Generalized Exponential Poisson Model for Software Reliability Growth

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Abstract: Software reliability modeling is challenging since no single Software Reliability Growth Model (SRGM) is considered suitable in all situations owing to poor goodness of fit, lack of predictive validity of the models and their sensitivity to fluctuations in the number of failures in the data sets. In this paper, we propose a Non-Homogenous Poisson Process Model whose failure intensity function has the same Mathematical form as that of the probability density function (pdf) of a generalized exponential distribution. The performance of the proposed model was verified and also compared with six chosen SRGMs using failure data from 18 software systems and the model is found to be adequate in terms of goodness of fit statistic and predictive validity. It is also less sensitive to fluctuations in data.

Key Words: failure intensity function, goodness of fit statistic, mean value function, predictive validity, NHPP Model, SRGM

1. Introduction

Applying Software Reliability Growth Models (SRGM) for system testing phase in the Software Development Life Cycle (SDLC) provides quantitative information on the software validation process [1]. Our focus in this paper is SRGM, which is used to predict the number of failures that will occur over some specified testing time in the future and to estimate the failure intensity that will be achieved after additional testing time. According to Littlewood [2], “there is certainly no single agreed model that can be relied upon to give accurate reliability measures in all circumstances”. He further adds “a model may be able to give acceptably accurate results when the ‘current reliability’ of the software is needed, but be poor at predicting the reliability at some future time, or at estimating the time at which the target reliability will be achieved”. Mullen [3], compares the performance of Log Normal Execution Time (LNET) model proposed by him, with Musa’s Logarithmic Poisson Execution Time (LPET) model and Basic Execution Time (BET) [1] model and concludes that none of the three models are able to fit Musa’s [4] collection of data sets P5, P6 and P40. To quote Mullen, “this is due in part to the wide fluctuations in number of failures in those data sets, rather than an unusual trend”. Furthermore, models such as Goel-Okumoto (G-O), BET and LPET are based on the
assumption that failure intensity decreases monotonically from the beginning of system test and hence does not address initially increasing and then decreasing (I/D) pattern of failure intensity function, observed in some projects. The failure intensity function of Yamada’s delayed S shaped [5] model has an increasing error detection rate (IEDR) (mean value) function if \( d(t) \) is non-decreasing in \( t, \geq 0 \) [6]. The models such as generalized Goel [7], Log Logistic[8] and Log Power, derived from the well-known Duane Model[9], proposed to address both the above patterns of failure intensity variations, are at times sensitive to fluctuations in the number of failures in the data sets. It is therefore desirable to evolve a model that will perform well in all situations, capture varying patterns of failure intensity and demonstrate goodness of fit and predictive validity despite fluctuations in data. In this paper, we propose a Non-Homogeneous Poisson Process (NHPP) Model whose rate of occurrence of failures (ROCOF), also known as failure intensity function has the same Mathematical form as that of the probability density function (pdf) of generalized exponential distribution. The performance of the model was evaluated and compared with six other models, using failure data from 18 selected projects and the model is found to provide better goodness of fit statistic and predictive validity.

This paper is organized as under. In section 2, we define the proposed SRGM and discuss about methodology for estimation of its parameters. In section 3, we discuss about the performance check carried out on the proposed model vis-à-vis other selected models and conclusions reached. A better predictive ability of the proposed model has been established and the same has been presented in section 4. Further, a case study on one application of the SRGM namely, to determine when to stop testing is also illustrated using the proposed model in section 5. Conclusions of the paper are given in section 6.

2. The Proposed SRGM

2.1 Generalized Exponential NHPP Model

A well-known family of SRGM is the Non-homogenous Poisson Process (NHPP) family of models. G-O [6] is one of the early NHPP models and a host of other models are also available in the literature [10]. Kapur et al. observe that the relationship between testing time and mean value function is either exponential or S shaped or the mix of the two [10]. After experimenting with various functions and studying how they handle various patterns of failure intensity variations as well as fluctuations in data, we choose the generalized exponential (GE) distribution [12] to define ROCOF of the NHPP model for SRGM. The cumulative distribution function (cdf) – \( F(t) \) and probability density function (pdf) – \( f(t) \) of the distribution are given below:

\[
F(t) = \left[1 - \exp\left(-\frac{t}{\theta}\right)\right]^\beta
\]

