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DETECTION OF BURR TYPE III RELIABLE SOFTWARE USING SPRT: AN ORDER STATISTIC APPROACH

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ABSTRACT

The acceptance of a software system depends on its reliability. Assessing reliability takes more time using classical hypothesis as the volume of data increases day by day. The volumes of data can be transformed using order statistics. Order statistics deals with applications of ordered random variables and functions of these variables. Sequential Analysis of Statistical science is very quick in deciding the reliability or unreliability on developed software. The method adopted is, Sequential Probability Ratio Test (SPRT) for continuous monitoring of the software. The likelihood based SPRT proposed by Wald is very general and it can be used for many different probability distributions. In this paper, the mean value function of Burr type III distribution based on Non-Homogenous Poisson Process (NHPP) with Order statistics and Sequential Probability Ratio Test is applied to analyze the results. Maximum Likelihood Estimation (MLE) is used to derive the unknown parameters of mean value function.

Keywords: *Order Statistics, Software Reliability, Sequential Probability Ratio Test, Burr Type III, Maximum Likelihood Estimation*

1. INTRODUCTION

Wald's procedure is particularly relevant if the data is collected sequentially. Sequential Analysis is different from Classical Hypothesis Testing where the number of cases tested or collected is fixed at the beginning of the experiment. In Classical Hypothesis Testing the data collection is executed without analysis and consideration of the data. After all data is collected the analysis is done and conclusions are drawn. However, in Sequential Analysis every case is analyzed directly after being collected, the data collected up to that moment is then compared with certain threshold values, incorporating the new information obtained from the freshly collected case. This approach allows one to draw conclusions during the data collection, and a final conclusion can possibly be reached at a much earlier stage as is the case in Classical Hypothesis Testing. The advantages of Sequential Analysis are easy to see as data collection can be terminated after fewer cases and decisions taken earlier.

In the analysis of software failure data, we often deal with either Time Between Failures or failure count in a given time interval. If it is further assumed that the average number of recorded failures in a given time interval is directly proportional to the length of the interval and the random number of failure occurrences in the interval is explained by a Poisson process then we know that the probability equation of the stochastic process representing the failure occurrences is given by a Homogeneous Poisson Process (HPP) with the expression.

$$P[N(t)=n]=\frac{[\lambda t]^n}{n!}e^{-\lambda(t)}$$

Stieber [4] observes that if classical testing strategies are used, the application of software reliability growth models may be difficult and reliability predictions can be misleading. However, he observes that statistical methods can be successfully applied to the failure data. He demonstrated his observation by applying the well-known sequential probability ratio test (SPRT) of Wald [3] for a software failure data to detect unreliable software components and compare the reliability of different software versions. In this paper, we consider Burr type III model and adopt the principle of Stieber [4] in detecting unreliable software components in order to accept or reject the developed software.

Concept of Order Statistics is given in Section2. The theory proposed by Stieber is described in Section 3. Implementation of SPRT for the proposed Burr type III Software Reliability Growth Model (SRGM) is illustrated in Section 4. Maximum Likelihood estimation method is used to estimate the unknown parameters is presented in Section 5. Analysis of the application of the SPRT on four data sets and conclusions drawn are given in Section 6 respectively.

2. ORDER STATISTICS

Order statistics deals with properties and applications of ordered random variables and of functions of these variables. The use of order statistics is significant when failures are frequent or inter failure time is less. Let X denote a continuous random variable with probability density function f(x) and cumulative distribution function F(x), and let (X1 , X2 , …, Xn) denote a random sample of size n drawn on X. The original sample observations may be unordered with respect to magnitude. A transformation is required to produce a corresponding ordered sample. Let (X(1) , X(2) , …, X(n)) denote the ordered random sample such that X(1) < X(2) < … < X(n); then (X(1), X(2), …, X(n)) are collectively known as the order statistics derived from the parent X. The various distributional characteristics can be known from Balakrishnan and Cohen [1]. The inter-failure time data is grouped into non overlapping successive sub groups of size 4 and 5 and add the failure times with in each sub group. The probability distribution of such a time lapse would be that of the r^{th} ordered statistics in a subgroup of size 'r', which would be equal to power of the distribution function of the original variable [m(t)]. The order statistics is preferable when the failure data set is large. We implemented the Burr Type III model for 4th order and 5th order statistics.

