SOFTWARE RELIABILITY COMBINATION OF MODELS

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Abstract: Three software reliability growth models (SRGMs) - one proposed by the authors and two existing in literature based on non homogeneous Poisson Process (NHPP) are considered. Combinations of the three models are suggested as super models to measure software reliability. A comparative study of the suggested models is made with reference to three criteria as applied to eight different data sets and is noticed that the suggested model has a good contribution in the combination to come out as a better SRGM model.

Index Terms--Mean value function, Inter failure times, Prequential likelihood, Estimates of parameters.

NOTATION

LPETM	Logarithemic Poisson Execution Time Model
N(t)	Cummulative Number of Experienced Failures upto time "t".
m(t)	Mean value function, s-expected value of N(t)
$\lambda(t)$	Intensity function, derivative of m(t)
λ_0	Initial failure intensity
Ө	Reduction in the normalized failure inensity
y	Realization of N(t)
a	Expected number of failures eventually
b	Proportional fall in $\lambda(t)$
NHPP	Non homogeneous Poisson process
GOM	Goel and Okumoto model
HLSRGM	Half Logistic Software Reliability Growth Model

I. INTRODUCTION

Software reliability is the probability of failure free operation of a computer program in a specified environment for a specified time. A failure is a departure of a program operation from program requirements. A software reliability model provides a general form in terms of a random process describing failures for characterizing software reliability or a related quantity as a function of experienced failures over time. In this backdrop Musa and Okumoto (1984) suggested a model for software reliability measurement and named it as logarithmic Poisson execution time model (LPETM). Motivated by their approach we develop a new software reliability model in this paper presents its performance in measuring software reliability. Lyu and Nikora(1991a) observe that a number of SRGMs based on NHPP exist in literature and that no best model exists for every case under all circumstances.

The users are left in dilemma as to which software reliability model is to be chosen. Accordingly there is a need to describe a low overhead, low risk and high performance approach to the software reliability prediction problem.The approach consists of selecting a set of popular SRGMs and the collection of software failure data sets, considering a suitable combination of SRGMs and evaluate each combination with respect to certain criteria. Four combinations of models namely equally weighted linear combination (ELC), median oriented linear combination (MLC), unequally weighted linear combination (ULC) and dynamically weighted linear combination (DLC) for model evaluation.

This paper to adopt these combinations to three SRGMs, namely, GOM, LPETM and HLSRGM.

(i) The one proposed was Goel and Okumoto (1979)
(ii) Logorithmic Poisson Execution Time model of Musa and Okumoto (1984)and
(iii) Half logistic SRGM of Satya Prasad (2007)

II. SRGMs BASED ON NHPP

Let $\left[N(t), t \geq 0\right], m(t), \lambda(t)$ be the counting process, mean value function and intensity function of a software failure phenomenon. LPETM was derived with the following assumptions:

Assumption (i): There is no failure observed at time t = 0. That is, N (0) =0 with probability one.

Assumption (ii): The failure intensity $\lambda(t)$ will decrease exponentially with the expected number of failures experienced up to time ' t' so that the relation between m (t) and $\lambda(t)$ is

$$\lambda(t) = \lambda_0 . e^{-\theta m(t)}$$

(1)

where λ_0 and θ are the initial failure intensity and the rate of reduction in the normalized failure intensity per failure respectively.

Assumption (iii): For a small interval Δt the probabilities of one, more than one failure during $[t, t+\Delta t]$ are $\lambda(t) . \Delta t + 0(\Delta t)$ and $0(\Delta t)$, respectively, where $\frac{0(\Delta t)}{\Delta t} \to 0$ as $\Delta t \to 0$. Note that the probability of no failure during $[t, t+\Delta t]$ is given by $1 - \lambda(t)\Delta t + 0(\Delta t)$. Using assumptions (i) and (ii) the mean value function and intensity function are derived to be

$$m(t) = \frac{1}{\theta} \log(\lambda_0 \theta t + 1)$$

(2)

$$\lambda(t) = \frac{\lambda_0}{(\lambda_0 \theta t + 1)}$$

(3)

It may be noted that $m(t) \to \infty$ as $t \to \infty$. Hence this model is also called 'infinite failures' model. Using assumptions (i) and (iii) the probability distribution of the stochastic process N(t) is given by

$$P[N(t) = y] = \frac{[m(t)]^y}{y!} . e^{-m(t)}$$

(4)

where m(t) is given by equation (2).

