A Unique Procedure for Accurate Recognition of Software Failures: A Software Reliability Growth Model Based on Special Case of Generalized Gamma Mixture Model

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*Abstract***:** *This paper pinpoints to detect and eliminate the actual software failures efficiently. The approach fit in a particular case of Generalized Gamma Mixture Model (GGMM), namely Weibull distribution. The approach estimates two parameters using Maximum Likelihood Estimate (MLE). Standard Evaluation metrics like Mean Square Error (MSE), Coefficient of Determination (R2), Sum of Squares (SSE), and Root Means Square Error (RMSE) were calculated. For the justification of the model selection and goodness of fit various model selection frameworks like Chi-Square Goodness of Fit, Wald's Test, Akaike Information Criteria (AIC), AICc and Schwarz criterion (SBC) were also estimated. The experimentation was carried out on five benchmark datasets which interpret the considered novel technique identifies the actual failures on par with the existing models. This paper presents a novel software reliability growth model which is more effectual in the identification of the failures significantly and help the present software organizations in the release of software free from bugs just in time.*

*Index Terms***:** *Benchmark Datasets, Error, Generalized Gaussian Mixture Model, Reviews, Software Reliability*

I. INTRODUCTION

Software Reliability is a specialized area of Software engineering where it concerns with the development of the software products to be released are faced boom errors so that the developed product can be readily installed or deployed by the client's side. Many models have been projected and are in practice that aims at the principles of reliability and however, these mythologies are highly dependent on particulars type of models based on Non-Homogeneous Poisson Process (NHPP) [1]-[4]. With this development of NHPP as the base, several methodologies have been coming into existence which includes Gompetz [5], S-shaped Distribution [6], [7]

and Inversed S-Shaped distribution [8]. Particular models like Jelinski and Moranda model [9], Littlewood & Verrall model [10], Goel – Okumoto model [11], Musa – Okumoto model [12], Kuo, Huang, & Lyu [13], Brown DB [14], Kapur PK [15], Khan, Ahmad and Rafi [16], Ohishi, Okamura and Dohi [17], Satya Prasad, Naga Raju and Kantam [18], Zou and Davis [19], Kiyoshi, Henrik and Poul [20] etc., are also highlighted in the literature with the aim, optimizing the errors in the developed software's. However, these, models are effectual when the errors are estimated most apparently and have a complete overview of discriminating between failure and non-failure. Moreover, these models are mostly confined towards the prediction of the next failure to occur & the Mean Time Between Failure (MTBF). As the technologies evolving at a rapid speed, most of the applications are now converted into computer-based & these by these no of users utilizing the software services are in need for software services are growing at an exponential way. Therefore, it is necessary to develop methodologies that can minimize the delivery time of the developed software. According to the studies presented in the software review's, the optimal time for the release of software best usable, if the errors during the development phase are minimized and there by the time to overcome these errors can be made to minimal. Since, the number of clients in demand for software's are creeping, latest software's are to be developed by the organization keeping in view of the client's requirements, in other words the organization should acquaint themselves for developing innovative software's with no previous available templates, i.e., software's are to be developed in an up supervised environment. The main challenging issue at this point as that, since no template is available discrimination of failures into actual failures or system developed failures a big task. System generated failures are due to failures in network, hardware, etc. Actual failures are failures due to software development. Along with another problem associated is that in some particular cases, the true failures i.e., failures are miss-classified into actual failure or vice versa. Therefore, it is necessary to develop approaches or methods which can clearly distinct the true failures and actual failures and also help in minimizing the errors instantaneously. This article makes an attempt in this direction by proposing a novel model based on the extension of Generalized Gamma Distribution (GGD).

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The experimentations are carried out on benchmark datasets and results are evaluated using metrics such as Coefficient of Determination (R^2), Residuals, Hazard Function, Survival Distribution Function and a case study was presented on Weibull distribution. The Tandem and Brooks and Motely datasets are considered for experimentation. The rest of the article is structured as follows: Section 2 of the article deals with Generalized Gamma Distribution together with considered particular case of Weibull distribution. The need for gamma distribution is also clearly highlighted. Section 3 of the article presents about the datasets considered. Section 4 presents the methodology that is carried out for this purpose and the results are presented in Section 5. The final concluding Section 6 summarizes the article.

