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A Comparative Study of Analyzing Software Reliability with Order Statistics Approach Using ANOM

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ABSTRACT

Software reliability is characterized as the probability that a product framework with no disappointment happening in a determined time on specified working conditions. Assessing software reliability and in this manner, keeping up quality during development and utilization of software is most significant, as software is being used in all domains alongside safety and non-security frameworks. Analysis of means (ANOM) can be applied to forecast software failures also, in this way contribute significantly to the improvement of software reliability. In this paper, we compared two models developed by us to analyze and assess software reliability using ANOM. The two models are based on Logarithmic Poisson Execution Time Model (LPETM) and GO model.

Key words: Order statistics, Analysis of means (ANOM), LPETM, GO, MLE, NHPP, Lower Decision Line (LDL), Upper Decision Line (UDL), Central Decision Line (CDL).

1. INTRODUCTION

Nowadays, computers are used in numerous areas and applications. In developing and testing new software products, software reliability assessment is progressively significant. Prior to releasing the product into the market, the newly developed software is tested thoroughly to identify errors. New errors may creep in when the distinguished errors are expelled during debugging. The failure costs will be high if the product with errors is released into the market. In this paper reliability is assessed by applying ANOM on order statistics failure data [3], [4].

Software reliability represents a client perspective on software quality. It relates legitimately to activity instead of the design of the program, and subsequently it is dynamic rather than static. Consequently, programming dependability is keen on disappointments happening and not shortcomings in a program. Unwavering quality measures are significantly more valuable than shortcoming measures.

In this paper, we compared two control mechanism developed by us to analyze and assess software reliability using ANOM. The two-control mechanism is based on time between failure observations using Logarithmic Poisson Execution Time Model (LPETM) and GO model.

2. MODELS DESCRIPTION AND PARAMETER ESTIMATION

Estimation of parameters is very influential in foreseeing the software reliability. After finishing up the analytical solution for the mean value function m(t) for the specific model, the MLE method is enforced for accomplishing the parameter estimation. The intension of MLE is to determine the parameters that magnify the probability of the fragment data. They yield estimators with good statistical factors. MLE techniques are flexible, adaptable and can be utilized to distinct models. To assess the software reliability, the unknown parameters ‘a’ and ‘b’ is to be treasured and they are to be anticipated utilizing the failure data of the software fragment data [1], [2].

Let ‘n’ be the time instances where the first, second,….Kth faults in the software are encountered. If Tk is the total time of the Kth failure, ‘tk’ is an observation of random variable Tk and ‘n’ such similar failures are successively recorded. The combined probability of such failure time handles t1,t2,………tn is given by the Likelihood function as

$$L = e^{-m(t_n)} . \prod_{K=1}^{n} m'(t_k) \qquad (1)$$

The logarithmic application of the equation (1) would result a log likelihood function and is given in equation (2).

$$\text{LogL} = \sum_{i=1}^{n} \log[\lambda(t)] - m(t_k)^r \qquad (2)$$

The MLE is highlighted to maximize L and estimate the values of ‘a’ and ‘b’. The process to maximize is by applying partial derivation with respective to the unknown variables and equate to zero to obtain a close form for the required variable. If the closed form is not destined, then the variable can be evaluated using Newton Raphson Method. In this manner ‘a’ and ‘b’ would be solutions of the equations [9].

$$\frac{\partial \log L}{\partial a} = 0 , \frac{\partial \log L}{\partial b} = 0 \; \frac{\partial^2 \log L}{\partial b^2} = 0$$

2.1 LOGARITHMIC POISSON EXECUTION TIME MODEL (LPETM)

The mean value function m (t) of LPETM is given

$$m(t) = a\log(1+bt) \qquad (3)$$

To get m(t) value for rth order statistics, take m(t) to the power ‘ r ‘

$$m(t)^r = a^r \,.\, \log(1+bt)^r \qquad (4)$$

The failure intensity function is

$$\lambda(t) = \frac{\partial}{\partial t}\, m(t)^r \qquad (5)$$

$$\lambda(t) = \frac{a^r.r.b}{(1+bt)} \qquad (6)$$

Implanting the equations for $m(t)^r$, λ(t) given by (4) & (6) equation in equation 2 and executing the aforementioned process and with the aid of few combined simplifications.