3. WALD'S SEQUENTIAL PROBABILITY RATIO TEST FOR POISSON PROCESS

The Sequential Probability Ratio Test (SPRT) was developed by Abraham Wald at Columbia University in 1943[3]. The SPRT procedure is used for quality control studies during the manufacturing of software products. The tests can be performed on fixed sample size sets with fewer observations. The SPRT methodology for Homogeneous Poisson Process is described below.

Let {N(t), t ≥ 0} be a Homogeneous Poisson Process with rate 'λ'. In this case, N(t) = number of failures up to time 't' and 'λ' is the failure rate (failures per unit time). If the system is put on test and that if we want to estimate its failure rate 'λ'. We cannot expect to estimate 'λ' precisely. But we want to reject the system with a high probability if the data suggest that the failure rate is larger than $\lambda_1$and accept it with a high probability, if it is smaller than λ_0. Here we have to specify two (small) numbers 'α' and 'β', where 'α' is the probability of falsely rejecting the system. That is rejecting the system even if $\lambda \leq \lambda_0$. This is the "producer's" risk. 'β' is the probability of falsely accepting the system. That is accepting the system even if $\lambda \leq \lambda_1$. This is the "consumer's" risk. Wald's classical SPRT is very sensitive to the choice of relative risk required in the specification of the alternative hypothesis. With the classical SPRT, tests are performed continuously at every time point as t > 0 additional data are collected. With specified choices of λ_0 and λ_1 such that $0 < \lambda_0 < \lambda_1$, the probability of finding N(t) failures in the time span (0, t) with λ_1, λ_0 as the failure rates are respectively given by

$$P_1 = \frac{e^{-\lambda_1 t}\left[\lambda_1 t\right]^{N(t)}}{N(t)!} \tag{1}$$

$$P_0 = \frac{e^{-\lambda_0 t}\left[\lambda_0 t\right]^{N(t)}}{N(t)!} \tag{2}$$

The ratio $\frac{P_1}{P_0}$ at any time 't' is considered as a measure of deciding the truth towards λ_0 or λ_1, given a sequence of time instants say $t_1 < t_2 < t_3 < \ldots\ldots < t_K$ and the corresponding realizations $N(t_1), N(t_2), \ldots\ldots N(t_K)$ of N(t)

Simplification of $\frac{P_1}{P_0}$ gives

$$\frac{P_1}{P_0} = \exp(\lambda_0 - \lambda_1)t + \left(\frac{\lambda_1}{\lambda_0}\right)^{N(t)}$$

The decision rule of SPRT is to decide in favor of , λ_1 in favor of λ_0 or to continue by observing the number of failures at a later time than 't' accordingly as $\frac{P_1}{P_0}$ is greater than or equal to a constant say A, less than or equal to a constant say B or in between the constants A and B. That is, we decide the given software product as unreliable, reliable or continue[3] the test process with one more observation in failure data, according to

$$\frac{P_1}{P_0} \geq A \tag{3}$$

$$\frac{P_1}{P_0} \leq B \tag{4}$$

$$B < \frac{P_1}{P_0} < A \tag{5}$$

The approximate values of the constants A and B are taken as

$$A \cong \frac{1-\beta}{\alpha}, \; B \cong \frac{\beta}{1-\alpha}$$

Where ' α ' and ' β ' are the risk probabilities as defined earlier. A simplified version of the above is:

To reject the system as unreliable if N(t) falls for the first time above the line

$$N_U(t) = a.t + b_2 \tag{6}$$

To accept the system to be reliable if N(t) falls for the first time below the line

$$N_L(t) = a.t - b_1 \tag{7}$$

To continue the test with one more observation on [t , N(t)] as the random graph of [t , N(t)] is between the two linear boundaries given by equations (6) and (7) where

$$a = \frac{\lambda_1 - \lambda_0}{\log\left(\frac{\lambda_1}{\lambda_0}\right)} \tag{8}$$

$$b_1 = \frac{\log\left[\frac{1-\alpha}{\beta}\right]}{\log\left(\frac{\lambda_1}{\lambda_0}\right)} \tag{9}$$

$$b_2 = \frac{\log\left[\frac{1-\beta}{\alpha}\right]}{\log\left(\frac{\lambda_1}{\lambda_0}\right)} \tag{10}$$

The parameters α, β, λ_0 and λ_1 can be chosen in several ways. One way suggested by Stieber is

$$\lambda_0 = \frac{\lambda.\log(q)}{q-1}, \quad \lambda_1 = q\frac{\lambda.\log(q)}{q-1}$$

$$where \; q = \frac{\lambda_1}{\lambda_0}$$

If λ_0 and λ_1 are chosen in this way, the slope of N_U (t) and N_L (t) equals λ. The other two ways of choosing λ_0 and λ_1 are from past projects (for a comparison of the projects) and from part of the data to compare the reliability of different functional areas (components).