II. GENERALIZED GAMMA DISTRIBUTION AND IT'S SPECIAL CASES

In this article we have considered Generalized Gamma Distribution (GGD) for identifying the error rate generated during the software execution process. The main advantage beyond the consideration the GGD is that error rates that are generated during development of software are of varying in nature and these errors range between the infinite side to the positive side and the most cases the errors are most frequent, the minimal values towards the negative side i.e., the data is extended towards negative side of distribution called low tail. In some abnormal cases it resembles the distribution having long infinite tails and hence to appropriately gauge the distribution which is not symmetric or uniform, GGD fits the best. Hence, with this assumption GGD is preferred moreover the error rates in the software developed, if plotted articulates the shape parameters and scale parameters as 0 and 2, which in other words resemble the Weibull distribution. This particular distribution is considered for modeling the failure rates in this article. The Probability Density Function (PDF) of GGD along with its particular case of Weibull Distribution is presented by the following equations.

$$f(x,k,c,a,b) = \frac{c(x-a)^{ck-1}e^{-\left(\frac{x-a}{b}\right)^c}}{b^{ck}\Gamma(k)} \qquad (1)$$

Where a, b, c, k are called the gamma variants and c, k are called shape parameters such that c, k >0, a is called location parameter, b is called shape parameter with a, b >0. In this article we have considered two different variants of generalized gamma distribution by changing the values of shape and scale parameters.

Case I:

When c=1 and a=0 the generalized gamma distribution takes the form of Weibull distribution and is given by

$$f(x,k,c,a,b) = \frac{(x)^{k-1}e^{-\left(\frac{x}{b}\right)}}{b^{k}\Gamma(k)} \qquad (2)$$

III. DATASETS CONSIDERED

In turn, to present the proposed methodology, we have considered two benchmark datasets namely, Tandem [21] and Brooks and Motely [22] for highlighting the proposed model. The first dataset of Tandem consists of failure data executed in four releases, Release 1 to Release 4. Each of the releases consisted of the failures generated. In the second dataset considered for the experimentation namely, Brooks and Motely contain a failure data set. These datasets are considered for the presentation of the proposed model is given below:

Table I: Original Failures in TANDEM Dataset.

TW	Release 1		Release 2		Release 3		Release 4	
	EH	ND	EH	ND	EH	ND	EH	ND
1	519	16	384	13	162	6	254	1
2	968	24	1186	18	499	9	788	3
3	1430	27	1471	26	715	13	1054	8
4	1893	33	2236	34	1137	20	1393	9
5	2490	41	2772	40	1799	28	2216	11
6	3058	49	2967	48	2438	40	2880	16
7	3625	54	3812	61	2818	48	3593	19
8	4422	58	4880	75	3574	54	4281	25
9	5218	69	6104	84	4234	57	5180	27
10	5823	75	6634	89	4680	59	6003	29
11	6539	81	7229	95	4955	60	7621	32
12	7083	86	8072	100	5053	61	8783	32
13	7487	90	8484	104	9604	36		
14	7846	93	8847	110	10064	38		
15	8205	96	9253	112	10560	39		
16	8564	98	9712	114	11008	39		
17	8923	99	10083	117	11237	41		
18	9282	100	10174	118	11243	42		
19	9641	100	10272	120	11305	42		
20	10000	100						

Note: Labels in the Table I TW represents the Test Weeks, EH represents the Execution Hours and ND represents the No. of defects.

Table II: Original Failures in Brooks and Motely Dataset.

W	EH	AD	W	EH	AD
1	7.25	7	19	759.18	888
2	10.42	29	20	799.85	978
3	17.5	61	21	896.6	1024
4	24.83	108	22	985.18	1081
5	32.08	134	23	1041.93	1110
6	44.66	159	24	1121.18	1150
7	64.58	175	25	1194.68	1166
8	117.08	223	26	1260.01	1184
9	164.26	259	27	1327.84	1221
10	259.36	312	28	1444.76	1236
11	315.11	369	29	1532.84	1244
12	374.36	408	30	1610.92	1272
13	417.94	479	31	1648.84	1278
14	462.69	559	32	1689.92	1283
15	505.02	624	33	1744.42	1286
16	580.02	681	34	1807.42	1289
17	642.85	771	35	1846.92	1301
18	716.43	831			

Note: Labels in the Table II TW represents the Test Weeks, EH represents the Execution Hours and AD represents the No. of defects.