$$a^r = \frac{n}{\log(1+bt_k)^r} \qquad (7)$$

$$g(b) = \frac{n}{b} - \sum_{i=1}^{n} \frac{t_i}{(1+bt_i)} - \frac{r.t_k}{(1+bt_k).\log(1+bt_k)} \qquad (8)$$

$$g^1(b) = -\frac{n}{b^2} + \sum_{i=1}^{n} \frac{t_i^2}{(1+bt_i)^2} + r.\left[\frac{t_k^2}{(1+bt_k)^2 * \log(1+bt_k)} + \frac{t_k^2}{(1+bt_k)^2 * (\log(1+bt_k))^2}\right] \qquad (9)$$

We get closure form for variable ‘a’ in terms of ‘b’. Iterative Newton-Raphson method is used to solving the equations (7), (8), (9) in order to get the approximated a & b value for the given set of failure data [9].

2.2 GO MODEL

The mean value function m (t) of GO Model is given

$$m(t) = a(1-e^{-bt}) \qquad (10)$$

To get m(t) value for rth order statistics, take m(t) to the power ‘ r ‘

$$m(t)^r = a^r \,.\, (1-e^{-bt})^r \qquad (11)$$

The failure intensity function is

$$\lambda(t) = a^r.b.e^{-bt}.r.(1-e^{-bt})^{r-1} \qquad (12)$$

Implanting the equations for $m(t)^r$, λ(t) given by (11) & (12) equation in equation 2 and executing the aforementioned process and with the aid of few combined simplifications [5].

$$a^r = \frac{n}{(1-e^{-bt_n})^r} \qquad (13)$$

$$g(b) = \frac{n}{b} + \sum_{i=1}^{n} \frac{(r-1).t_i.e^{-bt_i}}{(1-e^{-bt_i})} - \frac{r.t_n.e^{-bt_n}}{(1-e^{-bt_n})} - t_i \qquad (14)$$

$$g^1(b) = \frac{r.t_n{}^2.e^{-bt_n}}{(1-e^{-bt_n})^2} - \frac{n}{b^2} - \sum_{i=1}^{n} \frac{(r-1).t_i{}^2.e^{-bt_i}}{(1-e^{-bt_i})^2} \qquad (15)$$

We get closure form for variable ‘a’ in terms of ‘b’. Iterative Newton-Raphson method is used to solving the equations (13),(14),(15) in order to get the approximated a & b value for the given set of failure data [7], [8].

3. ESTIMATION OF PARAMETERS AND DECISION LINES USING ANOM

Table 1 shows the sample dataset contains 104 weeks failure data [6], from that we calculated mean value function m(t) from equation 3.

Table I: Failures Dataset [6].

Failure No	Time Betwee n Failures (Hrs)	Failure No	Time Betwee n Failures (Hrs)	Failure No	Time Betwee n Failures (Hrs)
1	33	36	5	71	55
2	9	37	66	72	409
3	4	38	289	73	36
4	66	39	3	74	15
5	0.5	40	9	75	573
6	18	41	12	76	583
7	149	42	18	77	60
8	14	43	9	78	19
9	15	44	75	79	20
10	50	45	15	80	79
11	81	46	291	81	24
12	34	47	212	82	540
13	85	48	4	83	52
14	54	49	5	84	1596

15	3	50	308	85	314
16	15	51	269	86	1
17	6	52	276	87	763
18	8	53	1	88	10
19	130	54	400	89	20
20	19	55	294	90	144
21	19	56	227	91	28
22	112	57	118	92	56
23	15	58	13	93	476
24	16	59	47	94	65
25	154	60	89	95	98
26	50	61	242	96	884
27	10	62	99	97	212
28	2	63	607	98	287
29	22	64	83	99	53
30	53	65	2	100	3
31	19	66	26	101	831
32	58	67	586	102	43
33	20	68	708	103	55
34	3	69	6	104	109
35	92	70	4		

From mean value m(t) we calculated upper decision line (UDL), central decision line (CDL), and lower decision line (LDL) using equation 16, 17, 18.

$$LDL = \bar{X} + h_{\alpha,I,N-I} \cdot S_{pooled} \cdot \sqrt{\frac{(r-1)}{N}} \qquad (16)$$

$$UDL = X - h_{\alpha,I,N-I} \cdot S_{pooled} \cdot \sqrt{\frac{(r-1)}{N}} \qquad (17)$$

$$CDL = \frac{LDL + UDL}{2} \qquad (18)$$

Where

$\bar{X}$ Represents the average of the individual means.

