Regression Based Software Reliability Estimation: Duane Model

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Software Reliability Growth Model(SRGM) is a mathematical model which represent, how the software reliability improves as faults are detected and repaired. The performance of SRGM is judged by its ability to fit to the software failure data. How good does a mathematical model fit to the data and reliability of software is presented in the current paper, considering Duane model. Regression method is used to estimate the model parameters. To assess the performance of the considered Software Reliability Growth Model, the parameters are estimated based on the real software failure data sets.

Keywords: Duane model, Regression, Goodness-of-fit, AIC, Reliability.

1.1. INTRODUCTION

Software Reliability became an important research area, as the software is being used in many life critical systems. It is one among a number of quality attributes of software. Reliability models can be of two types i.e. static and dynamic. A static model uses software metrics to estimate the number of failures in the software. A dynamic model uses the past failure discovery rate during software execution over time to estimate the number of failures. Various software reliability growth models (SRGMs) exist to estimate the expected number of total failures or the expected number of remaining failures. During the past four decades a number of software reliability growth models have been proposed and used to predict and assess the quality of software. The application of probabilistic methods for the analysis of stochastically occurrence of failures in a software system is called software reliability. It can be defined as the probability that no failure occurs up to time 't'.

A failure is the departure of software behavior from the user requirements. This phenomenon must be distinguished from the fault in the software code which causes the occurrence of failure as it is activated during program execution. The reliability of software will improve with time as the underlying fault is detected and fixed correctly after a failure has been experienced. A Software reliability growth model describes software error detection process and estimate software reliability. The reliability improvement phenomenon is called reliability growth. The size and the complexity of the software packages make it impossible to find and correct all existing faults. The best thing is to give software a reliability requirement and to try to attain a goal by testing the software and correcting the detected faults. However, obtaining the required software reliability is not an easy task. Thus, high reliability is usually estimated by using appropriate models applied on failure data from the software failure history.

A Software reliability model is a mathematical description of the debugging and fixing process. A software reliability model falls into two categories that depend on the operating domain. Thus, the most popular models are based on time. Their main feature of reliability measures, such as the failure intensity which is derived as a function of time. The second kind of software reliability models has a different approach. This approach is made by using operational inputs as their main features, which measure reliability as the ratio of successful runs to total runs. The second approach has some problems such as: many systems have runs of large lengths with output measures that are incompatible with the time-based measures. Due to these problems, this paper has been devoted to time-domain models. The time domain model employs either the observed time between failures or the number of discovered failures per time period. Thus, these two procedures were developed to estimate the model parameters from either failure count data or time between failures. Therefore, software reliability modelling and estimation can be grouped into two categories of general applicability.

Duane learning-curve property, was given a concrete stochastic basis by Crow (1974). He assumed that the failures during the developmental stage of a new system follow a NonHomogeneous Poisson Process (NHPP). The Bayesian estimation problem for the plp model was addressed by Higgins and Tsokos (1981). Ananda sen (1998) investigated the statistical inference concerning the current reliability of a reliability growth model. Satyaprasad et al. (2014) have applied SPC(Statistical Process control) amd Maximum likelihood estimation to assess the reliability of software on ungrouped data. Srisaila et al. (2015) have considered the ordered statistics to assess the reliability of software using Power Law Process model.

1.2. BACKGROUND THEORY

This section presents the theory that underlies NHPP models, the SRGMs under consideration and regression approach for parameter estimation for ungrouped data. If 't' is a continuous random variable with pdf: $f(t;\theta_1,\theta_2,\ldots,\theta_k)$. Where, $\theta_1,\theta_2,\ldots,\theta_k$ are k unknown constant parameters which need to be estimated, and cdf: $F(t)$. Where, The mathematical relationship between the pdf and cdf is given by: $f(t)=F^{'}(t)$. Let 'a' denote the expected number of faults that would be detected given an infinite testing time. Then, the mean value function of the NHPP models can be written as: $m(t)=aF(t)$, where F(t) is a cumulative distribution function. The failure intensity function $\lambda(t)$ in case of NHPP models is given by: $\lambda(t)=aF'(t)$ (Pham, 2006).