IV. METHODOLOGY

The experimentation is conducted by varying the shape and scale parameters of the generalized gamma distribution and considered the above case of Weibull distribution as presented in section 2 of this article. The methodology is carried out by considering each of the datasets presented in the section 3. For each dataset the initial estimates of the parameters of the proposed Generalized Gamma Mixture Model (GGMM), p and q are estimated.

Using the method of Maximum Likelihood Estimation (MLE) and the values so obtained are presented below Table III.

Table III: Parameter Estimation for the datasets considered.

Datasets Considered	p	q
Tandem Release 1	135.845	0.078
Tandem Release 2	179.573	0.063
Tandem Release 3	49.339	0.237
Tandem Release 4	605.941	0.005
Brooks and Motely	11981.548	0.004

Using these estimates the analysis of the proposed models is considered. The PDF's values for the respective data were estimated using the equation (2). The differences of the predicted errors against the PDF were anticipated to be the true failures. Against each of the dataset, the analysis is carried out in a phased manner wherein the first phase the true failures are estimated and the experimentation are processed to minimize the failure rate. For the data released, the number of the actual defects highlighted is considered and using these defects the actual failures are predicted and are presented section 5.

V. EXPERIMENTATION

To test the appropriateness of the models constructed various evaluation metrics such as Mean Square Error (MSE), R2, Sum of Squares (SSE), and Root Means Square Error (RMSE) were considered. For the validation of the derived results Chi-Square Goodness of Fit, Wald's Test, Akaike Information Criteria (AIC), AICc and Schwarz criterion (SBC) were estimated. The appropriate graphs for showcasing the impact of the model were represented using residual graphs.

$$\text{MSE} = \frac{\Sigma(|Actual\ Failure_i - Estimated\ Failure_i|)}{n-1} \quad (3)$$

$$SSE = \sum_{i=1}^{n}(x_i - \bar{x})^2 \quad (4)$$

$$R^2 = 1 - \frac{SSE_{res}}{SSE_{tot}} \quad (5)$$

$$RMSE = \sqrt{\frac{\sum(|Actual\ Failure_i - Estimated\ Failure_i|)^2}{n-1}} \quad (6)$$

$$AIC = n\ln\left(\frac{SSE}{n}\right) + 2p \quad (7)$$

$$AICC = n\ln\left(\frac{SSE}{n}\right) + \frac{2(p+1)}{n-p-2} \quad (8)$$

$$SBC = n\ln\left(\frac{SSE}{n}\right) + p\ln(n) \quad (9)$$

Table IV: Goodness of fit statistics for the Weibull Distribution.

Datasets Considered	Statistic	Independent	Full
TANDEM R1	-2 Log(Likelihood)	126.24	78.99
	AIC	130.24	84.99
	SBC	132.23	87.98
	AICc	130.95	86.49
TANDEM R2	-2 Log(Likelihood)	119.40	56.10
	AIC	123.40	62.10
	SBC	125.29	64.93
	AICc	124.15	63.70
TANDEM R3	-2 Log(Likelihood)	102.93	74.23
	AIC	106.93	80.23
	SBC	108.82	83.06
	AICc	107.69	81.83
TANDEM R4	-2 Log(Likelihood)	61.61	33.09
	AIC	65.61	39.09
	SBC	66.58	40.55
	AICc	66.95	42.09
BROOKS AND MOTELY	-2 Log(Likelihood)	295.48	222.84
	AIC	299.48	228.84
	SBC	302.59	233.51
	AICc	299.85	229.61

In order to analyze the Table IV, the metrics like Log (Likelihood), AIC, SBC and AICc have been considered. SBC helps to validate the choice of the model and it is assumed that the values, for which the SBC are low, can be interpreted as the best model. Similarly, Log (Likelihood) is a measure to estimate the likelihood of estimating the exactness of the model. AIC and AICc were considered to be the quality estimates and among these two AICc is considered in particular for smaller samples.

