widely. Bayesian estimation method with prior distribution belief about change point was discussed using test data in Yuan & Kuo, (2010). A confidence interval for parametric estimation of change point in two phase hazard model was given by Chen et al. (2001). In this study, we propose a novel change point detection method with determination of the separate hazard rate functions $h_1(t)$ and $h_2(t)$ via parametric analysis and processing the data with graphical inferences.

The data that we use, have TTF values between 1 and 36 months, since the product has 3 year warranty period. In our model, we do analysis for forward and backward time windows. While forward analysis is a widely used method in warranty analysis, investigating TTF values from backward is a new method that we introduce for accurate determination of the change point τ and the hazard functions $h_1(t)$ and $h_2(t)$. In our method, M_f and M_b are used as the number of months that constitute the boundaries of time windows. In Figure 5, an explicit demonstration of the time windows are shown.

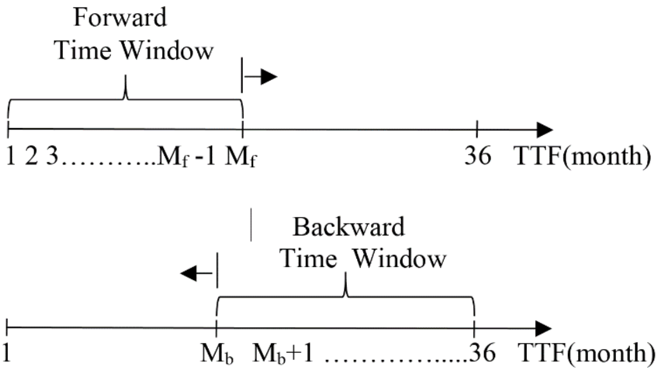

Figure 5. Demonstration of forward and backward time windows

The forward analysis is conducted by using the filtered data with TTF values less than or equal to M_f. For example, if M_f=3, the data to be analyzed will contain TTF values of 1, 2 or 3 months. After starting with M_f=1, M_f is increased by adding months one-by-one (M_f= 2, 3, 4…36). In other words, the forward time window is gradually expanding to the end of the TTF line as seen in the upper part of Figure 5. In forward time window analysis, we see that 2 parameter Weibull distribution is a good fit for almost all different M_f values. Although in some cases the best fitting is achieved with Lognormal or Gamma distribution, these distributions show almost the same DFR pattern as that from Weibull distribution in our analysis. Therefore we determine Weibull distribution for $h_1(t)$. Note that in forward analysis we do not see a change point for M_f from which the DFR pattern changes significantly.

The backward analysis is conducted by using the filtered data with TTF values between M_b and 36 months (1-36, 2-36 …30-36…). In other words, one end of the backward time window is fixed at 36-month and the other is gradually expanding to the beginning of the TTF line as seen in the lower part of Figure 5. In the backward time window analysis, we always achieve the best fitting with Lognormal or Gamma distribution for M_b < 14 (months) and Exponential distribution for $M_b \geq 14$ (months). Therefore there is a change point approximately in the 14th month and we determine Exponential distribution for $h_2(t)$. The change point τ =14 (months) also results in M_f =14 for $h_1(t)$ and M_b=14 for $h_2(t)$ that are shown in Figure 6 and Figure 7, respectively.

Note that in this study we determine the change point from the backward analysis, but this is not a necessary and sufficient condition. For different field data, corresponding to different products, we could have had multiple change points or a single change point derived from the forward analysis. These cases are beyond the scope of this paper and considered as future work.

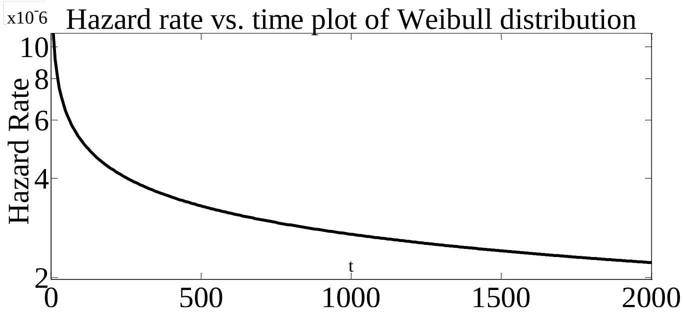

Figure 6. Hazard rate function $h_1(t)$ of forward analysis with Weibull distribution for M_f =14 months. Beta: 0,715 Eta (Day):2.44E+6