(1)

\[
f(t) = \left(\frac{\beta}{\theta}\right)\exp\left(-\frac{t}{\theta}\right)\left[1 - \exp\left(-\frac{t}{\theta}\right)\right]^{\beta-1}
\]

(2)

where \( t \) is the time \( \geq 0 \), \( \theta \) is the scale parameter \( \geq 0 \) and \( \beta \) is the shape parameter \( \geq 0 \). The mean value function [11] of the proposed model is therefore given by

\[
\mu(t) = NF(t) = N\left[1 - \exp\left(-\frac{t}{\theta}\right)\right]^\beta
\]

(3)
where, \( F(t) \) is the cdf of the time to failure of individual faults and \( N \), the eventual number of failures that will be observed over an infinite amount of testing time. The failure intensity function - \( \lambda(t) \) is the rate of change of mean value function over time or the number of failures per unit time and hence it is the derivative of mean value function with respect to time \([11]\), and is an instantaneous value. It is given by:

\[
\lambda(t) = Nf(t) = N \left( \frac{\beta}{\theta} \right) \exp \left( -\frac{t}{\theta} \right) \left[ 1 - \exp \left( -\frac{t}{\theta} \right) \right]^{\beta-1}
\] (4)

The hazard rate of the above generalized exponential distribution increases monotonically if \( \beta > 1 \), constant if \( \beta = 1 \) and decreases monotonically if \( \beta < 1 \). In fact, it is this phenomenon that enables us to propose a suitable NHPP model to model all patterns of variations of failure intensity function.

### 2.2 Determination of Parameters of the Model

The 3 parameters of the model for a given failure data set can be estimated using non-linear regression software tools and we use NCSS Statistical Software, Utah, USA (http://www.ncss.com) to estimate the values of the model parameters. When first few (say 15) failures are observed, the parameters may be estimated, with data consisting of the cumulative test time \((x)\) and the corresponding cumulative number of failures \((y)\) so as to result in best fit of the data to the equation for \( \mu(t) \) of the model as given below:

\[
y = N \left[ 1 - \exp \left( -\frac{x}{\theta} \right) \right]^{\beta}
\] (5)

The method of Maximum Likelihood Estimation (MLE) is preferred for parameter estimation because of its many desirable properties such as asymptotic normality, asymptotic efficiency and invariance \([11]\) and hence the same methodology may be selected in the tool for estimation of parameters. The software tool will estimate exact value of \( N, \beta \) and \( \theta \), but the ranges have to be specified by the user. The parameters thus obtained have to be substituted in the above equation to get the \( y \) values, namely \( \mu(t) \) corresponding to the cumulative test time at which the failures, 1, 2,...,15 actually occurred. Now, we have the observed failures and the estimated number of failures at the same cumulative test time \( x \) with which the goodness of fit of the model has to be checked as explained in section 3.1. If goodness of fit is not achieved then the parameters have to be estimated again with new ranges for the parameters and goodness of fit checked. Once the goodness of fit is achieved the parameters can be firmed up for the time being. The failure intensity achieved may be compared with the target. If target is not achieved, testing has to be continued. The parameters may be updated dynamically with more failures and failure intensity calculations revised periodically till system testing is completed.

### 2.3 Some salient features of the proposed GE NHPP model

- The model has been evolved on the assumption that when failures occur, defects causing them are corrected before testing resumes and defect fixing does not cause new failures.
- The failures are assumed to be independent.
- Depending on the \( \beta \) value, the failure intensity may initially increase and then decrease or start decreasing monotonically. Thus, the model will address both patterns of variations of failure intensities equally well.
• The model can be used with time \( t \) expressed in terms of execution time or test time or calendar time.

3. Performance Evaluation of the Proposed Model and Comparison with Other Models

The performance of SRGMs can be assessed by their ability to fit the past failure data (goodness of fit) and to predict occurrence of failures in the future satisfactorily (predictive validity) [13]. We will discuss about goodness of fit measures in this section and predictive validity in the next section. A number of metrics have been evolved over the years for finding Goodness of Fit (GoF) of a model with a given data. Only when goodness of fit is achieved the model can be used for prediction or other purposes. Some of the GoF measures are given below:

- Kolmogorov –Smirnov (K-S) test
- Bias, Variation and Root Mean Square Prediction error (RMSPE)
- Mean of Square Fitting Faults (MSF) which is also called Mean Square Error (MSE).