4. SEQUENTIAL TEST FOR SOFTWARE RELIABILITY GROWTH MODELS

We know that for any Poisson process, the expected value of N(t) = λ(t) called the average number of failures experienced in time 't'. Which is also called the mean value function of the Poisson process. On the other hand if we consider a Poisson process with a general function (not necessarily linear) m(t) as its mean value function the probability equation of a such a process is

$$P\left[N(t) = Y\right] = \frac{\left[m(t)\right]^y}{y!}.e^{-m(t)}, y = 0,1,2,----$$

Depending on the forms of m(t) we get various Poisson processes called NHPP, for the Burr Type III model. The mean value function is given as

$$m(t) = a\left[1 + t^{-c}\right]^{-b}$$

It can also be written as

$$P_1 = \frac{e^{-m_1(t)}.\left[m_1(t)\right]^{N(t)}}{N(t)!}$$

$$P_0 = \frac{e^{-m_0(t)}.\left[m_0(t)\right]^{N(t)}}{N(t)!}$$

Where $m_1(t)$, $m_0(t)$ represents the mean value function of stated parameters indicating reliable software and unreliable software respectively. The mean value function $m(t)$ comprises the parameters 'a', 'b' and 'c'. The two specifications of NHPP for b are considered as b_0, b_1 *where* ($b_0 < b_1$) *and* two specifications of c say c_0, c_1 *where* ($c_0 < c_1$). For our proposed model, m(t) at b_1 is said to be greater than b_0 and *m(t) at* c_1 is said to be greater than c_0. The same can be denoted symbolically as $m_0(t) < m_1(t)$. The implementation of SPRT procedure is illustrated below.

System is said to be reliable and can be accepted if

$$\frac{P_1}{P_0} \le B$$

i.e.,

$$\frac{e^{-m_1(t)}.\left[m_1(t)\right]^{N(t)}}{e^{-m_0(t)}.\left[m_0(t)\right]^{N(t)}} \le B$$

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i.e., $$N(t) \le \frac{\log\left(\frac{\beta}{1-\alpha}\right) + m_1(t) - m_0(t)}{\log m_1(t) - \log m_0(t)} \quad (11)$$

System is said to be unreliable and rejected if

$$\frac{P_1}{P_0} \ge A$$

i.e., $$N(t) \ge \frac{\log\left(\frac{1-\beta}{\alpha}\right) + m_1(t) - m_0(t)}{\log m_1(t) - \log m_0(t)} \quad (12)$$

Continue the test procedure as long as

$$\frac{\log\left(\frac{\beta}{1-\alpha}\right) + m_1(t) - m_0(t)}{\log m_1(t) - \log m_0(t)} < N(t) < \frac{\log\left(\frac{1-\beta}{\alpha}\right) + m_1(t) - m_0(t)}{\log m_1(t) - \log m_0(t)} \quad (13)$$

Substituting the appropriate expressions of the respective mean value function, we get the respective decision rules and are given in followings lines.

Acceptance Region

$$N(t) \le \frac{\log\left(\frac{\beta}{1-\alpha}\right) + a\left(\left(1+t^{-c_1}\right)^{-b_1} - \left(1+t^{-c_0}\right)^{-b_0}\right)}{\log\left[\frac{\left(1+t^{-c_1}\right)^{-b_1}}{\left(1+t^{-c_0}\right)^{-b_0}}\right]} \quad (14)$$

Rejection Region:

$$N(t) \ge \frac{\log\left(\frac{1-\beta}{\alpha}\right) + a\left(\left(1+t^{-c_1}\right)^{-b_1} - \left(1+t^{-c_0}\right)^{-b_0}\right)}{\log\left[\frac{\left(1+t^{-c_1}\right)^{-b_1}}{\left(1+t^{-c_0}\right)^{-b_0}}\right]} \quad (15)$$