S^2_{pooled} Represents the average of the individual variance.

r represents the number of observations in each group

N number of observations in overall groups.

H value from table of critical value for analysis of means at an alpha level= 0.05 using r and N-r

The decision lines LDL, CDL, UDL and the parameters a and b are the deciding factors of the software assessing process.

Table II: parameter values and their control lines of 4^{th}, 5^{th} order

Order	a	b	LDL	CDL	UDL
4	2.08493	0.199996	3.7235	5.0873	6.4511
5	1.28753	0.199998	1.6955	3.1515	4.6075
4	11.1343	0.190675	8.8553	9.9658	11.076
5	6.87594	0.190675	5.0098	6.1612	7.3125

Table II shows the value of a and b, we calculated a, b, and decision lines using LPETM model and their results are given in row1 and row2. In row3 and row4 we obtained values using GO model. Table III shows the mean and standard deviation values of 4^{th} order LPETM model for Table I.

Table III: Mean and standard deviation values of 4th order LPETM model for Table I.

Group	Count	Mean	Std
1	4	3.283125	1.955808
2	4	3.327475	2.868705
3	4	4.52595	1.282441
4	4	3.76055	2.276067
5	4	3.444475	2.3893
6	4	3.931475	1.768464
7	4	3.801025	2.884694
8	4	4.29475	1.048203
9	4	2.9907	2.36302
10	4	4.288175	3.404345
11	4	3.415125	1.633474
12	4	5.121325	3.61172
13	4	6.704325	3.508213
14	4	6.518025	4.11941
15	4	5.08685	1.776794
16	4	7.6152	1.86161
17	4	6.1992	4.732412
18	4	4.314525	3.713483
19	4	6.780075	3.678587
20	4	4.463975	1.347337
21	4	7.63695	3.925241
22	4	5.4578	4.881345
23	4	4.895625	1.649024
24	4	8.0329	2.533689
25	4	5.607775	3.415263
26	4	6.772125	2.710676

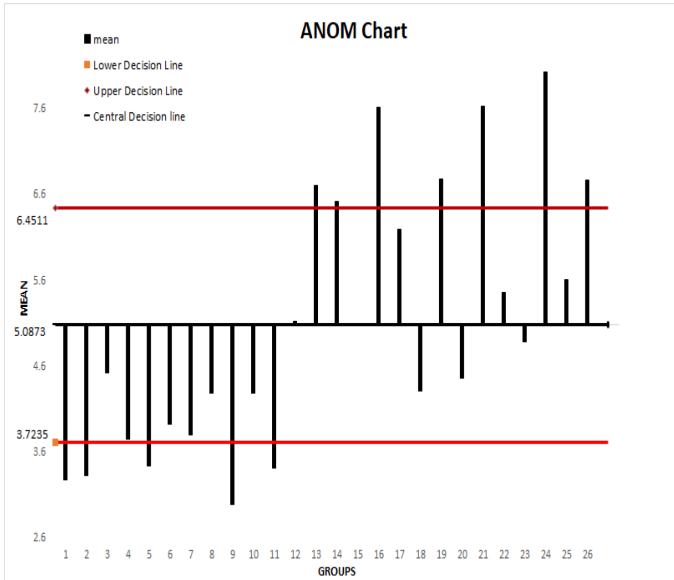

Figure 1: Analysis of Means using the 4^{th} order LPETM model for Table III.

Figure 1 shows the points 1, 2, 5, 9, 11 are below the decision line and points 13, 14, 16, 19, 21, 24, 26 are above the decision line using 4th order statistics using LPETM. Table IV shows the mean and standard deviation values of 5th order LPETM model for Table I.

Table IV: Mean and standard deviation values of 5th order LPETM model for Table I.

