Warranty Forecasting of Electronic Boards using Short-term Field Data

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SUMMARY & CONCLUSIONS

The main goal of our study is precisely predicting the reliability performance of electronic boards throughout the warranty period by using short-term field return data. We have cooperated with one of the Europe's largest manufacturers and use their well-maintained data with over 1000 electronic board failures. Before using the field data for our model of warranty forecasting, we filter it to eliminate improper data, correlated to incomplete and poorly collected data. Our model is based on a two-parameter Weibull distribution, chosen from many other distribution options regarding optimum curve fitting. In the fitting process we use and compare "Bayesian", "rank regression", and "maximum likelihood" fitting techniques. Our method has two steps. In the first step, we investigate how the Weibull parameter β changes by increasing the number of months of field data. For this purpose we use an electronic board with 36 months (full warranty period) of field return data. We develop a mathematical model of β as a function of the field data time interval and board dependent parameters. In the second step, we make a warranty forecasting of a new electronic board using its 3-month field data by using the mathematical model developed in the first step. The proposed method is evaluated by applying it to different electronic boards with 36 months (full warranty period) of field return data. The predicted results from our method and the direct results from the field return data matches well. This demonstrates the accuracy of our model.

1 INTRODUCTION

In recent years, the importance of electronics reliability has grown significantly. Getting more complex electronic systems and usage in large industrial fields requires high reliability. This demand for high reliability reveals a requirement for an accurate and early reliability prediction to give feedback for the design and warranty precautions.

There are many suggested methods to predict reliability of electronics in the literature such as accelerated life tests, component based numerical and probabilistic simulations, and statistical methods. Conventional accelerated reliability test do not meet the demands of today's very rapid electronic product cycles they can be time consuming and expensive. Using simulations for components and systems is another option, which is time saving, but simulation test data never reflects the real-world performance of the product and results in accuracy problems for various failure mechanisms [1]. Therefore, laboratory data based predictions can be deceptive for many applications. This underlines the importance of using the product's field return data for reliability analysis that is relatively accurate, cheap and time saving. In this study, we perform warranty forecasting of electronic boards by exploiting field return data. We have cooperated with one of the Europe's largest manufacturers and use their well-maintained data with over 1000 electronic board failures.

Considering the field-data based studies in the literature [2, 3], one of the common issues is data reliability, correlated to incomplete and wrong records. For this reason, a filtering process must be conducted [4]. In this study, we first make the data reliable by filtering it to eliminate incomplete and poorly collected data.

Conventional reliability prediction methods using field return data of a product has an important constraint. They can only predict very near future reliability of a product since they assume that failure mechanisms of a product do not change. Indeed, a product, consisting of many components, has different failure mechanisms for different operating time intervals corresponding to "early failure", "useful life", and "wear out" regions. For example, with conventional methods one cannot predict the product's reliability performance for the useful life period by using the data from the early failure period. In this study, we propose a new method to overcome this problem. Our model is based on two-parameter Weibull distribution, chosen from many other distribution options regarding optimum curve fitting.

The main goal of our study is to precisely predict the reliability performance of electronic boards throughout the warranty period by using very short-term field return data. For electronic boards targeted in this study, warranty period is 3 years, and we use the first 3 months field data. In the fitting process we use "Bayesian", "rank regression", and "maximum likelihood" estimation techniques and compare them in terms of performance on the field return data.

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Our method has two steps. In the first step, we investigate how the Weibull parameter β changes by increasing the number of months of field data. For this purpose we use an electronic board with 36 months (full warranty period) of field return data. We develop a mathematical model of β as a function of field data time interval and board dependent parameters. In the second step, we make a warranty forecasting of a new electronic board given its 3-month field data. We achieve this using the mathematical model developed in the first step. The proposed method is evaluated by applying it to different electronic boards with 36 months of field return data. The predicted results from our method and the direct results from the field return data matches well. This demonstrates the accuracy of our model.