Using these metrics, the evaluation is carried out and these type of evaluation is a novel in itself, where no literature review is hardly available in this direction. Basing on these evaluation criteria the results derived are presented in above Table IV for distribution namely Weibull. The experimentation is conducted module wise (Independent) and on the whole program code (Full). From the results, it can be seen that Weibull distribution is considered to be the better choice and in most of the cases it is giving maximum results over the existing models. All the Goodness of Fit statistics considered in this article viz., Log (Likelihood), AIC, SBC and AICc showcase exceptional results which add novelty to the proposed model.To evaluate the performance, we have conducted the experimentation using Chi-Square distribution and its variants like Wald and Score Tests. Further appropriateness of the model was also anticipated by considering Log (Likelihood) also.

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The experimentation is carried out on five benchmark datasets namely Tandem Release 1 to Release 4 and Brooks & Motely datasets. Here Chi-Square distribution is considered to estimate the Goodness of Fit for the model. Any model is considered to be the best if the predicted value is greater than the test value at the Chi-Square interval. The experimentation is carried out for Weibull distribution as considered in the above Table V. From the results derived it can be estimated that for the cases for which we have identified to be the true failure, the Chi-Square values are giving best Goodness of Fit. This confirms the considerations under our assumption are justified and the same was showcased against the other datasets. There are some cases where the actual failures are tested and the true failures are estimated. The methodology carried out clearly signifies that there are some values which are considered to be true failures and vice versa. The models considered were robust in nature for identifying the actual failures from the benchmark datasets considered. This considerably proves that the failure detection process was perfect and the true failures were estimated in accordance with the actual failures. This clearly specifies the proposed models were proven best in class under the comparisons of various variants in the Goodness of Fit.

Table V: Test of the null hypothesis H0: beta=0 for the Weibull Distribution.

Datasets Considered	Statistic	DF	Chi-square	Pr > Chi²
TANDEM R1	-2 Log(Likelihood)	1	47.24	< 0.0001
	Score	1	17522.64	< 0.0001
	Wald	1	977.80	< 0.0001
TANDEM R2	-2 Log(Likelihood)	1	63.29	< 0.0001
	Score	1	1.57E+11	< 0.0001
	Wald	1	2453.76	< 0.0001
TANDEM R3	-2 Log(Likelihood)	1	28.70	< 0.0001
	Score	1	16073.56	< 0.0001
	Wald	1	1516.16	< 0.0001
TANDEM R4	-2 Log(Likelihood)	1	28.52	< 0.0001
	Score	1	4512.75	< 0.0001
	Wald	1	238.27	< 0.0001
BROOKS AND MOTELY	-2 Log(Likelihood)	1	72.64	< 0.0001
	Score	1	118337.13	< 0.0001
	Wald	1	0.00	1

The results are further analyzed by considering the regression coefficients. The analysis is further carried out for the benchmark datasets considered in tune with previous cases and the results are analyzed by varying the Scale and Test Weeks. From the experimentation, the regression coefficients are evaluated and are presented in the above Table VI. If the values are positive, the estimated errors are true and in our case, we have tried to identify the actual failures and by doing so some of the actual failures were converted as true failures, resembles they are error-free.

During the evaluation of regression coefficients, we can observe that for the values for which we have changed from true failure to actual failure or vice versa, the regression coefficient estimate is attributing a value nearer to "0", which implies that the consideration is highly justified.

Table VI: Regression coefficients for the Weibull distribution.

Datasets Considered	Statistic	Value	Standard Error	Wald Chi-Square
TANDEM R1	Intercept	3.22	0.053	3663.54
	Test Week	0.10	0.006	336.48
	Scale	0.10	0.044	6.043
TANDEM R2	Intercept	2.61	0.076	1174.19
	Test Week	0.20	0.013	261.69
	Scale	0.07	0.021	13.93
TANDEM R3	Intercept	1.98	0.154	165.48
	Test Week	0.25	0.024	114.14
	Scale	0.12	0.035	12.83
TANDEM R4	Intercept	0.57	0.335	2.89
	Test Week	0.38	0.076	26.33
	Scale	0.28	0.080	12.79
BROOKS AND MOTELY	Intercept	3.47	0.327	113.14
	Test Week	0.19	0.021	82.35
	Scale	0.00	0.149	0.00