Group	Count	Mean	Std
1	5	1.64652	1.34896
2	5	2.59378	1.158524
3	5	2.76236	1.281684
4	5	2.05868	1.286968
5	5	2.83312	1.309848
6	5	2.05242	1.154487
7	5	2.3554	1.246766
8	5	2.29698	1.982768
9	5	2.04416	0.885554
10	5	3.41686	2.373693
11	5	4.30044	2.281702
12	5	3.50118	1.245164
13	5	3.84882	2.15336
14	5	3.3304	2.747906
15	5	3.89912	1.90288
16	5	3.43296	1.675067
17	5	4.84302	2.118345
18	5	2.91476	2.499354
19	5	3.76454	1.294404
20	5	4.10448	2.322369
21	4	4.1821	1.673948

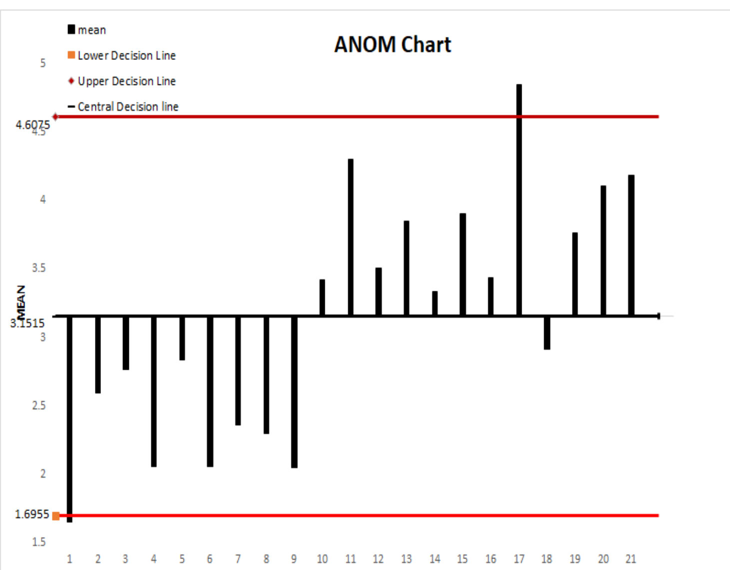

Figure 2: Analysis of Means using 5th order LPETM model for Table IV.

Figure 2 shows, below the decision line and above the decision line points are 1 and 17 using 5th order statistics using LPETM. The results of mean values are shown in the Figure 1 and Figure 2, for the given failure dataset using 4th order and 5th order, respectively. Table V shows the mean and standard deviation values of 4th order GO model for Table I.

Table V: Mean and standard deviation values of 4th order go model for Table I.

Group	Count	Mean	Std
1	4	9.330475	2.446765
2	4	8.32105	4.882554
3	4	10.97048	0.31588
4	4	9.403875	3.050551
5	4	9.567875	1.704639
6	4	10.76893	0.281849
7	4	8.8196	3.611349
8	4	11.0179	0.144162
9	4	8.429	3.092586
10	4	9.062925	2.962695
11	4	10.26155	0.887897
12	4	9.6767	2.508406
13	4	10.06148	2.14585
14	4	8.834025	4.60075
15	4	10.90063	0.466551
16	4	11.1344	0
17	4	9.2138	3.78918
18	4	8.94935	2.61087
19	4	10.97208	0.316898
20	4	10.99853	0.158131
21	4	11.10558	0.057251
22	4	8.420475	4.394786
23	4	11.0595	0.116676
24	4	11.13437	5.00E-05
25	4	9.56325	3.141967
26	4	11.13352	0.001495