The paper is organized as follows. We first introduce the filtering method of the field return data in Section 2. Then, we give information about estimation methods showing their results and comparisons on the filtered field return data in Section 3. Finally, we offer a warranty prediction method via change of β parameter of Weibull distribution with time in service and its mathematical model in Section 4.

2 FILTERING

In order to obtain accurate results for warranty analysis, it is necessary that the field return data contain correct records in terms of assembly dates, return date, and number of sales and failures. However, most of the time field-return data includes both obvious and hidden errors. Obvious errors can be easily detected by looking at the failure record of an item. These errors usually appear as wrong records on field return data. Frequently encountered hidden errors are missing records, which can affect warranty analysis badly since failed items in a product group are seen suspended (missing) in the warranty analysis. In this case, a statistical process is needed to detect hidden errors.

In this section, a systematic approach, given in details in [5], to detect hidden errors in the field return data is used. For this study statistical inferences are based on Weibull distribution and its beta (β) parameter. Weibull β parameter can take values in three region; $0< \beta < 1$, $\beta = 1$, $\beta > 1$. These three regions correspond to early failure, useful life and wear out regions respectively in the hazard rate curve [6]. It is logical to expect to see early failure and useful life in a warranty analysis of an industrial product especially for electronic systems.

To detect hidden errors, 54 months field return data, including failures in the product groups assembled in the first 54 months, is analyzed by separating the field return data into different assembly time intervals. Examined field return data includes only warranty records of three years. Time intervals are expanded in the forward direction by adding six months intervals like 1-6 months, 1-12 months, etc., and then β values are observed. Also field return data is analyzed in separate time intervals like 1-6 months, 7-12 months, etc. Weibull β values of these two analyses are given in Figure 1 and Figure 2, respectively. According to Figure 1 and Figure 2, β values of the first 18 months are significantly greater than 1. On the other hand β values of the data covering the whole warranty period cannot be higher than 1. Therefore it is clear that the first 18 months records in the field return data are problematic; they must be filtered. In the next two sections, filtered field return data is used for our analysis.

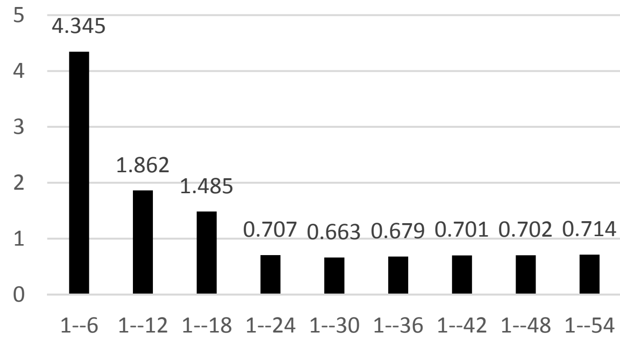

Figure 1-Beta values in forward analysis.

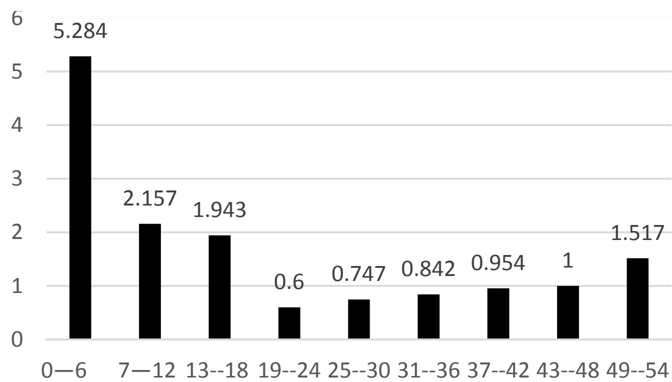

Figure 2-Beta values for six month separate periods

3 ESTIMATION METHODS

Our main purpose in this study is predicting the β (Weibull parameter) values of the boards throughout their 3 year warranty periods by using the β values of the data with time to failure (TTF) values less than or equal to 3 months. Therefore the β values for TTF $\leq$ 3 months is crucial and should be calculated accurately. For this calculation we review and compare MLE, Bayesian, and rank regression methods. We also give a brief background about the Weibull distribution.

