

Dynamically Weighted Combination of Fault - based Software Reliability Growth Models

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Abstract

Background/Objective: The Software Reliability Growth Models (SRGMs) are mainly used to plan and execute system testing in the Software Development Life Cycle (SDLC). The objective of this research paper is to propose a dynamically weighted fault based combination model for application during this phase of reliability growth testing of software systems.

Methods: A dynamically weighted fault based SRGM, which describes equally well the exponential growth and S-shaped growth of mean value function in a software testing process is proposed. Non-linear regression methodology was deployed for parameter estimation of (SRGMs). The curve fitting tool in MATLAB[™] is used for this purpose. The coefficient of determination R^2 , Sum of Squared Errors (SSE), Root Mean Squared Error (RMSE) is the goodness of fit measures used to assess the quality of fitting of the SRGMs. **Findings:** It is found that the proposed combination model describes the failure data better than the constituent models used for combining as revealed by the goodness of fit measures. **Applications/Improvements:** The new model can be applied to model reliability growth during testing in software projects with varying characteristics. The model additionally provides vital quality metrics, which can be used to manage the current and future software projects.

Keywords: Dynamically Weighted Combination Model, Exponential Growth, Goodness of Fit, S-shaped Growth, Software Reliability Growth Model

1. Introduction

Some software reliability growth models (SRGMs) have been published for assessing the reliability growth of the software systems achieved during the testing phase in software development life cycle (SDLC). Some SRGMs assume exponential growth of mean value function (cumulative number of failures) with testing time, and some assume S-shaped growth of the same. The recent flexible models ^{1 2 3 4 5} address both the phenomena. However, the failure rate function of these models follow either generalized exponential or Weibull distribution. It is possible to achieve the same objective by dynamically combining simple and popular models, whose Rate of Occurrence of Failures (ROCOF) follow the widely used exponential distribution.

There are two types SRGMs as given below

- Failure Based^{1 2 3 6}
- Fault Based^{4 5}

The failure based models assume perfect debugging meaning that a failure is caused by one fault and vice-versa. In such cases, there is only one equation for mean value function since failures and faults are used interchangeable. In the case of fault based models a failure may be caused by 1 or more faults and vice-versa. Therefore, there is one equation for mean value function for failures and another for faults in this case.

During the testing phase, every failure leads to a debugging process to identify the fault causing the failure. There are three situations far as the quality of debugging is concerned as given below:

- Perfect debugging
- Imperfect debugging
- Efficient debugging^{4 5}

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Models in ^{1-3,6} are failure based and assume perfect debugging. Models in ^{4,5} are fault based and can reveal the quality of debugging as above.

In this paper, we propose a fault based dynamically weighted combination model to describe both exponential growth and S-shaped growth of mean value function. The derivation of the combinational model is given in Section 2. The goodness of fit performances measured in the constituent models and combined model are given in Section 3. Summary and conclusions are given in Section 4.

2. Derivation of Dynamically Weighted Fault-based Combination Model

In order to cater to both the types of growth of mean value functions, we need one fault based SRGM for Exponential Growth and another fault based SRGM for S-shaped growth.

We choose model in ⁷ proposed by Kapur and Garg for describing the exponential growth of mean value function and model in ⁸ proposed by Yamada et al. for S-shaped growth and modify them to address various types of debugging and to use them as the two constituent models for deriving the dynamically weighted fault based combination model.

The equation for mean value function of the model ⁷ is given below

$$f(x) = \frac{a}{p} (1 - \exp(-bpx)) \quad (1)$$

where,

a = statistically expected number of software faults to be eventually detected.

b = constant of probability.

p = probability of perfect debugging.

Here, p is a probability and can at best be 1. In ^{4,5} a new term efficient debugging has been introduced in addition to imperfect and perfect debugging⁹. In efficient debugging one failure may lead to correction of more than one fault. Therefore, we adopt the same term of debugging index ⁴ which is a real number greater than 0. We adopt this modification to the first constituent model as given below.

$$f(x) = \frac{a}{c} (1 - \exp(-bcx)) \quad (2)$$

Here, c is the debugging index whose value can exceed 1 if efficient debugging is witnessed in the software project. It will be less than 1 if imperfect debugging is witnessed in the software project. It will be equal to 1 when perfect debugging is witnessed. We choose the Yamada delayed S-shaped model⁸ as the second constituent model whose equation for mean value function $f(x)$ is given below

$$f(x) = a(1 - (1 + bx)\exp(-bx)) \quad (3)$$

We transform this equation to address all the 3 types of debugging as given below.

$$f(x) = \frac{a}{c} (1 - (1 + fcx)\exp(-fcx)) \quad (4)$$

where,

a : Statistically expected number of software faults to be eventually detected.

c : Debugging index

f : Constant

It is pertinent to note that in the literature fault and failure are used interchangeably. However, this is clarified in ^{2,3,4,5}.

The Fault-based models provide the following quality metrics

- Total number of faults indicated by a .
- The Quality of debugging as indicated by c .

Now we combine both the models as a sum of the constituent models since a sum of NHPP models is also an NHPP¹⁰ due to its property of superposition.

The mean value function $f(x)$ of the combined model is given below

$$f(x) = \left[w \left(\left(\frac{a}{c} \right) (1 - \exp(-bcx)) \right) \right] + (1 - w) \left[\left(\frac{a}{c} \right) (1 - (1 + fcx)\exp(-fcx)) \right] \quad (5)$$

Where w : weightage for the first constituent model
We have designed the model to be flexible and give appropriate weightages to combine the constituent models as required by the data by changing the weight. For instance, if S-Shaped growth is dominant, the value may be low, and if it is weak, the value may be high.

In ¹¹ an artificial neural network based logistic growth curve model is proposed and it is also stated that the most popular SRGMs are the NHPP models. In ¹² a classification of reliability. In ¹³ it is stated that more accurate models are needed to reduce the testing cost.

3. Performance Evaluation

We choose dataset MUSA P1 ¹⁴ for evaluating the goodness of fit performance of both the constituent models and the proposed combined model.

We choose the following measures to assess the goodness of fit of the models, R^2 , SSE, RMSE¹⁵. We first estimated the GOF statistics for modified Kapur & Garg ⁷ using P1 dataset. The estimation was repeated with the modified Yamada delayed S-shaped model ⁸ using the same dataset. Then the process is repeated for the proposed combinational model. The results obtained are given in Table 1.

Table 1. Goodness of fit performance of the SRGMs

S. No	Model	R^2	RMSE	SSE
1	Modified Kapur and Garg(1990)	0.9541	2.387	193.7
2	Modified Yamada	0.8844	3.786	487.4
3	Proposed Combination Model	0.9833	1.485	70.54

The dynamically weighted fault based combinational model characterizes a better fit with R-Square closer to 1 and smaller RMSE and SSE values. Both the constituent models lag behind in performance as compared to the proposed model. It can be concluded that combining carefully chosen SRGMs, improves the goodness of fit performance significantly.

4. Summary and Conclusions

Complex Rate of Occurrence of Failures (ROCOF) was proposed to construct flexible models, which are in demand to describe software failure data from modern software projects. In this paper, we propose a dynamically weighted combinational model comprising of two simple SRGMs to achieve similar results. It is found that the goodness of fit performance of the combination model is comparable with the flexible models. However, simpler models make the job of the derivation of other equations

such as for failure intensity, conditional reliability and release time easier as compared to the traditional complex models. Therefore, the proposed model will be found to be eminently useful to the industry and academia.

5. References

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