Continuation Region:

$$\frac{\log\left(\frac{\beta}{1-\alpha}\right) + a\left(\left(1+t^{-c_1}\right)^{-b_1} - \left(1+t^{-c_0}\right)^{-b_0}\right)}{\log\left[\frac{\left(1+t^{-c_1}\right)^{-b_1}}{\left(1+t^{-c_0}\right)^{-b_0}}\right]} < N(t) < \frac{\log\left(\frac{1-\beta}{\alpha}\right) + a\left(\left(1+t^{-c_1}\right)^{-b_1} - \left(1+t^{-c_0}\right)^{-b_0}\right)}{\log\left[\frac{\left(1+t^{-c_1}\right)^{-b_1}}{\left(1+t^{-c_0}\right)^{-b_0}}\right]} \quad (16)$$

For the specified model, it may be observed that the decision rules are exclusively based on the strength of the sequential procedure (α, β) and the value of the mean value functions namely m0(t) m1(t). As described by Stieber, these decision rules become decision lines if the mean value function is linear in passing through origin, that is m(t) = λt. The equations (11) and (12) are considered as generalizations for the decision procedure of Stieber. SPRT procedure is applied on live software failure data sets and the results that were analyzed are illustrated in Section 6.

5. PARAMETER ESTIMATION

We present expressions for the parameter estimates of the Burr type III model. Parameter estimation is very significant in software reliability prediction. Once the analytical solution form is known for a given model, parameter estimation is achieved by applying a well-known estimation, Maximum Likelihood Estimation (MLE).The main idea behind Maximum Likelihood parameter assessment is to decide the parameters that maximize the probability (likelihood) of the specimen data. In the other words, MLE methods are versatile and applicable to most models and for different types of data. Here parameters are estimated from the time domain data [5].

The mean value function of Order Burr Type III is given as

$$m(t) = \left(a\left(1 + (t_i)^{-c}\right)^{-b}\right)^r \quad (17)$$

The constants a, b and c in the mean value function are called parameters of the proposed model. To assess the software reliability, it is necessary to compute the expressions for finding the values of a, b and c. For doing this, Maximum Likelihood estimation is used whose Log Likelihood Function(LLF) is given by

$$\text{LLF}=\sum_{i=1}^{n} Log[\lambda(t_i)^r - m(t_n)^r \quad (18)$$

Differentiating m(t) with respect to ‘t’ we get λ (t)

$$\lambda\,(t)= \frac{rabc}{(t_i)^{(c+1)} * [1+(t_i)^{-c}]^{(br+1)}} \quad (19)$$

The log likelihood equation to estimate the unknown parameters a, b, c after substituting (19) in (18) is given by

$$\text{LogL}=-[a[1+(t_n)^{-c}]^{-b}]^r+\sum_{i=1}^{n}[\log r+\log a+\log b+\log c]+\sum_{i=1}^{n}[-(br+1)\log(1+(t_i)^{-c})-(c+1)\log(t_i)] \quad (20)$$

Differentiating LogL with respect to 'a' and equating to 0 (i.e., $\frac{\partial \log L}{\partial a}=0$) we get

$$a^r=\frac{n(1+(t_n)^{-c})^{br}}{r} \quad (21)$$

Differentiating LogL with respect to 'b' and equating to 0 (i.e., $\frac{\partial \log L}{\partial b}=0$) we get

$$g(b)=\frac{n}{b}+\sum_{i=1}^{n} r\log(1+(t_i)^{-1})+\frac{n^2(1+(t_n)^{-1})^{br}}{r}\log(1+(t_n)^{-1}) \quad (22)$$

Again Differentiating g(b) with respect to 'b' and equating to 0 (i.e., $\frac{\partial^2 \log L}{\partial b^2}=0$) we get

$$g'(b)=\frac{-n}{b^2}+n^2(1+(t_n)^{-1})^{br}.\log^2(1+(t_n)^{-1}) \quad (23)$$

Differentiating LogL with respect to 'c' and equating to 0(i.e., $\frac{\partial \log L}{\partial c}=0$) we get

$$g(c)=\frac{n}{c}+\sum_{i=1}^{n}\left(\frac{(r+1)(t_i)-c}{1+(t_i)-c}-1\right)\log t_i-\frac{n(t_n)-c\log t_n}{(1+(t_n)^{-c})} \quad (24)$$

Again Differentiating g(c) with respect to 'c' and equating to 0 (i.e., $\frac{\partial^2 \log L}{\partial c^2}=0$) we get

$$g'(c)=\frac{-n}{c^2}+\sum_{i=1}^{n}\frac{(r+1)(\log t_i)^2(t_i)^{-c}}{(1+(t_i)^{-c})^2}+\frac{n\log(t_n)^2(t_n)^{-c}}{(1+(t_n)^{-c})^2} \quad (25)$$

The parameters 'b' and 'c' are estimated by iterative Newton-Raphson Method using

$$b_{n+1}=b_n-\frac{g(b_n)}{g'(b_n)} \quad (26)$$

$$c_{n+1}=c_n-\frac{g(c_n)}{g'(c_n)} \quad (27)$$

which are substituted in (21) to determine 'a'.