3.1 Estimation of parameters for Two-Parameter Weibull distribution

The Weibull distribution is one of the most popular and widely used models of failure time in life testing and reliability theory. The estimation of the its parameters were considered by many authors such as Hossain and Zimmmer [7], Balakrishnan and Kateri [8], Teimouri et al. [9], and references cited therein. More details about the Weibull distribution can be found in Muthy et al. [10] and Rinne [11].

A Weibull distribution with the shape parameter β and the scale parameter α is denoted by $WE(\beta,\alpha)$. The cumulative density function (cdf) and probability density function (pdf) of a random variable $X : WE(\beta,\alpha)$ are given as

$$F(x;\beta,\alpha) = 1 - e^{-\left(\frac{x}{\alpha}\right)^{\beta}}, x > 0, \quad (1)$$

and

$$f(x;\beta,\alpha) = \frac{\beta}{\alpha}\left(\frac{x}{\alpha}\right)^{\beta-1} e^{-\left(\frac{x}{\alpha}\right)^{\beta}}, x > 0.$$

The estimation of the parameters β, α can be obtained by using Classical (MLE and Rank R.) and Bayesian approaches.

3.2 *MLE Estimation*

In this part, we consider the maximum likelihood estimates (MLE) of the parameters for the Weibull distribution. Let $X_1,..., X_n$ be a independent random sample from Weibull distribution with parameters (β,α). Then the likelihood function is

$$L(\beta,\alpha;x) = \prod_{i=1}^{n} f(x_i;\beta,\alpha) = \frac{\beta^n}{\alpha^{n\beta}} \exp(\beta-1)\sum_{i=1}^{n}\ln(x_i) - \frac{1}{\alpha^{\beta}}\sum_{i=1}^{n} x_i^{\beta}$$

Taking the natural logarithm, we get the log-likelihood function

$$l(\beta,\alpha;x) = n\ln(\beta) - n\beta\ln(\alpha) + (\beta-1)\sum_{i=1}^{n}\ln(x_i) - \frac{1}{\alpha^{\beta}}\sum_{i=1}^{n} x_i^{\beta} \quad (2)$$

The MLEs of the parameters β and α (denoted by $\widehat{\beta}$ and $\hat{\alpha}$ r espectively) are the set of values of the model parameters that maximizes the likelihood function given in (2) based on the samples $x_1,\ldots,x_n$. These estimates are derived from the following equations

$$\frac{\partial l}{\partial \beta} = \frac{n}{\beta} - n\ln\alpha + \sum_{i=1}^{n}\ln(x_i) + \frac{\ln\alpha}{\alpha^{\beta}}\sum_{i=1}^{n} x_i^{\beta} + \frac{1}{\alpha^{\beta}}\sum_{i=1}^{n} x_i^{\beta}\ln(x_i) = 0,$$

$$\frac{\partial l}{\partial \alpha} = \frac{-n\beta}{\alpha} + \frac{\beta}{\alpha^{\beta+1}}\sum_{i=1}^{n} x_i^{\beta} = 0$$

Then, the MLE of α, $\hat{\alpha}$ is given by

$$\hat{\alpha} = \frac{\sum_{i=1}^{n} x_i^{\hat{\beta}}}{n} \quad (3)$$

and the MLE of β, $\hat{\beta}$ is the solution of the following non-linear equation

$$\frac{n}{\beta} + \sum_{i=1}^{n}\ln(x_i) - \frac{n}{\sum_{i=1}^{n} x_i^{\beta}}\sum_{i=1}^{n} x_i^{\beta}\ln(x_i) = 0.$$