3.1 Kolmogorov –Smirnov (K-S) test

Kolmogorov–Smirnov (K-S) test is a common way of testing GoF of an SRGM [11], since it is non-parametric, it treats individual observations directly and is applicable even in the case of very small sample size, which is usually the case with SRGM validation. Here, if \( X_1, X_2, ..., X_n \) is a random sample of size \( n \) from distribution function \( F(x) \) and \( F_n^*(x) \), the corresponding empirical distribution function, then

\[
D_n = \sup_{x} |F_n^*(x) - F(x)|
\]  

(6)

\( D_n \) is called the K-S statistic and it is the maximum vertical distance between \( F_n^*(x) \) and \( F(x) \). Goodness of Fit is achieved when \( D_n \) is \( \leq \) the critical value as per the K-S table. Rohatgi and Saleh [14] caution that K-S assumes continuity of the distribution function and if the distribution is actually discontinuous, the K-S test is conservative and it favors \( H_0 \), the null hypothesis.

On the other hand, Kan [15] who also uses K-S test, compares the normalized cdf of the observed failure count with normalized cdf of expected failure count at each point in time, takes the absolute difference and sums them. In this case, the distance is given by:

\[
D_n = \sum_{i=1}^{n} |F_n^*(x) - F(x)|
\]  

(7)

If \( D_n \), where \( n \) is the sample size, is less than the corresponding critical value, then the model is considered to fit the data adequately. This is based on the method advocated by Goel [16]. It is found that the maximum distances calculated were too optimistic and hence result in incorrect conclusions sometimes. On the contrary, finding sum of distances as advocated by Goel gives a realistic picture consistently and hence the latter is used to find K-S statistic.

3.2 Selection of Models

In addition to the proposed generalized exponential (GE) NHPP model, we have selected 6 more models for validating them through Goodness of Fit tests.
3.3 Selection of Data Sets

We have chosen 18 data sets to check the GoF of the models, as given below:

- Mullen’s [3] failure data sets, Stratus-1 (str1) and Stratus-2 (str2), each representing several hundred years of customer exposure on an operating system with one million lines of code.

The data sets Musa’s P14C, P17, SS1A, SS2, SS3 and SS4 depicted I/D pattern of failure intensity variations. There are fluctuations in the data sets – P5, P6, P14C, SS2, P27 and P40.

3.4 Testing GoF with K-S statistic

Since GoF is checking about the ability of a model to fit past data, each data set is divided into 10 parts at 10% intervals of cumulative test time. The cumulative number of failures observed at 10%, 20%... 100% of cumulative test times are the y values and the corresponding cumulative times are the x values. The model parameters are estimated with these 10 sets of data. The sum of distances between observed and estimated failures are calculated at the same time intervals. The K-S statistic calculated for all the seven models are given in Table 1. The critical value for K-S (n=10, \( \alpha = 0.05 \)) is 0.409.

