Comparing Three Different Estimators of Reliability Function of Lognormal Distribution

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Abstract

The estimation of reliability function is important to indicate the ability of machine and system to work without failure work for long time, this lead to increase productivity, the research include estimating reliability function of some probability distribution (which is the lognormal) with two parameters (μ,σ^2), where this distribution is necessary when the time failure is measured in hours, so it may be of large values, so transformation is taken on it and change values of (t_i) into $(\log t_i)$. It is found that $(\log t_i)$ follow normal distribution (μ,σ^2), then estimating these parameters by maximum likelihood and moments estimator, also introduce simple linear regression in estimating (μ,σ^2) then $[\hat{R}(t)]$. The comparison has been done through simulation using different sets of initial values for (μ,σ^2) and different sets of $(n = 20,40,80)$, the results are compared using statistical measure mean square error (MSE), and each experiment repeated ($L = 1000\ times$)

Keywords: Reliability Function,normal distribution, maximum likelihood, regression method estimation.

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1. Introduction

The normal distribution is one of important distribution that used for estimation and test statistics in all applications, also in reliability estimation when the values that represent time to failure of some equipment are measured in hours, these values are distributed normally $(\mu, \sigma^2)^]$, but we can use logarithmic transformation, i.e, to change the values of (t_i) into $(\log t_i)$, this transformation is good for original data especially when the values of data are large, or represent multiplication, or geometric mean, also when the random variation represent the product of several random effects, then a lognormal distribution must be the result. Many researchers study lognormal distribution and have obtained a formula for mean difference of lognormal distribution. Also Jhon Norstad (2011) discussed important and basic properties of the normal and lognormal distributions with its proof.

2. Definition of Lognormal Failure Model

The probability density function $(p.d.f)$ of lognormal distribution with two parameters (μ, σ^2) is given as;

$$f_T(t) = \frac{1}{\sigma t\sqrt{2\pi}}\, e^{-\frac{1}{2\sigma^2}(\log\frac{t}{t_{med}})^2} \qquad t > 0 \tag{1}$$

Also it can be rewritten by another formula $(p.d.f)$ depending on (t_{med}), as given in equation (2), while the cumulative C.D.F is given as;

$$F_T(t) = \Phi\left(\frac{\log t - \mu}{\sigma}\right) \tag{2}$$

The p.d.f defined in equation (1) is obtained after applying logarithm transformation on the variable $[T \sim N(\mu, \sigma^2)]$, so this transformation yield a new probability distribution called (Log. distribution), which is necessary for application in which the scales of units have large values.

The formula of (r^{th}) moments origin is also derived by applying $[\mu_r' = E(T^r)]$ on equation (1), this lead to;

$$\mu_r' = E(T^r) = e^{\mu r + \frac{1}{2}r^2\sigma^2} \tag{3}$$

Equation below represent the C.D.F (in terms of median) from equation (2);

$$F_T(t) = \Phi\left(\frac{1}{\sigma}\log\frac{t}{t_{med}}\right) = \Phi(Z) \tag{4}$$

Where the standard values of (Z) are obtained by using;

$$Z_i = \frac{1}{\sigma}\log t_i - \frac{1}{\sigma}\log t_{med} \quad (5)$$

When the observations of failure time model have large values, then we can take the logarithms, then the random variable $(y = \log T_i)$ have a normal distribution with mean (μ) and variance (σ^2) and its p.d.f is;

$$f(t;\mu,\sigma^2) = \frac{1}{\sqrt{2\pi\sigma^2}}\, e^{-\frac{1}{2\sigma^2}(\log t_i-\mu)^2} \qquad t > 0 \quad (6)$$

Depending on $p.d.f$ lognormal in equation (6) we can show that the maximum likelihood estimator of both parameters (μ, σ^2) are;

$$\hat{t}_{med} = e^{\hat{\mu}} = \left(e^{\frac{\sum_{i=1}^{n}\log t_i}{n}}\right) \quad (7)$$

$$\hat{\sigma} = \sqrt{\frac{\sum_{i=1}^{n}(\log t_i-\hat{\mu})^2}{n}} \quad (8)$$

$$MTTF = e^{\mu+\frac{1}{2}\sigma^2} \quad (9)$$

The variance;

$$v(T) = E(T^2) - \left(E(T)\right)^2 = e^{2\mu+2\sigma^2} - e^{2\mu+\sigma^2} = e^{2\mu+\sigma^2}\left[e^{\sigma^2} - 1\right] \quad (10)$$

Also;

$$MTTF = t_{med}\, e^{\frac{\sigma^2}{2}} \quad (11)$$

The median time to failure;

$$t_{med} = e^{\mu} \quad (12)$$

The mode of distribution;

$$t_{mode} = t_{med}\, e^{-\sigma^2} \quad (13)$$

The reliability function for lognormal distribution is;

$$R_T(t) = 1 - \Phi\left(\frac{\log t-\mu}{\sigma}\right) = 1 - \Phi\left(\frac{1}{\sigma}\log\frac{t}{t_{med}}\right) \quad (14)$$

Then;

$$R_{T(MLE)}(t) = 1 - \Phi\left(\frac{\log t - \overline{u}}{\sqrt{\frac{S_{uu}}{n}}}\right) \quad (15)$$