From the corresponding Table VII to Table XI showcase the experimentation carried out on Weibull distribution for the datasets considered. The evaluation of the developed methodology is tested through benchmark statistics like Residuals, Cumulative Distributions, Hazard functions, Survival distribution Function. From the above tables mentioned, each of the metrics was evaluated and tabulated. From the developed model among the failures listed, we have differentiated into actual failure and true failure i.e., the values which are not failures actually but showcased as failures and vice versa. From the derived results after discriminating actual failures and true failures, the above metrics are evaluated. From the above metrics, it can be clearly seen that in from Table VII to Table XI, the values which are identified as non-failure, the residues at these values are estimated to be the positive and Survival Distribution Function value is minimal at these values. In Table VII, our model identifies the No. of defects under 49, 54, 69 and 75 possess a positive residual value of 0.047, 0.031, 0.052 and 0.023 respectively. Where in the case for the rest of the defects the residual values are negative. This clearly signifies with the consideration of the Survival Distribution Function also. The values of Survival distribution function for the No. of defects under 49, 54, 69 and 75 possess a minimum value considered to the rest of the defects in the dataset.

These indicate that our model has appreciably identified the true failures and the same can be reflected from other Table VIII to Table XI.

118	-20.672	0.000	0.000	0.000	1.000	Y
120	-23.146	0.000	0.000	0.000	1.000	Y

Table VII: Predictions and Residuals for the TANDEM Dataset Release 1 in Weibull distribution.

No. of Defects	Residuals	Cox-Snell Residuals	Cumulative Distributions	Hazard Function	Survival Distribution Function	Failure (YES/NO)
16	-0.511	0.600	0.451	0.329	0.549	Y
24	-0.218	0.804	0.553	0.360	0.447	Y
27	-0.213	0.809	0.554	0.360	0.446	Y
33	-0.124	0.883	0.587	0.365	0.413	Y
41	-0.019	0.981	0.625	0.368	0.375	Y
49	0.047	1.048	0.649	0.367	0.351	N
54	0.031	1.032	0.644	0.368	0.356	N
58	-0.009	0.991	0.629	0.368	0.371	Y
69	0.052	1.053	0.651	0.367	0.349	N
75	0.023	1.023	0.641	0.368	0.359	N
81	-0.012	0.988	0.628	0.368	0.372	Y
86	-0.065	0.937	0.608	0.367	0.392	Y
90	-0.132	0.877	0.584	0.365	0.416	Y
93	-0.211	0.810	0.555	0.360	0.445	Y
96	-0.292	0.747	0.526	0.354	0.474	Y
98	-0.383	0.682	0.494	0.345	0.506	Y
99	-0.485	0.615	0.460	0.333	0.540	Y
100	-0.588	0.556	0.426	0.319	0.574	Y
100	-0.700	0.497	0.391	0.302	0.609	Y

Table VIII: Predictions and Residuals for the TANDEM Dataset Release 2 in Weibull distribution.

| No. of Defects	Residuals	Cox-Snell Residuals	Cumulative Distributions	Hazard Function	Survival Distribution Function	Failure (YES/NO)
13	-3.361	0.035	0.034	0.432	0.966	Y
18	-1.856	0.156	0.145	1.723	0.855	Y
26	0.193	1.213	0.703	4.649	0.297	N
34	0.961	2.613	0.927	2.469	0.073	N
40	0.365	1.440	0.763	4.398	0.237	N
48	0.024	1.024	0.641	4.741	0.359	N
61	0.423	1.526	0.783	4.276	0.217	N
75	0.395	1.485	0.774	4.336	0.226	N
84	-0.835	0.434	0.352	3.625	0.648	Y
89	-2.780	0.062	0.060	0.752	0.940	Y
95	-4.630	0.010	0.010	0.125	0.990	Y
100	-6.660	0.001	0.001	0.016	0.999	Y
104	-8.845	0.000	0.000	0.002	1.000	Y
110	-10.813	0.000	0.000	0.000	1.000	Y
112	-13.272	0.000	0.000	0.000	1.000	Y
114	-15.734	0.000	0.000	0.000	1.000	Y
117	-18.090	0.000	0.000	0.000	1.000	Y

Table IX: Predictions and Residuals for the TANDEM Dataset Release 3 in Weibull distribution.