<table>
<thead>
<tr>
<th>Data Set</th>
<th>BET</th>
<th>LPET</th>
<th>Log Power</th>
<th>Log Logistic</th>
<th>Goel</th>
<th>GE NHPP</th>
<th>Yamada S shaped</th>
</tr>
</thead>
<tbody>
<tr>
<td>P1</td>
<td>0.41</td>
<td>0.15</td>
<td>0.17</td>
<td>0.27</td>
<td>0.13</td>
<td>0.11</td>
<td>0.77</td>
</tr>
<tr>
<td>P2</td>
<td>0.38</td>
<td>0.24</td>
<td>0.20</td>
<td>0.22</td>
<td>0.20</td>
<td>0.2</td>
<td>1.01</td>
</tr>
<tr>
<td>P3</td>
<td>0.63</td>
<td>0.21</td>
<td>0.24</td>
<td>0.21</td>
<td>0.21</td>
<td>0.18</td>
<td>1.33</td>
</tr>
<tr>
<td>P4</td>
<td>0.27</td>
<td>0.70</td>
<td>0.78</td>
<td>0.25</td>
<td>0.27</td>
<td>0.23</td>
<td>0.53</td>
</tr>
<tr>
<td>P5</td>
<td>0.24</td>
<td>0.23</td>
<td>0.23</td>
<td>0.65</td>
<td>0.70</td>
<td>0.21</td>
<td>0.49</td>
</tr>
<tr>
<td>P6</td>
<td>0.37</td>
<td>0.45</td>
<td>0.46</td>
<td>0.43</td>
<td>0.43</td>
<td>0.37</td>
<td>0.52</td>
</tr>
<tr>
<td>P14C</td>
<td>0.69</td>
<td>0.81</td>
<td>0.77</td>
<td>0.48</td>
<td>0.71</td>
<td>0.22</td>
<td>0.31</td>
</tr>
<tr>
<td>P17</td>
<td>0.57</td>
<td>0.57</td>
<td>0.58</td>
<td>0.25</td>
<td>0.32</td>
<td>0.23</td>
<td>0.30</td>
</tr>
<tr>
<td>P27</td>
<td>0.49</td>
<td>0.39</td>
<td>0.54</td>
<td>0.39</td>
<td>0.39</td>
<td>0.37</td>
<td>2.09</td>
</tr>
<tr>
<td>P40</td>
<td>1.16</td>
<td>0.75</td>
<td>0.73</td>
<td>0.82</td>
<td>0.99</td>
<td>0.52</td>
<td>1.58</td>
</tr>
<tr>
<td>SS1A</td>
<td>0.31</td>
<td>0.32</td>
<td>0.30</td>
<td>0.41</td>
<td>0.24</td>
<td>0.16</td>
<td>0.22</td>
</tr>
<tr>
<td>SS1B</td>
<td>0.35</td>
<td>0.36</td>
<td>0.81</td>
<td>0.35</td>
<td>0.33</td>
<td>0.29</td>
<td>0.59</td>
</tr>
<tr>
<td>SS1C</td>
<td>0.25</td>
<td>0.23</td>
<td>0.23</td>
<td>0.80</td>
<td>0.25</td>
<td>0.22</td>
<td>0.61</td>
</tr>
<tr>
<td>SS2</td>
<td>0.43</td>
<td>0.42</td>
<td>0.98</td>
<td>0.32</td>
<td>0.35</td>
<td>0.23</td>
<td>0.25</td>
</tr>
<tr>
<td>SS3</td>
<td>0.22</td>
<td>0.28</td>
<td>0.37</td>
<td>0.33</td>
<td>0.34</td>
<td>0.21</td>
<td>0.24</td>
</tr>
<tr>
<td>SS4</td>
<td>0.18</td>
<td>0.18</td>
<td>0.55</td>
<td>0.26</td>
<td>0.16</td>
<td>0.14</td>
<td>0.34</td>
</tr>
<tr>
<td>Str1</td>
<td>0.36</td>
<td>0.24</td>
<td>0.12</td>
<td>0.23</td>
<td>0.10</td>
<td>0.09</td>
<td>1.34</td>
</tr>
<tr>
<td>Str2</td>
<td>0.58</td>
<td>0.29</td>
<td>0.22</td>
<td>0.47</td>
<td>0.30</td>
<td>0.22</td>
<td>0.93</td>
</tr>
</tbody>
</table>

3.5 Summary of Observations

The following is the summary of observations based on the 18 data sets.

3.5.1 Overall performance of SRGMs

An analysis of Table 1 will reveal that Musa BET and Generalized Goel Model gives best fit some times, but the proposed GE NHPP model gives the best fit consistently. It is attributable to the function chosen, namely Generalized Exponential, to represent ROCOF.