On lines of Goel and Okumoto (1979), let us specify that the mean value function m(t) is finite valued, non decreasing, non negative and bounded with the boundary conditions

$$m(t) = \begin{cases} 0, & t = 0 \\ a, & t \to \infty \end{cases}$$

Here 'a' represents the expected number of software failures eventually detected. If $\lambda(t)$ is the corresponding intensity function, the basic assumption of LPETM says that $\lambda(t)$ is a decreasing function of $m(t)$ as a result of repair action following early failures. We model this assumption as a relation between $m(t)$ and $\lambda(t)$ so that one can be expressed in terms of the other. Our proposed relation is

$$\lambda(t) = \frac{b}{2a}\left[a^2 - m^2(t)\right]$$

where 'b' is a positive constant, serving the purpose of constant of proportional fall in $\lambda(t)$. This relation indicates a decreasing trend for $\lambda(t)$ with increase in $m(t)$ - a characteristic similar to that of LPETM which requires exponential decrease of $\lambda(t)$ with increase in $m(t)$, whereas our proposed model requires a quadratic decrease of $\lambda(t)$ with $m(t)$.

According to our proposition we get the following differential equation

$$\frac{dm(t)}{dt} = \frac{b}{2a}\left[a^2 - m^2(t)\right]$$

whose solution is

$$m(t) = \frac{a\left(1-e^{-bt}\right)}{\left(1+e^{-bt}\right)} \tag{5}$$

We propose an NHPP with its mean value function given in equation (5). Its intensity function is

$$\lambda(t) = \frac{2abe^{-bt}}{\left(1+e^{-bt}\right)^2} \tag{6}$$

Our proposed model is derived on lines of Goel and Okumoto (1979) specifying a relation between m(t) and λ(t) as motivated from LPETM .Our model turns out to be the probability model of half logistic distribution of Balakrishnan (1985). This model is paid a considerable attention as a reliability model recently by many authors and some of those published works are Kantam *et al*.,(1994), Kantam and Dharmarao (1994), Kantam and Rosaiah (1998), Kantam *et al*.,(2000), Kantam and Srinivasarao (2004) and the references therein. In short, we abbreviate this model as HLSRGM.

III. PROPOSED LINEAR COMBINATIONS OF MODELS

1) Equally-weighted linear combination (ELC) model: This model is formed by assigning the three component models a constant equal weight, namely,

$$ELC = \frac{1}{3}GOM + \frac{1}{3}LPETM + \frac{1}{3}HLSRGM$$

These weights remain constant and unchanged throughout the measurement process.

2) Median-Oriented Linear Combination (MLC) Model: Instead of choosing the arithmetic mean for the prediction in ELC, the median value is used. In other words, each time when a prediction is called for, the component model whose predicted value is the median is selected as the output of this model.

3) Dynamically-Weighted Linear Combination (DLC) Model: In this model, we use a meta-predictor to form a linear combinations of several predictions with the weights chosen in some optimal way (e.g., posterior probabilities). A Bayesian interpretation of "prequential likelihood" as a posteriori could be dynamically calculated in a long run or in a short time window to determine the weight assignments. For this model, the weight functions for each of the component models vary with time. In this approach, the weight factor for prediction system stage n is :

$$\omega_n^{\,r} = \frac{PL^r_{1,n-1}}{\sum_{k=1}^{m} PL^k_{1,n-1}} = \frac{\prod_{j=1}^{n-1} f_j^{\,r}(t_j)}{\sum_{k=1}^{m}\prod_{j=1}^{n-1} f_j^{\,k}(t_j)} \quad , \; r = 1, m$$

The above three linear combinations of models are from Lyu and Nikora (1991a, 1991b). Based on the similar notion in this chapter we adopt the three types of weight factors using the measures accuracy, bias and noise. The weighted linear combination of the considered models with the proposed three types of weight factors are named as dynamic linear combinations - DLC1, DLC2, DLC3 respectively.