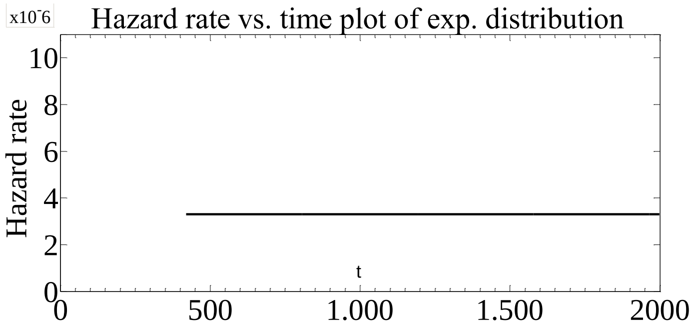

Figure 7. Hazard rate function $h_2(t)$ of backward analysis with Exponential distribution for M_b =14 months. Mean time (Day):303179.252, Gamma (Day):382.086

After determination of the change point, two phase hazard rate function, consisting of Weibull and

Exponential distributions, can be constructed directly. In this case, there is a discontinuity problem at the change point; overall hazard rate function is not continuous. In order to solve this problem, we propose a smoothing and fitting method similar to the method suggested by Selmic & Levis (2002) for neural networks.

We achieve smoothing with a sigmoid function as a smooth step function approximation. Sigmoid function is given as follows.

$$s(t,\tau) = \frac{1}{1+e^{-b(t-\tau)}} \tag{2}$$

In Equation 2, τ is the change point in a unit of day. In our case its value is 14×30 days. Sharpness parameter b of the sigmoid function, can be calculated empirically. As a result, overall hazard rate function is given as:

$$h_o = \left(1 - s(t,420)\right) \times h_1 + s(t,420) \times h_2 \tag{3}$$

$$h_o = \left(1 - \frac{1}{1+e^{-b(t-420)}}\right)\frac{\beta t^{\beta-1}}{\eta^{\beta}} + \frac{1}{1+e^{-b(t-420)}}\,\lambda \tag{4}$$

where β and η are the shape and scale parameters of the Weibull distribution $h_1(t)$, respectively. Additionally, λ is the hazard rate of the Exponential distribution $h_2(t)$. A plot of $h_o(t)$, $h_1(t)$ and $h_2(t)$ are shown in Figure 8 that clearly shows the idea under our smoothing operation.

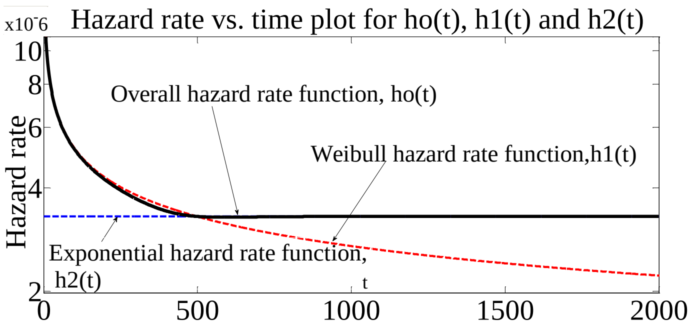

Figure 8. Proposed modeling approach. Plot of $h_o(t)$, $h_1(t)$ and $h_2(t)$

A small distortion and error around the change point is an expected situation with this kind of smoothing. In our smoothing process, there is a slight difference between the overall hazard function $h_o(t)$ and $h_1(t)$ just before the change point at the 14^{th} month (420^{th} day). This can be seen in Figure 8. Fortunately, hazard rate values of $h_1(t)$ and $h_2(t)$ near the change point are very close to each other's because of neutrality of the data that results in very low error values.

It should be noted that there may be seen different distributions in the forward and backward analysis. The distributions do not have to be only Weibull and Exponential. We already know that distributions like Gamma, Lognormal, etc. can give all phases of bathtub curves with DFR, CFR and IFR tendencies according to values of the distribution parameters. Therefore, the proposed method of having continuous hazard rate functions can be directly applicable to different distributions.

4 CONCLUSION

In this study, we propose a methodology to process field return data and model the hazard rate function of electronic boards. We cooperate with one of the Europe's largest manufacturers and use their well-maintained data with over 1000 electronic board failures. The main goal of our study is developing a precise reliability model for electronic boards including warranty forecasting. To reach our goal, we follow two steps that are filtering and modeling.

In the filtering step, we propose a new systematic approach to determine and eliminate both obvious and hidden errors. Our method separately investigates the data in six-month time intervals, and shows us the problematic time spans corresponding to incomplete data that need to be excluded. In the modeling step, we use the filtered data to develop our reliability model. Our model is achieved by performing forward and backward time analysis of the data, and eventually finding the best fitting distributions for different time-to-failure intervals. In the fitting process we use "rank regression" and "maximum likelihood" methods. Throughout our analysis we benefit from Weibull++ by ReliaSoft Corporation.

The proposed methodology, targeting a specific electronic board, can also be applied to the return data of other electronic boards. We apply it and the results, not to be disclosed here, show us clear evidence of our methodology's success.

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