No. of Defects	Residuals	Cox-Snell Residuals	Cumulative Distributions	Hazard Function	Survival Distribution Function	Failure (YES/NO)
6	-3.567	0.028	0.028	0.219	0.972	Y
9	-2.376	0.093	0.089	0.676	0.911	Y
13	-1.487	0.226	0.202	1.439	0.798	Y
20	-0.094	0.910	0.597	2.924	0.403	Y
28	0.545	1.725	0.822	2.454	0.178	N
36	-13.822	0.000	0.000	0.000	1.000	Y
38	-15.437	0.000	0.000	0.000	1.000	Y
39	-17.276	0.000	0.000	0.000	1.000	Y
39	-19.323	0.000	0.000	0.000	1.000	Y
40	1.346	3.842	0.979	0.658	0.021	N
41	-20.970	0.000	0.000	0.000	1.000	Y
42	-22.824	0.000	0.000	0.000	1.000	Y
42	-24.871	0.000	0.000	0.000	1.000	Y
48	0.755	2.128	0.881	2.023	0.119	N
54	-0.351	0.704	0.505	2.780	0.495	Y
57	-1.966	0.140	0.131	0.972	0.869	Y
59	-3.738	0.024	0.024	0.186	0.976	Y
60	-5.650	0.004	0.004	0.028	0.996	Y
61	-7.565	0.001	0.001	0.004	0.999	Y

Table X: Predictions and Residuals for the TANDEM Dataset Release 4 in Weibull distribution.

| No. of Defects	Residuals	Cox-Snell Residuals	Cumulative Distributions	Hazard Function	Survival Distribution Function	Failure (YES/NO)
1	-3.346	0.035	0.035	0.119	0.965	Y
3	-0.865	0.421	0.344	0.965	0.656	Y
8	1.205	3.338	0.964	0.414	0.036	N
9	0.263	1.301	0.728	1.236	0.272	N
11	-0.390	0.677	0.492	1.201	0.508	Y
16	-0.435	0.647	0.476	1.183	0.524	Y
19	-1.189	0.305	0.263	0.784	0.737	Y
25	-1.584	0.205	0.185	0.583	0.815	Y
27	-2.669	0.069	0.067	0.226	0.933	Y
29	-3.773	0.023	0.023	0.078	0.977	Y
32	-4.783	0.008	0.008	0.029	0.992	Y
32	-6.136	0.002	0.002	0.008	0.998	Y

Table XI: Predictions and Residuals for the Brooks and Motely Dataset in Weibull distribution.

No. of Defects	Residuals	Cox-Snell Residuals	Cumulative Distributions	Hazard Function	Survival Distribution Function	Failure (YES/NO)
7	-1.72E+12	0.000	0.000	0.000	1.000	Y
29	-4.88E+11	0.000	0.000	0.000	1.000	Y
61	6.39E+10	0.000	1.000	65535.000	0.000	N
108	4.44E+11	0.000	1.000	65535.000	0.000	N
134	4.68E+11	0.000	1.000	65535.000	0.000	N
159	4.48E+11	0.000	1.000	65535.000	0.000	N
175	3.53E+11	0.000	1.000	65535.000	0.000	N
223	4.04E+11	0.000	1.000	65535.000	0.000	N
259	3.62E+11	0.000	1.000	65535.000	0.000	N
312	3.57E+11	0.000	1.000	65535.000	0.000	N
369	3.33E+11	0.000	1.000	65535.000	0.000	N
408	2.43E+11	0.000	1.000	65535.000	0.000	N
479	2.12E+11	0.000	1.000	65535.000	0.000	N
559	1.75E+11	0.000	1.000	65535.000	0.000	N
624	9.35E+10	0.000	1.000	65535.000	0.000	N
681	-1.03E+10	0.000	0.000	0.000	1.000	Y
771	-7.75E+10	0.000	0.000	0.000	1.000	Y
831	-1.94E+11	0.000	0.000	0.000	1.000	Y
888	-3.19E+11	0.000	0.000	0.000	1.000	Y
978	-4.14E+11	0.000	0.000	0.000	1.000	Y
1024	-5.59E+11	0.000	0.000	0.000	1.000	Y
1081	-6.96E+11	0.000	0.000	0.000	1.000	Y
1110	-8.61E+11	0.000	0.000	0.000	1.000	Y
1150	-1.02E+12	0.000	0.000	0.000	1.000	Y
1166	-1.19E+12	0.000	0.000	0.000	1.000	Y
1184	-1.37E+12	0.000	0.000	0.000	1.000	Y
1221	-1.53E+12	0.000	0.000	0.000	1.000	Y
1236	-1.71E+12	0.000	0.000	0.000	1.000	Y
1244	-1.89E+12	0.000	0.000	0.000	1.000	Y
1272	-2.06E+12	0.000	0.000	0.000	1.000	Y
1278	-2.25E+12	0.000	0.000	0.000	1.000	Y
1283	-2.44E+12	0.000	0.000	0.000	1.000	Y
1286	-2.63E+12	0.000	0.000	0.000	1.000	Y
1289	-2.82E+12	0.000	0.000	0.000	1.000	Y
1301	-3E+12	0.000	0.000	0.000	1.000	Y