1.2.1. NHPP MODEL

The reliability growth models are better described by a Non-Homogeneous Poisson Process (NHPP). These NHPP based software reliability growth models (SRGMs) are proved to be quite successful in practical software reliability engineering. The NHPP has been frequently proposed as a model for the failure of repairable systems. The main issue in the NHPP model is to determine an appropriate mean value function to denote the expected number of failures experienced up to a certain time point. The importance of the NHPP resides in the fact that it does not require the process to be stationary over time, so it allows for the possibility that events may be more likely to occur at some times than at others. Thus, the NHPP has been widely used as a model for systems subject to deterioration. Various NHPP SRGMs have been built upon various assumptions. Many of the SRGMs assume that each time a failure occurs, the fault that caused it can be immediately removed and no new faults are introduced. Which is usually called perfect debugging. Imperfect debugging models have proposed a relaxation of the above assumption.

1.2.2. THE DUANE MODEL

Software reliability growth models (SRGM's) are useful to assess the reliability for quality management and testing-progress control of software development. They have been grouped into two classes of models concave and S-shaped. The most important thing about both models is that they have the same asymptotic behavior, i.e., the defect detection rate decreases as the number of defects detected (and repaired) increases, and the total number of defects detected asymptotically approaches a finite value. This model is proposed by Duane(1964). The model has been applied in analyzing failure data of repairable systems. The Duane model belongs to the non-homogeneous Poisson process models, and it is sometimes called the power law process. This model has been used and studied extensively in software reliability context khoshgoftaar and woodstock(1991), Lyu and Nikora (1991). This model is characterized by the following mean value function:

$$m(t)=at^{b}. \quad \text{Where,} \quad a,b>0,t\geq 0. \tag{1.2.2.1}$$

The failure intensity function of the model, which is defined as the derivative of the mean value function $m(t)$, is given by

$$\lambda(t)=abt^{b-1}. \tag{1.2.2.2}$$

Where 'a' is the scale and 'b' is the shape parameters, which are unknown constants greater than Zero. The Duane model has been widely used because of its flexibility. It can be used for the modelling of a deteriorating system or improving system depending on the value of b. Statistical hypothesis testing for the parameters 'a' and 'b' of Duane with intensity function given in equation 1.2.2.2 have been considered by some authors. When b = 1, Duane becomes a Homogenous Poisson Process (HPP) and the frequency of failures is time-independent. For b > 1, the frequency of failures increases with time, while for b < 1, the failure frequency decreases with time. Thus from the viewpoint of system reliability, the hypothesis mean that the system is experiencing no change over time, degradation over time and improvement over time.

1.2.3. REGRESSION APPROACH FOR PARAMETER ESTIMATION

In this paper, Regression method is used to estimate the reliability based on failure data of a system using a two parameter SRGM, Duane model. For this model, instead of estimating the parameters 'a' and 'b' through the standard method of MLE, we estimate these parameters through regression (least squares) approach. In addition, we also compute the AIC and Reliability measures.

For the Duane model, the MTBF can be approximated by the inverse of the intensity function (Ascher and Feingold, 1984), (Suresh,1992).

i.e,

$$MTBF = \frac{1}{\lambda(t)} = (ab)^{-1} t^{(1-b)} \qquad (1.2.3.1)$$

Where 't' is the failure time.

Taking the natural logarithm, we get:

$$\ln(MTBF) = -\ln(ab) + (1-b)\ln(t) \qquad (1.2.3.2)$$

we can rewrite (1.2.3.2) as a linear equation

$$Y = mX + c \qquad (1.2.3.3)$$

By writing, $Y = \ln(MTBF)$, $c = -\ln(ab)$, $m = (1-b)$ and $X = \ln(t)$

Using the method of least squares for the linear regression model, we can derive least squares estimators of a and b as $\hat{a}$ and $\hat{b}$, where

$$\hat{m} = \frac{\sum X_i Y_i - n\bar{X}\bar{Y}}{\sum X_i^2 - n\bar{X}^2} \quad \text{and}$$

$$\hat{c} = \bar{Y} - \hat{m}\bar{X}$$

Now, using the above derivation

$m = (1-b)$ implies $b = (1-m)$,

$c = -\ln(ab)$ implies

$$a = \frac{1}{(1-m)}\frac{1}{e^{c}} = \frac{e^{-c}}{(1-m)}$$

We get the regression estimators of the Duane parameters a and b, denoted by:

$$\hat{a} = \frac{e^{-\hat{c}}}{\left(1-\hat{m}\right)} \quad \text{and}$$

$$\hat{b} = \left(1-\hat{m}\right)$$

1.3. TIME DOMAIN FAILURE DATA SETS

The techniques examined here deal with data about the time at which failures occurred; or alternatively, data about the time between failure occurrences. These two forms can be considered equivalent. Although most software reliability growth models use data of this form, and such models have been in use for several decades, finding suitable data to verify models and improvement techniques is difficult. Early work generally focused on data based on calendar or wall clock time. Musa asserts that CPU execution time is a better measure than wall clock time, during which the actually time spent running a program can vary greatly based on CPU load, man hours, and other factors.