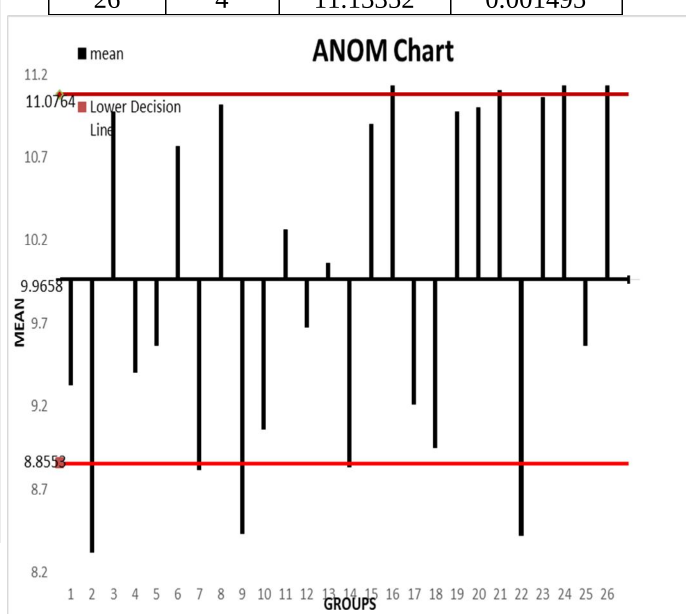

Figure 3: Analysis of Means using the 4th order GO model for TableV.

Figure 3 shows the points 2, 7, 9, 14, 22 are below the decision line and points 16, 21, 24, 26 are above the decision line using 4th order statistics using GO model. Table VI shows the mean and standard deviation values of 5^{th} order GO model for Table I.

Table VI: Mean and standard deviation values of 5^{th} order go model for Table I.

Group	Count	Mean	Std
1	5	4.73464	2.643735
2	5	6.65734	0.219367
3	5	6.09764	1.734267
4	5	6.02328	0.947043
5	5	6.69538	0.181378
6	5	5.71158	2.020305
7	5	6.0327	1.700062
8	5	5.32252	1.698942
9	5	6.36598	0.479288
10	5	5.70448	1.616063
11	5	5.73946	2.541157
12	5	6.76044	0.257729
13	5	5.93674	2.100026
14	5	5.78684	1.512681
15	5	6.7957	0.175278
16	5	6.80884	0.092516
17	5	6.8617	0.031585
18	5	5.50482	2.44717
19	5	6.86928	0.014747
20	5	6.09974	1.735435
21	4	6.875375	0.000922

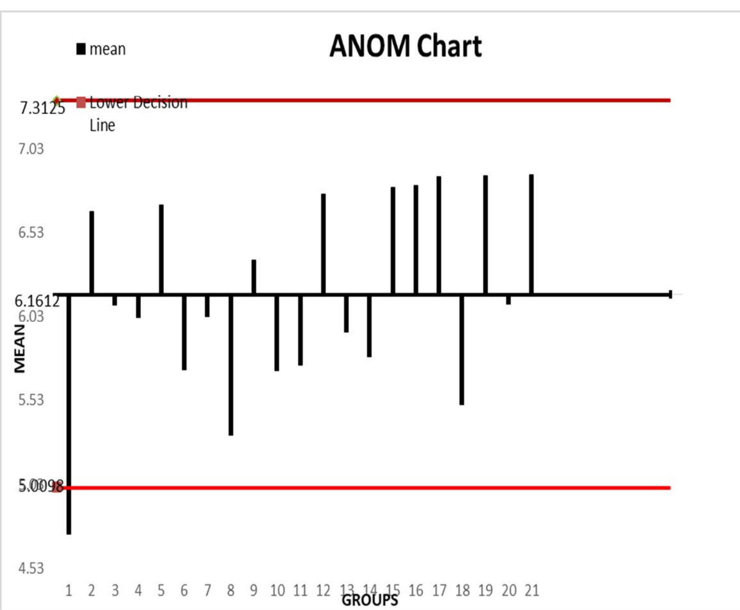

Figure 4: Analysis of Means using 5th order GO model for Table VI.

Figure 4 shows, below the decision line point is 1 using 5th order statistics using the GO Model. The results of mean values are shown in the Figure 3 and Figure 4, for the given failure dataset using 4^{th} order and 5^{th} order respectively

4. CONCLUSION

Our proposed methods LPETM and GO models using order statistics approach has successfully identified the failures. When the decision lines are outside, this indicates that these means, or failures are statistically significant. When the decision lines are below LCL, it is likely that there are assignable causes leading to significant process and it should be investigated. The early detection of software failure with order statistics using ANOM will increase the software reliability. Hence, both proposed mechanisms are making the detection, either mechanism based on LPETM or GO model is preferable. We conclude that our proposed models give positive recommendation.

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