The residuals were represented pictographically for the distributions of Weibull distribution for the datasets of Tandem R1, Tandem R2, Tandem R3, Tandem R4 and Brooks and Motely from Fig. 1 to Fig. 5.
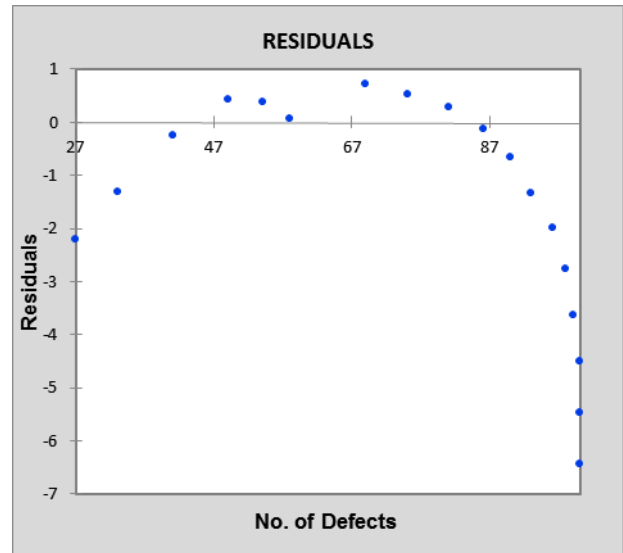
Fig. 1: Standard Residuals versus No. of Defects for the TANDEM Dataset Release 1 for Weibull distribution.
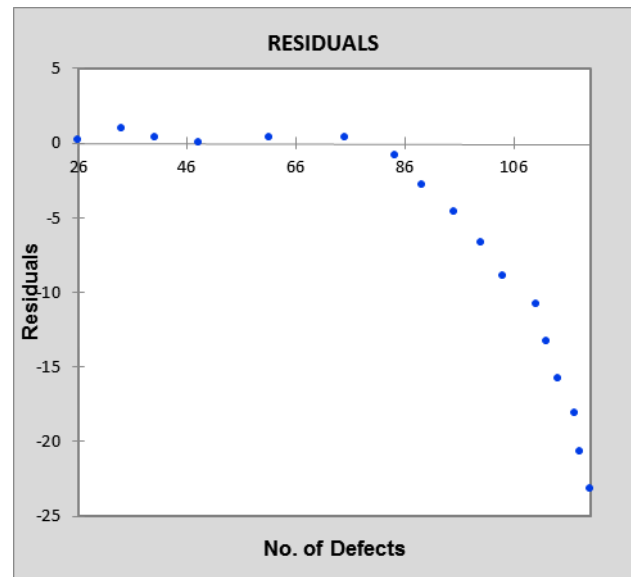
Fig. 2: Standard Residuals versus No. of Defects for the TANDEM Dataset Release 2 for Weibull distribution.