The performance of the model under consideration is exemplified by applying on the data sets given below.

Data Set #1: AT&T System T Project (Ehrlich et al., 1993).

Data Set #2: On-Line Data Entry IBM Software Package Ohba (1984)

Data Set #3: (Lyu, 1996)

Data Set #4: US Naval Tactical Data Systems (NTDS) (Jelinski and Moranda, 1972),

Data Set #5: SONATA Software Limited (Ashoka, 2010).

Data Set #6: Data collected from (Xie et al., 2002).

1.4. ESTIMATED PARAMETERS

The estimated parameters for AT&T, IBM, LYU, NTDS, SONATA & Xie datasets are given in Table 1.4.1 for the model. The estimated values of 'a' and 'b' represented as $\hat{a}$ and $\hat{b}$ are as follows.

Table1.4.1: Estimates of a, b for Duane model

Data set	$\hat{a}$	$\hat{b}$
1 (AT&T)	7.837651	0.208889
2 (IBM)	0.648328	0.572320
3 (LYU)	12.246815	0.421371
4 (NTDS)	7.286835	0.289831
5 (SONATA)	0.313930	0.616067
6 (Xie)	10.248983	0.214795

1.5. GOODNESS-OF-FIT AND RELIABILITY ESTIMATION

Model comparison and selection are the most common problems of statistical practice, with numerous procedures for choosing among a set of models proposed in the literature. Goodness-of-fit tests for this process have been proposed by (Rigdon, 1989). The Akaike information criterion (AIC) is a measure of the relative quality of a statistical model, for a given set of data. As such, AIC provides a means for model selection. AIC deals with the trade-off between the goodness-of-fit of the model and the complexity of the model.

$$AIC = -2 * L + 2 * K \tag{1.5.1}$$

Where, 'k' is the number of parameters in the statistical model, and 'L' is the maximized value of the likelihood function for the estimated model.

Given a set of candidate models for the data, the preferred model is the one with the minimum AIC value. Hence, AIC not only rewards goodness of fit, but also includes a penalty that is an increasing function of the number of estimated parameters. This penalty discourages over-fitting. The AIC and the Reliability for real life failure data sets for the model under consideration is given in table 1.5.1 as follows.

Software Reliability is an important to attribute of software quality and is defined as the probability of failure-free software operation for a specified period of time in a specified environment under specified conditions. Software Reliability is hard to achieve, because the complexity of software tends to be high. While any system with a high degree of complexity, including software, will be hard to reach a certain level of reliability. It is defined as a probabilistic function, and comes with the notion of time.

$$R(x|t) = e^{-[m(t+x)-m(t)]} \tag{1.5.2}$$

The performance of SRGM is judged by its ability to fit the software failure data. The term goodness of fit denotes the question of "How good does a mathematical model fit to the data?". Inorder to validate the model under study and to assess its performance, experiments on a set of actual software failure data have been performed. The considered model fits more to the data set whose Log Likelihood is most negative. Given a set of candidate models for the data, the preferred model is the one with the minimum AIC value.

Table 1.5.1: Reliability estimation using Duane model.

Date set	**Log L**	**AIC**	**R(t_n+25)**
1	-126.196126	256.392252	0.793164
2	-54.049183	112.098366	0.449534
3	-46.703325	97.406650	9.91497E-12
4	-126.512416	257.024832	0.363785
5	-118.581002	241.162003	0.763788
6	-177.157723	358.315447	0.737989

1.6. CONCLUSION

In order to find the goodness-of-fit and the reliability after 25 units of time of the 't_n' for every data set under consideration with the use of Duane model, the parameter estimation is carried out by the application of regression approach on cumulative failure data against time. Out of the Six data sets collected from the literature, Lyu data set is exhibiting the lowest reliability and the AT & T is exhibiting the Highest reliability. The corresponding goodness-of-fit measure of each data set is given table 1.5.1.

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