$\hat{\beta}$ can be obtained as the solution of the nonlinear equation of the form $H(\beta) = \beta$ where

$$H(\beta) = n\left[\frac{n}{\sum_{i=1}^{n} x_i^{\beta}}\sum_{i=1}^{n} x_i^{\beta}\ln(x_i) - \sum_{i=1}^{n}\ln(x_i)\right]^{-1} \quad (4)$$

Since, $\hat{\beta}$ is a fixed point solution of the nonlinear equation (4), its value can be obtained using an iterative scheme like: $\beta_{(j+1)} = H(\beta_{(j)})$, where $\beta_{(j)}$ is the j th iterate of $\hat{\beta}$. The iteration procedure should be stopped when $|\beta_{(j)} - \beta_{(j+1)}|$ is sufficiently small. After $\hat{\beta}$ is obtained, $\hat{\alpha}$ is obtained from equation (3).

3.3 Bayesian Estimation

Bayesian approach has a number of advantages over the conventional frequentist approach where data is a repeatable random sample - there is a frequency. Bayes theorem is a consistent way to modify our beliefs about the parameters given the data that actually occurred. In the Bayesian inference, the most commonly used loss function is the squared error (SE) loss function, $L(\theta^*,\theta) = (\theta^* - \theta)^2$, where θ^* is an estimate of θ. This loss function is symmetrical and gives equal weight to overestimation as well as underestimation.

In this part, we consider the Bayes estimates of the parameters of Weibull distribution under the SE loss function when the parameters β and α are both unknown and random variables.

The Bayesian approach assumes that the parameters α and β are random variables rather then being fixed as in classical approach. In this study, we assume that β has exponential distribution with the hyper-parameter λ and the parameter α has uniform distribution in (a,b)(2)That is the prior distribution of β is $\pi(\beta) = \frac{1}{\lambda}e^{-\beta/\lambda}$, $\lambda > 0$ and the prior distribution of α is $\pi(\alpha) = \frac{1}{b-a}$. Then the joint posterior density function of β and α is given by

$$\pi(\beta,\alpha|x) = \frac{L(\beta,\alpha;x)\pi(\alpha)\pi(\beta)}{\int_0^{\infty}\int_0^{\infty} L(\beta,\alpha;x)\pi(\alpha)\pi(\beta)\,d\beta\,d\alpha}$$

$$= \frac{\frac{\beta^n}{\lambda\alpha^{n\beta+1}}\exp\left(\frac{-\beta}{\lambda} + (\beta-1)\sum_{i=1}^{n}\ln(x_i) - \frac{1}{\alpha^{\beta}}\sum_{i=1}^{n} x_i^{\beta}\right)}{\int_0^{\infty}\int_0^{\infty}\frac{\beta^n}{\lambda\alpha^{n\beta+1}}\exp\left(\frac{-\beta}{\lambda} + (\beta-1)\sum_{i=1}^{n}\ln(x_i) - \frac{1}{\alpha^{\beta}}\sum_{i=1}^{n} x_i^{\beta}\right)d\beta\,d\alpha}$$

The Bayes estimate of a given measurable function of β and α, say $g(\beta,\alpha)$ under the SE loss function is its posterior mean. Therefore, the Bayes estimate of $g(\beta,\alpha)$ under the SE loss function

$$\hat{g}_{BS} = E_{\beta,\alpha|\mathbf{x}}(g(\beta,\alpha)) = \frac{\int_0^{\infty}\int_0^{\infty} g(\beta,\alpha)L(\beta,\alpha;x)\pi(\alpha)\pi(\beta)\,d\beta\,d\alpha}{\int_0^{\infty}\int_0^{\infty} L(\beta,\alpha;x)\pi(\alpha)\pi(\beta)\,d\beta\,d\alpha}$$