3.5.2 Increasing/Decreasing pattern of failure intensity

Out of the models studied, Musa’s models are not meant to capture the I/D pattern of failure intensity variations. The variations of failure intensity with respect to time in respect of the models for data set P14C where I/D pattern is present are shown in Fig. 1. In addition to Musa’s models, Log Power model is also unable to capture I/D pattern of failure intensity. This data set possesses both the characteristics namely, fluctuations in number of failures and I/D pattern of failure intensity, which affect the performance of the SRGMs. Generalized Goel model designed to capture I/D pattern of failure intensity, could not capture it due to the wide fluctuations in data and hence is not able to fit the data set. Although Log Logistic model captures I/D pattern as Fig. 1 reveals, could not fit the data well due to the fluctuations. Thus, a fluctuation in number of failures in the data set is a serious problem, which is handled well by the proposed GE NHPP model.

![Fig. 1: Failure Intensity Predicted by Models for Musa's Project P14C](image)

3.5.3 Yamada’s Delayed S Shaped Model

Our study confirms that Yamada’s delayed S-Shaped SRGM assumes always initially increasing and then decreasing pattern of variation of failure intensity function (learning curve), whether it is actually present or not. Hence it fits well only in such cases where I/D pattern are really present. It cannot be used with monotonically decreasing failure intensity. Furthermore, perusal of Table 1 will reveal the vulnerability of the other models to fluctuations in data. In summary, the proposed GE NHPP model demonstrated GoF in spite of the data sets possessing varying patterns of failure intensities and fluctuations in number of failures. Thus the GoF of the proposed model is well established.
3.6 Other Measures for GoF

3.6.1 Mean of Square Fitting Faults

Mean of Square Fitting Faults (MSF) is given by:

$$MSF = \left( \frac{1}{n} \right) \sum_{i=1}^{n} (x_i - E_i)$$

(8)

where \( n \) denotes the number of data points, \( x_i \) is the number of failures observed and \( E_i \) is the number of failures estimated to occur by the model at the same instant of test time. Table 2 below contains MSF for the chosen data sets for three chosen models.

<table>
<thead>
<tr>
<th>Data set</th>
<th>Generalized Goel</th>
<th>Musa BET</th>
<th>GE NHPP</th>
</tr>
</thead>
<tbody>
<tr>
<td>Musa P1</td>
<td>5.3</td>
<td>31.9</td>
<td>4.1</td>
</tr>
<tr>
<td>P2</td>
<td>1.8</td>
<td>8.1</td>
<td>1.8</td>
</tr>
<tr>
<td>P14C</td>
<td>8.3</td>
<td>6.2</td>
<td>1.2</td>
</tr>
<tr>
<td>P17</td>
<td>2.2</td>
<td>3.1</td>
<td>1.4</td>
</tr>
<tr>
<td>P27</td>
<td>3.8</td>
<td>5.7</td>
<td>3.3</td>
</tr>
<tr>
<td>Stratus2</td>
<td>24.0</td>
<td>72.5</td>
<td>24.6</td>
</tr>
</tbody>
</table>

A smaller MSF indicates a smaller fitting error and better performance [13]. Table 2 reconfirms consistent performance of the proposed model.

3.6.2 Additional Metrics for Goodness of Fit

Additional metrics are available in the literature [10] to check the goodness of fit of SRGMs. They are defined below:

i). Prediction Error (PE): The difference between the observation and prediction of number of failures at any instant of time \( i \) is known as \( PE_i \).

ii). Bias: The average of the PEs is called bias.

iii). Variation (var): The standard deviation of the PEs is known as variation.

$$\text{var} = \sqrt{\frac{\sum_{i=1}^{n} (PE_i - \text{Bias})^2}{n-1}}$$

(9)

Where, \( n \) is the number of observations. It is used as a measure of variance in the predictions.

iv). Root Mean Square Prediction Error (RMSPE): It is a measure of closeness with which a model predicts the observation. It is given by:

$$RMSPE = \sqrt{\text{Bias}^2 + \text{var}^2}$$

(10)

The additional metrics for goodness of fit calculated for 3 models are given below in Table 3.
4. Predictive Validity

The predictive validity metrics are used to evaluate forecasting quality of the SRGMs. According to Kapur and Garg [17], "predictive ability is defined as the ability of the model to determine future failure behaviour from present and past failure behaviour". The Relative Prediction Error (RPE) is defined as given below [13]:

\[
RPE = \left[ \frac{(m(t_k) - m_k)}{m_k} \right]
\]

(11)

where, \(m(t_k)\) is the number of failures estimated and \(m_k\) is the actually observed number of failures at the same instant of time \(t_k\).