6. SPRT ANALYSIS OF LIVE DATASETS

In this section, the SPRT methodology is applied on four different data sets for 4th ordered and 5th ordered statistics referred from (LYU 1996)] and the decisions are evaluated on the mean value function.

The specifications for parameters b_0, b_1 and c_0, c_1 are chosen on the parameter estimates b and c as $b_0 = b - \delta$, $b_1 = b + \delta$ and $c_0 = c - \delta$, $c_1 = c + \delta$, and apply SPRT such that $b_0 < b < b_1$ and $c_0 < c < c_1$. Assuming the δ value of 0.0125 the choices are given in Table 1.

Using the specification b_0, b_1, and c_0, c_1 the mean value functions $m_0(t)$ and $m_1(t)$ are computed for each 't'. Later the decisions are made based on the decision rules specified by the equations (14), (15), (16) for the data sets. At each 't' of the data set, the strengths (α, β) are considered as (0.6, 0.6). SPRT procedure is applied on four different data sets and the necessary calculations are given in Table 2 and Table 3.

Table 1: Estimates of a, b, c & specifications of b_0, b_1, c_0, c_1

Data sets	Order	Estimate of 'a'	Estimate of 'b'	b_0	B_1	Estimate of 'c'	c_0	c_1
CSR2	4	8.925826	0.099999	0.087499	0.112499	0.101418	0.088918	0.113918
	5	5.702856	0.099998	0.087498	0.112498	0.106519	0.094019	0.119019
CSR3	4	7.37184	0.099999	0.087499	0.112499	0.50032	0.48782	0.051282
	5	4.655946	0.099988	0.087488	0.112488	0.10824	0.09574	0.12074
SYS3	4	14.45599	0.099992	0.099995	0.112492	0.102957	0.090457	0.115457
	5	9.531293	0.099992	0.099995	0.112492	0.10794	0.09544	0.12044
SYS2	4	5.858959	0.099999	0.087499	0.112499	0.100322	0.087822	0.113918
	5	3.873422	0.099999	0.087499	0.112499	0.105221	0.094019	0.119019

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Table 2: SPRT Analysis for 4th Order data sets

Data Set	T	N(t)	R.H.S. of equation (3.4) Acceptance region (≤)	R.H.S. of equation (3.5) Rejection region (≥)	Decision
CSR2	1557	1	-7.43086	8.737562	REJECT
	1639	2	-7.48319	8.776151	
	1973	3	-7.67517	8.918006	
	2183	4	-7.7818	8.996983	
	2714	5	-8.01605	9.170961	
	3455	6	-8.28354	9.370387	
	5045	7	-8.72012	9.697572	
	5087	8	-8.72992	9.704941	
	5222	9	-8.76095	9.72828	
	5608	10	-8.84599	9.792279	
CSR3	112	1	-37.0073	38.69894	CONTINUE
	293.5	2	-61.3552	62.78365	
	473.5	3	-78.9502	80.24203	
	630.5	4	-91.8462	93.05423	
	793.5	5	-103.728	104.8679	
	955.5	6	-114.454	115.5381	
	1171.5	7	-127.514	128.5361	
	1323.5	8	-136.041	137.0256	
	1443.5	9	-142.456	143.4134	
	1810.5	10	-160.674	161.5608	
	1924.5	11	-165.975	166.8427	
	2446.5	12	-188.577	189.3674	
	3304.5	13	-221.32	222.013	
	4226.5	14	-252.349	252.9613	
	4493.5	15	-260.732	261.3239	
	5524.5	16	-291.124	291.6462	
	6846.5	17	-326.476	326.9255	
	7320.5	18	-338.368	338.7947	
	8527.5	19	-367.138	367.5115	
	8705.5	20	-371.217	371.5834	
	10917.5	21	-419.028	419.315	
	12005.5	22	-440.892	441.1449	
	12253.5	23	-445.746	445.9915	
	13776.5	24	-474.613	474.8166	
	14331.5	25	-484.763	484.9525	
	15369.5	26	-503.272	503.4364	
SYS3	89	1	-4.4902	4.971262	REJECT
	193	2	-5.01692	5.223775	
	269	3	-5.25786	5.341915	
	354	4	-5.46433	5.444417	
	482	5	-5.70454	5.565082	
	796	6	-6.11416	5.774245	