$$= \frac{\int_0^{\infty}\int_0^{\infty} g(\beta,\alpha)\frac{\beta^n}{\lambda\alpha^{n\beta+1}}\exp\left(\frac{-\beta}{\lambda} + (\beta-1)\sum_{i=1}^{n}\ln(x_i) - \frac{1}{\alpha^{\beta}}\sum_{i=1}^{n} x_i^{\beta}\right)d\beta\,d\alpha}{\int_0^{\infty}\int_0^{\infty}\frac{\beta^n}{\lambda\alpha^{n\beta+1}}\exp\left(\frac{-\beta}{\lambda} + (\beta-1)\sum_{i=1}^{n}\ln(x_i) - \frac{1}{\alpha^{\beta}}\sum_{i=1}^{n} x_i^{\beta}\right)d\beta\,d\alpha}$$

It is not possible to compute the above equation analytically. Different approaches are available in the literature such as Lindley's approximation, Tierney-Kadane method, or Markov chain Monte Carlo (MCMC) method. The Lindley's approximation can be applied to obtain the Bayes estimates of β and α. The bayesian estimate of β is obtained using one of these approximation when $g(\beta,\alpha) = \beta$, similarly for α when $g(\beta,\alpha) = \alpha$. Morever, the hyper-parameters can be obtained using method of moments.

3.4 Linear Rank Regression

One of the simplest method for parameter estimation is that of probability plotting. This methodology involves plotting the failure times to determine the fit of the data to a given distribution by using the linear rank regression, which is a simple technique that engages replacing the data with their corresponding ranks [12]. With this method only the position where the failure occurred is taken into account, and not the exact time-to-suspension. This shortfall is significant when the number of failures is small and the number of suspensions is large and not spread uniformly between failures, as with these data. Therefore, in this study we do not use rank regression method; we only consider maximum likelihood (MLE) or Bayesian estimation methods to estimate the parameters instead of using least squares. A comparison of the MLE and Bayesian methods follows.

3.5 Comparison of MLE and Bayesian Methods

We compare the methods on different sample sizes. The comparison is shown in Table 1. We select exponential distribution with a hyperparameter λ for the prior fuction of the Bayesian method. The hyperparameter λ is calculated as the arithmetic mean of the TTF values. As shown in the second row of the table (bold), for very large sample sizes, MLE and Bayesian methods give very close results. This is expected considering that the larger the sample size the more accurate the estimation. However decreasing sample sizes results in very different β values. While β values of the Bayesian method remains almost the same (that is the sign of accuracy), β values of the MLE method changes significantly. In the Bayesian approach, the uncertainty about the parameter is represented by a probability density function which may result in more accurate estimates. As a result, in this study we prefer to use Bayesian method to estimate β values of the data with TTF $\leq$ 3 months.

Sample Size	β from MLE	β from Bayesian
538	0,39526	0,381216
177	0,471275	0,432028
73	0,55383	0,442491
56	0,72817	0,501102
42	0,750407	0,415987

Table 1- Beta values for different sample sizes for MLE and Bayesian methods; TTF $\leq$ 3 months.

4 WARRANTY FORECASTING

Conventional reliability prediction methods using field return data have an important constraint. They can only predict very near term reliability of a product.

Field return data of an electronic board can be used to get some inferences about reliability of next generation boards, which have similar components and production methods. We call these similar boards a family. While doing prediction about next generation boards, it is expected to get fast reliability prediction in early phase of products. For this reason a new method is offered in this section. The method, we introduce, consists of two steps. Firstly, we investigate how the β parameter of Weibull distribution changes with increasing time and failures. We calculate β values via Bayesian estimation method, whose performance is better than MLE method as pointed in previous section. Then we fit a curve to denote β as a function of service time, namely time to failure (TTF). Due to this fitting, we obtain 2 parameters and examine change of β values of another similar electronic board with time.

In this study, we base our analysis and methods on the two-parameter Weibull distribution and its parameter β since we see that estimated values of the Weibull α parameter don't change considerably with TTF values in the warranty analysis of field return data. Also β affects hazard rate function directly.