Let $W_{a_i}, W_{b_i}, W_{n_i}$ (i=1,2,3) be the values of accuracy, bias, noise of a model 'i' corresponding to the use of a particular dataset. Here the numbers 1, 2, 3 indicate the names of the model in the following order.

Model 1: HLSRGM; Model 2: GOM; Model 3: LPETM

Further let a_i, b_i, n_i be the magnitudes of the measures - accuracy, bias, noise for the ith model when used for a data set. Then

The accuracy measure using DLC1 is the weighted linear combination of accuracies of model 1, model 2, model 3 with W_{a_i} as weights. The accuracy measure using DLC2 is the weighted linear combination of accuracies of model 1, model 2, model 3 using W_{b_i} as weights. Similarly the accuracy measure of DLC3 is the weighted linear combination of accuracies of model 1, model 2, model 3 with W_{n_i} as weights.

The two other measures namely bias, noise of DLC1, DLC2, DLC3 for a data set can be computed in the similar manner. Thus in all, we have three basic models and five different linear combinations of the three basic models with the following labels.

1: HLSRGM, 2:GOM, 3:LPETM, 4:ELC, 5:MLC, 6:DLC1, 7:DLC2, 8:DLC3.

It can be seen that the measures-accuracy, bias, noise associated with a SRGM are to be basically obtained from the mathematical expressions of $\bar{f}_i(.)$ and $\bar{F}_i(.)$, the predictive density function and distribution function of the time to i-th failure, when a particular SRGM is used, evaluated at the estimated parameters of the SRGM. We know that $\bar{f}_i(.), \bar{F}_i(.)$ can be respectively taken from the expressions of intensity function, mean value function of the corresponding SRGM and estimates of the parameters for a data set can be had from the respective estimating equation, in which inter failure time data analysis is presented. With a view to avoiding the repeated presentation of complicated mathematical equations existing in literature, This paper make reference to the required equations/research articles as given in the following table

Model Requirements	**GOM**	**LPETM**	**HLSRGM**
Mean value function $(\bar{F}_i)$	G-O(1979)*	Eq.(2.1.2)	Eq.(2.2.1)
Intensity function $\bar{f}_i$	G-O(1979)*	Eq.(2.1.3)	Eq.(2.2.2)
Estimates for 'b'	G-O(1979)*	M-O(1984)**	Eq.(2.4.5)
Estimates for 'a'	G-O(1979)*	M-O(1984)**	Eq.(2.4.4)

* Goel and Okumoto(1979); **Musa and Okumoto(1984)

The paper computed accuracy, bias, noise for these 8 models using 8 distinct software failure data sets, the first one from Goel and Okumoto (1979) and the other seven from Grottke and Trivedi (2005.). The results are given in Tables 4.3.1 through 4.3.8. Consolidated tables of these versions are also prepared and the over all assessment is presented in Section 4.

Table 4.3.1: NTDS Data

MEASURE	HLSRGM	GOM	LPETM	ELC	MLC	DLC1	DLC2	DLC3
Accuracy	-62.9(4)	-56(1)	-69.6(8)	-62.83(3)	-62.9(4)	-63.32(6)	-62.75(2)	-67.32(7)
Bias	0.9547(8)	0.9479(6)	0.9126(1)	0.9384(4)	0.9479(6)	0.9372(5)	0.9388(3)	0.9214(2)
Noise	2.114(1)	2.114(1)	14.59(8)	6.273(5)	2.114(1)	6.72(4)	6.16(7)	11.79(6)
Rank	(5)	(1)	(8)	(4)	(2)	(6)	(2)	(7)