SYS2	1576	1	-6.21469	8.445398	REJECT
	4149	2	-7.05728	9.121103	
	5827	3	-7.3793	9.38095	
	10071	4	-7.92966	9.826981	
	11836	5	-8.09994	9.965455	
	15280	6	-8.37693	10.19115	
	16860	7	-8.48622	10.28036	
	19572	8	-8.65469	10.41803	
	23827	9	-8.88216	10.60423	
	28257	10	-9.08434	10.77001	
	31886	11	-9.23047	10.89001	

Table 3: SPRT Analysis for 5th Order data sets

Data Set	T	N(t)	R.H.S. of equation (3.4) Acceptence region (≤)	R.H.S. of equation (3.5) Rjection region (≥)	Decision
CSR2	1579	1	-6.53061	8.765538	REJECT
	1738	2	-6.61658	8.835579	
	2030	3	-6.75817	8.951058	
	2714	4	-7.03115	9.174181	
	3491	5	-7.27683	9.375512	
	5054	6	-7.6538	9.685355	
	5222	7	-7.68806	9.713568	
	5608	8	-7.76331	9.775576	
	6602	9	-7.93837	9.919968	
	7233	10	-8.03805	10.00229	
	7603	11	-8.09307	10.04776	
CSR3	112.5	1	-11.4611	13.46317	CONTINUE
	358.5	2	-13.4942	15.24818	
	615.5	3	-14.5771	16.20418	
	793.5	4	-15.1193	16.68408	
	1109.5	5	-15.8697	17.34955	
	1246.5	6	-16.14	17.58965	
	1438.5	7	-16.4798	17.89167	
	1810.5	8	-17.0423	18.39225	
	1939.5	9	-17.2148	18.54591	
	2759.5	10	-18.1301	19.36232	
	3999.5	11	-19.1534	20.2771	
	4493.5	12	-19.4879	20.57658	
	5526.5	13	-20.0988	21.12399	
	6856.5	14	-20.7586	21.71609	
	7944.5	15	-21.2235	22.13368	
	8705.5	16	-21.5182	22.39858	
	11231.5	17	-22.3639	23.15958	
	12169.5	18	-22.6379	23.40645	
	12892.5	19	-22.8375	23.58629	
	14331.5	20	-23.2087	23.92091	

SYS3	93	1	-5.79193	1.76024	REJECT
	243	2	-5.99538	1.818877	
SYS2	2610	1	-12.9566	15.54412	CONTINUE
	4436	2	-13.9495	16.4418	
	8163	3	-15.2031	17.57807	
	11836	4	-16.0317	18.33066	
	15685	5	-16.6951	18.93413	
	17995	6	-17.0305	19.23954	
	22226	7	-17.5618	19.72358	
	28257	8	-18.1897	20.29631	
	32346	9	-18.5549	20.62965	
	39856	10	-19.1364	21.16074	
	46147	11	-19.5574	21.54566	
	53223	12	-19.978	21.93028	
	58996	13	-20.2882	22.2142	
	67374	14	-20.6968	22.58828	
	80106	15	-21.2442	23.0898	
	91190	16	-21.6653	23.47592	
	98692	17	-21.9272	23.71607	

7. CONCLUSION

The SPRT methodology for the proposed software reliability growth model Burr type III is applied for four software failure data sets. This model has given a decision of rejection for 3 data sets i.e., CSR2, SYS3 and SYS2 at 10th ,6thand 11th instances respectively ,a decision of continue for 1 data set i.e., CSR3 using 4th order .It has given a decision of rejection for 2 datasets i.e., CSR2 and SYS3 at 11th and 2nd instances respectively, a decision of continue for 2 data sets i.e., CSR3 and SYS2 using 5th order. Hence, it is observed that we are able to come to a conclusion in less time regarding the reliability or unreliability of a software product by applying SPRT.

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