4.1 Analysis of change of Beta in warranty analysis

To determine the change of β, we analyze filtered field return TTF data. Due to the filtering, we now have the data obtained in the last 36 months (initially 54 months). This is irrelevant from the warranty duration which is also 36-month. We perform warranty analysis for 1, 2, 3, 6, 9, 12, 18, 24, 30, 36 month TTF in Reliasoft Weibull++ program using Weibull distribution. For each month (1, 2, 3, 6, 12, 18, 24, 30, 36) we examine the β parameter. In the method, n-month TTF analysis refers to the analysis of field return records which have 1, 2, 3, 4, ,,,, n-1, n month TTF value. Namely, 36 months analysis involves all the filtered data since the warranty has 36 months. Result of the analysis for an electronic board, Board-B, is given in Table 2 and Figure 3. As seen from Figure 3, β of filtered field return data has a logarithmic growth model which approaches 1 (useful life region) toward to the end of the warranty period as expected for an electronic board whose wear out region is assumed to be 10-15 years.

Month	Beta
1	0.332
2	0.369
3	0.381
6	0.436
9	0.489
12	0.551
18	0.648
24	0.699
30	0.588
36	0.588

Table 2- Beta values for different time to failures analysis

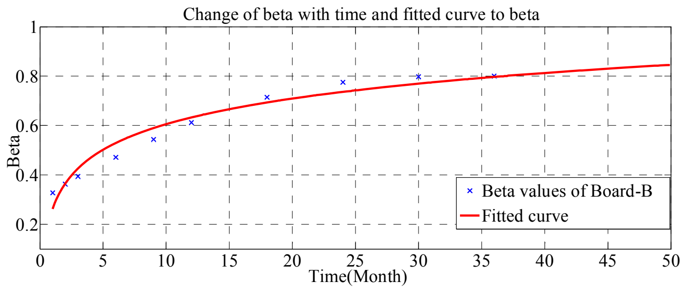

Figure 3- Beta values and their fitted curve for Board-B

4.2 Warranty forecasting with curve fitting

In the second step, we fit β values to a curve to implement β as a function of time as seen in Figure 3 .Here, we use logarithmic curve fitting using the least square method. The equation of the curve is obtained as;

$$\beta(t) = a \times \ln(b \times t), \text{ t} > 0 \text{ (Month)} \qquad (5)$$

As a result of our experiments with different real field return data, we know that β curves of products in the same family have similar trends and close values to each other. Therefore with this motivation, we make two definitions. We define parameter a as product dependent parameter since it is closely correlated with β values in early months. Parameter b is defined as technology dependent parameter since change of b create slight differences in equation (5) and this situation is more suitable for the evaluation of electronic board in terms of technology change. For this reason it is reasonable to assume that technology dependent parameter may be same for a family. Therefore we assume that b is fixed and a is variable for products in a family.

Fitting results of Board-B for a and b are 0.149 and 5.77 respectively. Therefore we expect that β equation of family including Board-B is $\beta(t) = a \times \ln(27.7 \times t)$. Due to this equation, change of β with time can be estimated approximately from the early warranty data. If we know b for a family, we can calculate a in (5) from β values obtained by early warranty analysis with the proposed method in section (4.1). Two experimental results are given by Figure 4 and Figure 5. These graphics show a comparison of real β values of Board-F and Board-E and their estimated curves from Board-B, β (t) $= a \times \ln(27.7 \times t)$. The values of a are calculated directly from their 3-month analyses, since by the third month there are usually an adequate number of record to get a healthy estimations. Parameter a is calculated for Board-E as 0.1339 and for Board-F as 0.1266.