Table 4.3.2: Software Reliability Data for Project SS1A

MEASURE	HLSRGM	GOM	LPETM	ELC	MLC	DLC1	DLC2	DLC3
Accuracy	-387.43(6)	-426.9(8)	-242.8(1)	-352.4(4)	-387.43(6)	-370.18(5)	-310.7(2)	-317.7(3)
Bias	1.00000(1)	1.0000(1)	2.8440(8)	1.6150(5)	1.00000(1)	1.42400(4)	2.0830(7)	2.0180(6)
Noise	8.63(1)	11.5(2)	24.812(8)	14.98(5)	11.5(2)	13.51(4)	18.72(7)	18.3(6)
Rank	(1)	(3)	(8)	(4)	(2)	(6)	(6)	(5)

Table 4.3.3: Software Reliability Data for Project SS1B

MEASURE	HLSRGM	GOM	LPETM	ELC	MLC	DLC1	DLC2	DLC3
Accuracy	-1030.74(3)	-1443.6(8)	-702.23(1)	-1058.9(6)	-1030.7(3)	-1145.7(7)	-1045.6(5)	-969.28(2)
Bias	0.874600(2)	0.865(1)	0.9647(8)	0.9014(5)	0.8746(2)	0.8902(4)	0.9037(6)	0.9131(7)
Noise	28.916(5)	17.57(1)	37.862(8)	28.116(3)	28.916(5)	25.74(2)	28.48(4)	30.57(7)
Rank	(1)	(1)	(8)	(5)	(1)	(4)	(6)	(7)

Table 4.3.4: Software Reliability Data for Project SS3

MEASURE	HLSRGM	GOM	LPETM	ELC	MLC	DLC1	DLC2	DLC3
Accuracy	-650.32(2)	-1079.3(8)	-579.9(1)	-769.84(6)	-650.32(2)	-836.95(7)	-679.5(4)	-750.96(5)
Bias	0.92560(2)	0.59310(1)	2.11(8)	1.21(5)	0.92560(2)	1.06800(4)	1.56(7)	1.32600(6)
Noise	15.48(1)	17.27(2)	24.040(8)	18.9300(5)	17.27(2)	18.466(4)	20.750(7)	19.65(6)
Rank	(1)	(3)	(6)	(5)	(2)	(4)	(8)	(6)

Table 4.3.5: Software Reliability Data for Project SS4

MEASURE	HLSRGM	GOM	LPETM	ELC	MLC	DLC1	DLC2	DLC3
Accuracy	-755.49(8)	-140.79(1)	-472.86(3)	-456.38(2)	-472.86(3)	-594.67(7)	-473.3(5)	-581.96(6)
Bias	0.9999(8)	0.8474(1)	0.9383(4)	0.9285(2)	0.9383(4)	0.9629(7)	0.9328(3)	0.9582(6)
Noise	17.9010(8)	5.996(2)	4.23300(1)	9.377(4)	5.996(2)	11.96(6)	9.6755(5)	13.31(7)
Rank	(8)	(1)	(2)	(2)	(4)	(7)	(5)	(6)

Table 4.3.6: Software Reliability Data for Project 14 C

MEASURE	HLSRGM	GOM	LPETM	ELC	MLC	DLC1	DLC2	DLC3
Accuracy	-130.4(6)	-139.1(8)	-84.5(1)	-118(3)	-130.4(6)	-122.86(4)	-109.07(2)	-129.09(5)
Bias	.9999(1)	.9999(1)	2.09(8)	1.363(6)	.9999(1)	1.26(5)	1.56000(7)	1.16(4)
Noise	6.52(2)	17.5(8)	4.13(1)	9.4(5)	6.52(2)	10.28(6)	7.996(4)	13.03(7)
Rank	(1)	(8)	(3)	(5)	(1)	(6)	(4)	(7)