VI. CONCLUSION

In this article, a methodology is highlighted to estimate the error rate more optimistically with a clear-cut procedure of estimating the actual failures & true failures. The article also presents the developed model using two distributions & considering two particular cases of Generalized Gamma Distribution. The experimentation results showcase that the developed model helps to identify the errors more clearly and also help to minimize the time for reviews so that the software's can be released just in time.
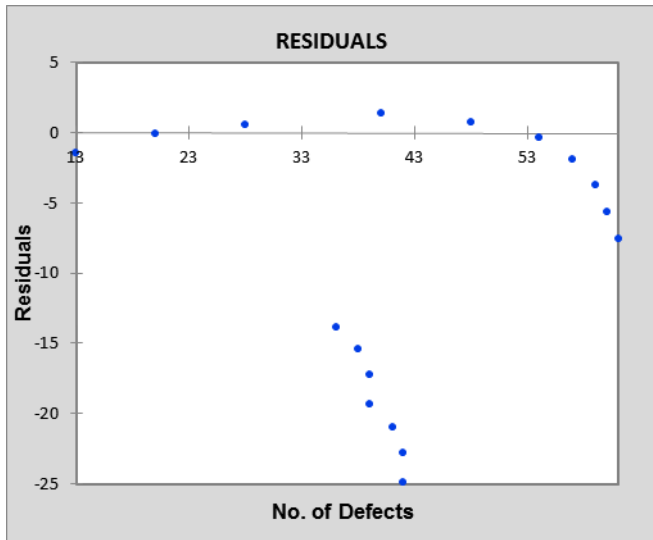
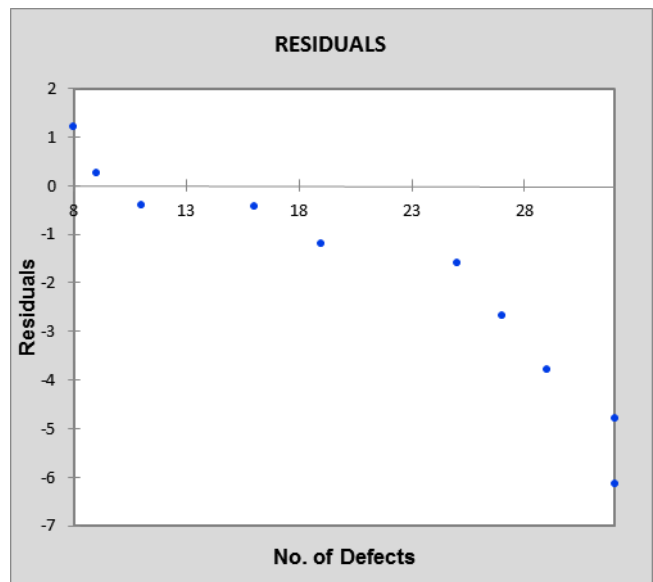**Fig. 3: Standard Residuals versus No. of Defects for the TANDEM Dataset Release 3 for Weibull distribution.**

Fig. 4: Standard Residuals versus No. of Defects for the TANDEM Dataset Release 4 for Weibull distribution.
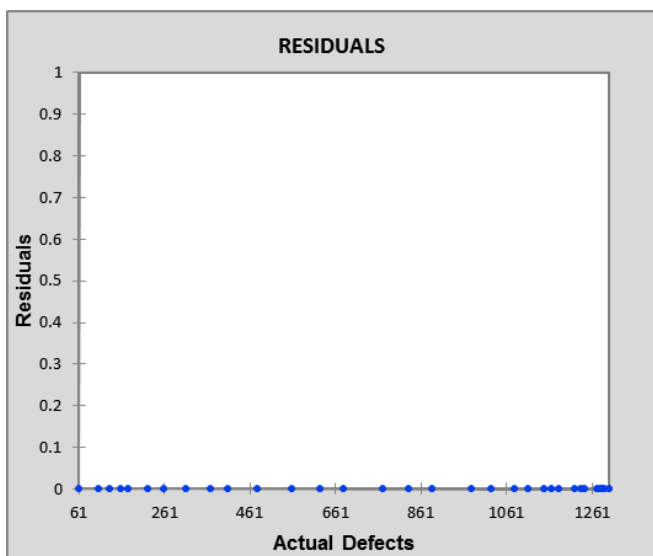

Fig. 5: Standard Residuals versus No. of Defects for the Brooks and Motley Dataset for Weibull distribution.

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