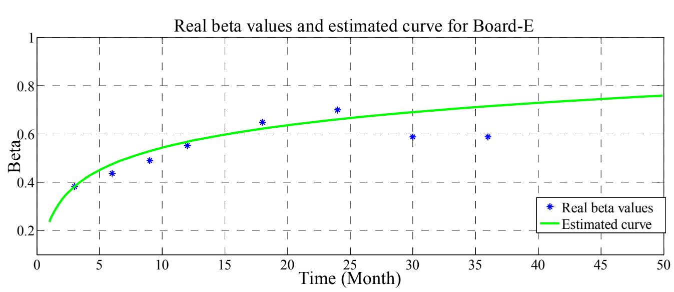

Figure 4- Comparison of estimated curve and real values for Board-E

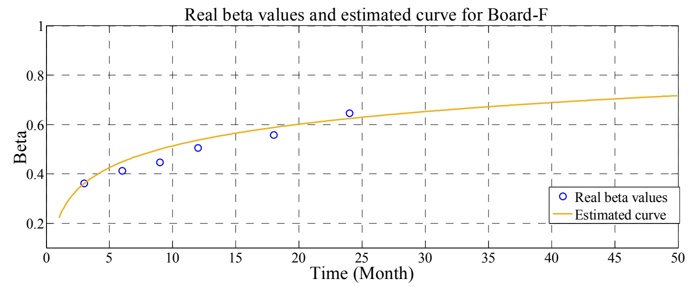

Figure 5- Comparison of estimated curve and real values for Board-F

In Figure 4 and 5, discrete points represents real β values obtained from whole field return data analysis in terms of TTF (1, 2, 3, ,,,) as in the first step of this section. Curves in Figure 4 and 5 are derived from equation (5). It is clear from these figures that as expected there is a significant match with real values in the warranty period. The most important advantage of this method is the ability to work with past products warranty data and early warranty data of next generation products. An additional result that shows consistency of our method is given in Figure-6, which shows result of the analysis conducted for another electronic board, Board-K, not a member of the family of Board B-E-F. The estimated curve of Board-K is obtained from the same process used for other boards by using the same value for b. There is a substantial difference between real beta values and the estimated curve in the Figure-6. This happens mainly because Board-K is not a member of the family of Board B-E-F. As a future work, we improve our model to be applicable for different electronic products.

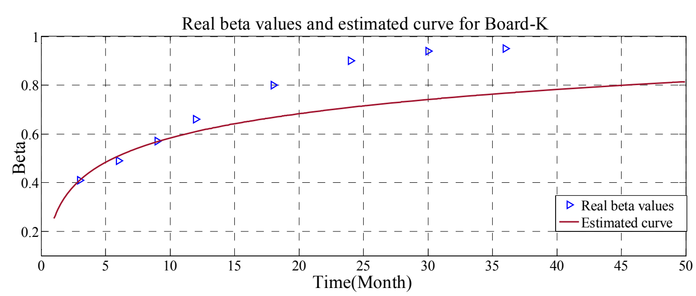

Figure 6- Comparison of estimated curve and real values for Board-K

In our method, the main challenge is accurately calculating the β values from early field return data. In this section we calculate the β values from a large field data to show the consistency of our method. But in the offered situation namely in the case of early warranty returns, data size (sample size) may not be sufficient relative to the whole field data, which affects the estimated β values in warranty analysis. Such a difference in the β values will cause a difference in parameters of the equation in (5). In this situation, we propose to use Bayesian estimation method that gives more accurate results in the case of low sample size as discussed in section (3.5). Table I illustrates this by comparing MLE and Bayesian methods for different sample sizes.

5 CONCLUSION

The main goal of our study is precisely predicting the reliability performance of electronic boards throughout the warranty period by using very short-term field return data. For electronic boards targeted in this study, warranty period is 3 years, and we use field data of their first 3 months. Conventional reliability prediction methods can only predict very near future reliability of a product since they assume that failure mechanisms of a product do not change. In this study, we propose a new method to overcome this problem. The proposed method is evaluated by applying it to different electronic boards with field return data of 36 months (full warranty period). The predicted results from our method and the direct results from the field return data matches well. This demonstrates the accuracy of our model.

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