Table 4.3.7: Software Reliability Data for Project 1

MEASURE	HLSRGM	GOM	LPETM	ELC	MLC	DLC1	DLC2	DLC 3
Accuracy	-45.95(4)	-69.16(8)	-11.17(1)	-42.09(3)	-45.95(4)	-55.59(6)	-30.87(2)	-62.08(7)
Bias	.7059(1)	.8896(2)	2.27(8)	1.29(6)	.8896(2)	.945(4)	1.67(7)	.9625 (5)
Noise	2.67(2)	16.4 4(8)	1.44 (1)	6.85(5)	2.67(2)	10.103(6)	5.11 7(4)	13.6(7)
Rank	(1)	(7)	(3)	(5)	(2)	(6)	(4)	(8)

Table 4.3.8: Software Reliability Data for Project 27

MEASURE	HLSRGM	GOM	LPETM	ELC	MLC	DLC1	DLC2	DLC3
Accuracy	-130.3(8)	-117.9(6)	-64.67(1)	-104.29(3)	-117.9(6)	-112.06(4)	-83.79(2)	-114.65(5)
Bias	.8673(3)	.7134(1)	3.3812(8)	1.65400(6)	.7134(1)	1.329(5)	2.56(7)	1.076(4)
Noise	6.01(3)	14.55(8)	2.83(2)	7.8(5)	6.01(3)	8.57(6)	2.24(1)	10.94(7)
Rank	(4)	(6)	(3)	(4)	(1)	(6)	(1)	(8)

IV. OVERALL ASSESSMENT

The performance comparisons for all the eight data sets is done by using all the three measures of predictability jointly or by using each individual measure overall the data sets. Tables 4.3.1 through 4.3.8 of the earlier sections are jointly consolidated for all the models with the help of the fourth row of each table and the same is presented in the Table 4.4.1. Similarly the measures accuracy, bias, noise are individually consolidated over the 8 data sets, 8 models (including the proposed linear combinations) and are given in Tables 4.4.2, 4.4.3, 4.4.4 respectively.

In general, a model or a specific combination of models as being satisfactory if and only if it is ranked 3 or better. To extend this idea we borrow a "handicap" value which is calculated by subtracting 3 from the rank of a model for each data set, before its ranks being summed up in the overall evaluation (or equivalently we subtract 24=8*3 from the sum of ranks"). A negative "handicap" value indicates an overall good performance. These 4 tables reveal that one of the proposed linear combination models has a preferable rank like (1) or (2) in each one of these 4 tables. It is generally MLC with frequency 3, DLC2, ELC with frequency 1 each. Hence this paper concludes that the proposed linear combination DLC2 in a way has got a preferable predictability which is specifically proposed in this chapter. More over our proposed HLSRGM when combined with the two popular SRGMs GOM, LPETM has also recorded as one of the most preferable linear combinations namely MLC (median based linear combination). We thus conclude that on lines of Lyu and Nikora (1991a,1991 b) our HLSRGM of this paper can have a good contribution as an entry into software reliability measurements through combination of models.

Table 4.4.1: Summary of Model Ranking using all Measures

DATA SET	HLDSRGM	GOM	LPETM	ELC	MLC	DLC1	DLC2	DLC3
NTDS	(8)	(6)	(1)	(4)	(6)	(5)	(3)	(2)
Proj SS1A	(1)	(1)	(8)	(5)	(1)	(4)	(7)	(6)
Proj SS1B	(2)	(1)	(8)	(5)	(2)	(4)	(6)	(7)
Proj SS3	(2)	(1)	(8)	(5)	(2)	(4)	(7)	(6)
Proj SS4	(8)	(1)	(4)	(2)	(4)	(7)	(3)	(6)
Proj 14C	(1)	(1)	(8)	(6)	(1)	(5)	(7)	(4)
Proj 17	(1)	(2	(8)	(6)	(2)	(4)	(7)	(5)
Proj 27	(3)	(1)	(8)	(6)	(1)	(5)	(7)	(4)
Sum	26	14	53	39	19	38	47	40
'Handicap'	2	-10	29	15	-5	14	23	16
Total Rank	(3)	(1)	(8)	(5)	(2)	(4)	(7)	(6)