<table>
<thead>
<tr>
<th>Data Set</th>
<th>Generalized Goel</th>
<th>Musa BET</th>
<th>GE NHPP</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bias</td>
<td>var</td>
<td>RMS PE</td>
<td>Bias</td>
</tr>
<tr>
<td>P1</td>
<td>0.50</td>
<td>2.43</td>
<td>2.48</td>
</tr>
<tr>
<td>P2</td>
<td>0.40</td>
<td>1.41</td>
<td>1.47</td>
</tr>
<tr>
<td>P14C</td>
<td>0.50</td>
<td>3.04</td>
<td>3.08</td>
</tr>
<tr>
<td>P17</td>
<td>0.80</td>
<td>1.56</td>
<td>1.76</td>
</tr>
<tr>
<td>P27</td>
<td>0.40</td>
<td>2.05</td>
<td>2.09</td>
</tr>
<tr>
<td>Str2</td>
<td>0.40</td>
<td>5.16</td>
<td>5.18</td>
</tr>
</tbody>
</table>

Lower the value of Bias, Variation and RMSPE, the better is the goodness of fit.

In this connection, Chan et al. [18] have defined normalized time \(\Psi\) as given below:

\[
\Psi = \frac{t_x}{T_x}
\]

(12)

where, \(T_x\) is the total observation interval for a failure data set \(X\) or in other words, the cumulative test time at which the last failure is observed and \(t_x\) is the time at which the model parameters are estimated for the same data set. In fact K-S statistic is evaluated at \(\Psi = 1\). However, to study predictive validity, we estimate the model parameters for the data set at different points in time \(t_x\) i.e. various values of \(\Psi\) less than 1.

There are two types of predictive validity as given below [18]:

- Short Term Predictive Validity
- Long Term Predictive Validity

The long-term predictive validity gives the relative error between estimated and observed values at the end of observation time window. The model parameters are estimated at \(\Psi\) values of 1/6, 2/6, 3/6, 4/6 and 5/6 to calculate long-term RPE. The same for the proposed model for Musa’s data set P1 are given below in Table 4. The short-term predictions are carried out at shorter intervals such as 5 or 10 failures from the failure at which parameters are estimated. The short-term RPE for Musa’s data set P1 are given in Table 5.
5. Case Study – One application of the Model

This case study confirms predictive ability of GE NHPP Model and provides an example of determining when to stop testing. Musa’s Project P2 was selected towards establishing the ability of GE NHPP model to replicate the past and predicting the future. The parameters were estimated from the first ten defects. The tenth failure occurred at 3405 seconds. The corresponding failure intensity was found to be 0.00163 failure per second. The target failure intensity was fixed at 0.001 failure per second. Then the total testing time needed as well as the number failures to be detected for achieving the target was found using spreadsheet as given below:

| Testing time needed: 9850 seconds; Number of failures to be observed: 19 |

Actually as per the Musa data set P2, 19th failure occurred early, at 9299 seconds. Hence the target failure intensity has not been achieved at the 19th failure. Therefore testing should be continued. The 20th failure occurred at 10211 seconds. Hence testing can be stopped after observing the 20th failure, when the failure intensity has reduced below 0.001 failure per second. The above example establishes that the proposed GE NHPP model is able to both replicate the past failures and predict failures in the future accurately.

6. Conclusions

Although, a host of SRGMs have been evolved in the last three decades, it is widely believed that no single model is suitable in all situations. If the user is definite that the failure intensity initially increases and then decreases due to learning curve in the given project, then Yamada’s delayed S shaped model can be used since it is a simpler model with 2 parameters. If there are fluctuations in data and/or if the failure intensity initially increases and then decreases, then the proposed NHPP model with generalized exponential function ROCOF is preferred for software reliability growth modeling. It is found that the model also possesses reasonable predictive quality, both long-term and short-term. This model enables prediction of reliability growth with testing, determining testing time needed to achieve the required failure intensity and the number of failures to be observed before the target failure intensity will be achieved. The model parameters can be estimated through non-linear regression software tools. This model may be used in whatever manner the testing time is computed such as execution time, testing time or calendar time.
References


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