Abstract

Background/Objective

Since testing consumes more than 50% of the total resources for software development, software reliability growth models (SRGMs) are utilized during system testing phase to check attainment of the target reliability. While there is a plethora of continuous time SRGMs, there are only a few discrete models, and hence there is a need for further research in this area to model datasets from modern projects.

Methods

We propose a discrete SRGM suitable for various patterns of test data. MATLAB™ is used for fitting reliability models.

Findings

The proposed model seems to fit the data better than the other discrete SRGMs proposed hitherto.

Application/Improvements

The proposed model will be useful when we model discrete data sets of software fault removal process from challenging software projects. The model additionally provides an insight into the software development and testing processes.

Keywords—Combination Model, Discrete SRGM, Dynamically weighted.

1. Introduction

The model used for Planning and executing software system testing, where reliability grows owing to correction of faults is known as Software Reliability Growth Model (SRGM). The first well-known SRGM was proposed by Jelinsky –Moranda¹.

Software Reliability Growth Models describe an association between time and cumulative number of failures observed during testing. Most of the SRGMs proposed are continuous time SRGMs. If the number of failures is counted during discrete time intervals such as an hour, day, week and test cases, then we may require discrete SRGMs for better accuracy. It is to be noted that the first SRGM based on the assumption that the fault removal process follows Non-Homogeneous Poisson Process (NHPP) proposed by Schneidewind² is a discrete SRGM. The first continuous time SRGM based on NHPP assumption proposed by Goel-okumoto³ in the year 1979 is in fact, re-parameterized Schneidewind² model. While continuous time models have been published in large number⁴-¹⁴, the discrete time models are a few and hence there is an urgent need for research in this area.

Rafi and Akbar¹⁵ proposed imperfect debugging discrete reliability growth models with the test effort functions as given below:

- Discrete Exponential.
- Discrete Gompertz.
- Discrete Logistic Equation.

Omar¹⁶ proposes two discrete SRGMs – basic model and extended model which take into account fault generation and imperfect debugging combined with the learning phenomenon of the testing team.

The paper is organized as under: We propose a new discrete dynamically weighted combination model in Section 2. In Section 3 we evaluate the goodness of fit statistic of the proposed model and compare the same with the classical Schneidewind’s model. In Section 4 the summary and conclusions are provided.

2. Proposed Model

2.1. NHPP modeling of the fault detection Process

The cumulative number of failures \( f(x) \) in \( t \) is:

\[
 f(x) = \left( \frac{a}{b} \right) [1 - \exp(-bx)] 
\]

(1)

\( a = \) total number of software faults that will be detected at an infinite time.

\( b = \) Constant.

It can be seen from the above that the classical model can only fit the ideal data accurately. Furthermore, the model
does not distinguish between fault and failure since the model assumes that the debugging is perfect and one fault causes one failure and vice versa.

**2.2. Motivation of proposed Model**

The authors carried out research to evolve a combination model that will:
- Address Exponential growth of mean value function as well as S-shaped growth and thereby address the learning phenomenon of the testing team and provide information such as:
  - Debugging index
  - The number of faults in the software system at various times during testing.

**2.3. Derivation Fault-based Combination Model**

In\(^{17-18}\) proposed a model with the above objective for continuous time. The model\(^{17}\) is re-parameterized and proposed as a discrete model in this paper. The mean value function \(f(x)\) of the proposed discrete dynamically weighted combination model is given below:

\[
f(x) = \left( w \left( \frac{a}{c} \right) \left( 1 - \exp(-b \cdot c \cdot x) \right) \right) + \left( 1 - \left( \frac{a}{c} \right)^n \left( 1 - \left( 1 + b \cdot c \cdot x \right) \exp(-b \cdot c \cdot x) \right) \right)
\]

Where:
- \(a\): total number of faults that will be detected at an infinite time.
- \(b\): Constant.
- \(c\): Debugging index greater than zero and a real number.
- \(w\): proportion of the first described model in the above equation; 0 < \(w\) < 1.

A perusal of the proposed discrete model reveals the following.

In the proposed model, two NHPP models have been combined. The first constituent model is modified Kapur–Garg Model\(^{19}\).

The second constituent model is modified Yamada delayed S-shaped Model\(^{20}\). The key to the proposed model lies in combining them with dynamic weights. If the data possesses exponential growth then ‘\(w\)’ will be dominant, else it will be small. It can also lie in the middle depending on the data.

**3. Goodness-of-Fit Evaluation**

In order to assess fitting performance of models, we selected datasets and measures as given below:

Datasets used for evaluating the models

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Schneidewind’s Model</th>
<th>Proposed Discrete Combination Model</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(R^2)</td>
<td>RMSE</td>
</tr>
<tr>
<td>P14C Discretized</td>
<td>0.92</td>
<td>3.4</td>
</tr>
<tr>
<td>DS 3</td>
<td>0.99</td>
<td>4.5</td>
</tr>
<tr>
<td>DS 1</td>
<td>0.99</td>
<td>10.11</td>
</tr>
<tr>
<td>DS 2</td>
<td>0.96</td>
<td>12.58</td>
</tr>
</tbody>
</table>

It can be seen that the proposed fault based discrete dynamic combinational model seems to provide a better fit compared to Schneidewind’s model. A perusal of Table1 will indicate that when \(w\) is high due to the date possessing exponential growth of mean value function, both the models appear to give better performance.

In other cases, combination model seems to perform better than the Schneidewind’s model. Besides, the proposed model provides two quality metrics \(a\), the total number of faults in the software before testing begins and \(c\), the debugging index, which will be useful to the software development organizations. For instance, the project DS1 and DS2 had 450 and 170 initial faults and debugging index was 0.9 and 0.74 respectively as revealed by \(a\) and \(c\) values.

**4. Summary & Conclusions**

In this paper, we propose a dynamically weighted combination model to describe discrete software failure data. We compare the performance of the proposed fault based discrete combination model with the Schneidewind’s classical model and demonstrate the
advantages of the latter. Discrete SRGMs are needed for modeling discrete software failure data for better goodness of fit performance. However, not much research papers have been published in the past for software reliability growth modeling of discrete data. Therefore we studied the discrete models and proposed a dynamically weighted combination model in this paper for modeling discrete failure data for consistently better goodness of fit performance. Each software project is unique, and hence the software failure data will not follow any predetermined pattern. Hence, assuming weights for models like equally weighted combination, weighted arithmetic, etc. apriori may not be appropriate and hence we propose dynamically weighted combination model that will describe software failure data from various projects equally well.

References