Table 4.4.2: Summary of Model Ranking Using the Accuracy Measure

DATASET	HLDSRGM	GOM	LPETM	ELC	MLC	DLC1	DLC2	DLC3
NTDS	(4)	(1)	(8)	(3)	(4)	(6)	(2)	(7)
Proj SS1A	(6)	(8)	(1)	(4)	(6)	(5)	(2)	(3)
Proj SS1B	(3)	(8)	(1)	(6)	(3)	(7)	(5)	(2)
Proj SS3	(2)	(8)	(1)	(6)	(2)	(7)	(4)	(5)
Proj SS4	(8)	(1)	(3)	(2)	(3)	(7)	(5)	(6)
Proj 14C	(6)	(8)	(1)	(3)	(6)	(4)	(2)	(5)
Proj 17	(4)	(8)	(1)	(3)	(4)	(6)	(2)	(7)
Proj 27	(8)	(6)	(1)	(3)	(6)	(4)	(2)	(5)
Sum	41	48	17	30	34	46	24	40
'Handicap'	17	24	-7	6	10	22	0	16
Total Rank	(6)	(8)	(1)	(3)	(4)	(7)	(2)	(5)

Table 4.4.3: Summary of Model Ranking Using the Bias Measure

DATASET	HLDSRGM	GOM	LPETM	ELC	MLC	DLC1	DLC2	DLC3
NTDS	(8)	(6)	(1)	(4)	(6)	(5)	(3)	(2)
Proj SS1A	(1)	(1)	(8)	(5)	(1)	(4)	(7)	(6)
Proj SS1B	(2)	(1)	(8)	(5)	(2)	(4)	(6)	(7)
Proj SS3	(2)	(1)	(8)	(5)	(2)	(4)	(7)	(6)
Proj SS4	(8)	(1)	(4)	(2)	(4)	(7)	(3)	(6)
Proj 14C	(1)	(1)	(8)	(6)	(1)	(5)	(7)	(4)
Proj 17	(1)	(2)	(8)	(6)	(2)	(4)	(7)	(5)
Proj 27	(3)	(1)	(8)	(6)	(1)	(5)	(7)	(4)
Sum	26	14	53	39	19	38	47	40
'Handicap'	2	-10	29	15	-5	14	23	16
Total Rank	(3)	(1)	(8)	(5)	(2)	(4)	(7)	(6)

Table 4.4.4: Summary of Model Ranking Using the Noise Measure

DATA SET	HLDSRGM	GOM	PETM	ELC	MLC	DLC1	DLC2	DLC3
NTDS	(1)	(1)	(8)	(5)	(1)	(4)	(7)	(6)
Proj SS1A	(1)	(2)	(8)	(5)	(2)	(4)	(7)	(6)
Proj SS1B	(5)	(1)	(8)	(3)	(5)	(2)	(4)	(7)
Proj SS3	(1)	(2)	(8)	(5)	(2)	(4)	(7)	(6)
Proj SS4	(8)	(2)	(1)	(4)	(2)	(6)	(5)	(7)
Proj 14C	(2)	(8)	(1)	(5)	(2)	(6)	(4)	(7)
Proj 17	(2)	(8)	(1)	(5)	(2)	(6)	(4)	(7)
Proj 27	(3)	(8)	(2)	(5)	(3)	(6)	(1)	(7)
Sum	23	32	37	37	19	38	39	53
"Handicap"	-1	8	13	13	-5	14	15	29
Total Rank	(2)	(3)	(4)	(4)	(1)	(6)	(7)	(8)

V. Conclusion:

A comparative study of the suggested models is made with reference to three criteria as applied to eight different data sets and is noticed that the suggested model has a good contribution in the combination to come out as a better SRGM model. HLSRGM of this paper can have a good contribution as an entry into software reliability measurements through combination of models.

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