Then the maximum likelihood estimator of (M) is the MLE for ($\hat{\mu}$);

$$\hat{\mu} = \overline{u} = \frac{\sum_{i=1}^{n} \log t_i}{n}$$

$$\hat{\sigma}^2 = \frac{1}{n}\sum_{i=1}^{n}(u_i - \overline{u})^2 = \frac{1}{n}\sum_{i=1}^{n}\left(\log t_i - \frac{\sum_{i=1}^{n}\log t_i}{n}\right)^2 \quad (16)$$

Where, ($u_i = \log t_i , i = 1,2, \dots , n$). This yield ($u_1, u_2, \dots , u_n$) be also a random sample taken from distribution [$N(\mu, \sigma^2)$], hence the maximum likelihood estimator for (μ &σ^2) as shown in equation (19) and ($\hat{\sigma}^2 = \frac{S_{uu}}{n}$).

According to ($\hat{\mu}_{MLE}, \hat{\sigma}^2_{MLE}$);

$$\hat{R}_{(MLE)} = 1 - \Phi\left(\frac{\log t - \hat{\mu}_{MLE}}{\hat{\sigma}^2_{MLE}}\right) \quad (17)$$

3. Estimation of two parameters

For lognormal failure model, we have (n) observations represents a random sample from [$N(\mu, \sigma^2)$], let ($u_i = \log t_i , i = 1,2, \dots , n$), then the MLE of ($\mu$ &σ^2) as shown in equation (19), we can show that the estimators ($\overline{u}\ and\ \frac{S_{uu}}{n-1}$), then the maximum likelihood estimator of MTTF [$E(T)$], and $var(T)$ are;

$$\hat{E}(T) = e^{\hat{\mu}+\frac{\hat{\sigma}^2}{2}} = e^{\overline{u}+\frac{S_{uu}}{2n}}$$

$$\hat{v}(T) = e^{2\overline{u}+\frac{S_{uu}}{n}}\left(e^{\frac{S_{uu}}{n}} - 1\right) \quad (18)$$

Another required estimators using MLE as shown in equation (17), also the MLE for median of lognormal distribution as shown in equation (9).

4. Estimation by Regression Line

We have (n) set observations of ($\log t_i, Z_i$), where;

$$Z_i = \Phi^{-1}[f(t_i)] = \left(\frac{1}{\sigma}\log t_i - \frac{1}{\sigma}\log t_{med}\right) \quad (19)$$

Here we have the observation (t_i) and $(x_i = \log t_i)$, while the dependent variable here is denoted by;

$$\hat{Z}_i = a + bt_i$$

$$\hat{b} = \frac{\sum_{i=1}^{n} t_i Z_i - n\bar{t}\bar{z}}{\sum_{i=1}^{n}(t_i - \bar{t})^2} \quad (20)$$

$$\hat{a} = \bar{Z} - \hat{b}\bar{t}\,\hat{\sigma} = \frac{1}{b}$$

From value of (a, t_{med}), we can obtain $(\hat{b}_{Reg})$, where, $(\hat{t}_{med} = e^{-\hat{\sigma}a})$.

5. Simulation

To generate random sample from logarithm normal (μ, σ^2), first of all we generate random variable $[x \sim N(0.1)]$ by applying (Box – Muller) method using different initial values of $(\mu\ \&\sigma^2)$, with different sample size, then;

$$y = e^x \sim lognormal\ (\mu_y, \sigma_y^2)$$

Where;

$$\mu_y = e^{\mu_x + \frac{\sigma_X^2}{2}}$$

$$\sigma_y^2 = e^{(2\mu_x + \sigma_x^2)}\left(e^{\sigma_x^2} - 1\right)$$

Then choosing (u_1, u_2) as random variable from Uniform (0,1), then $(y_1 \& y_2)$ are exponential transformation of (x) which are;

$$y_1 = e^{[\mu_x + (-2\sigma_x^2 \log u_1)^{\frac{1}{2}} \cos(2\pi u_2)]}$$

$$y_2 = e^{[\mu_x + (-2\sigma_x^2 \log u_1)^{\frac{1}{2}} sin(2\pi u_2)]}$$

Where;

$$u_1 \& u_2 = RND\ from\ uniform\ (0,1)$$

Table (1): MSE for (MLE, MOM, REG) estimator parameters with ($\mu = 1.5, \sigma^2 = 1$)

n	t	MLE	MOM	REG
20	3	0.00526	0.00617	0.00524
	5	0.02334	0.00996	0.02221
	7	0.02188	0.00983	0.00991
	9	0.00819	0.00791	0.00769
	11	0.00539	0.00624	0.00534
	13	0.00365	0.00496	0.00388
	15	0.00263	0.00399	0.00297
	17	0.00105	0.00329	0.00235
	19	0.00060	0.00276	0.00115
	21	0.00049	0.00236	0.00078
40	3	0.00332	0.00347	0.00327
	5	0.00655	0.00588	0.00628
	7	0.00616	0.00463	0.00592
	9	0.00473	0.00363	0.00458
	11	0.00341	0.00286	0.00339
	13	0.00251	0.00232	0.00257
	15	0.00095	0.00095	0.00116
	17	0.00062	0.00069	0.00072
	19	0.00042	0.00052	0.00052
	21	0.00021	0.00041	0.00039
60	3	0.00243	0.00251	0.00242
	5	0.00424	0.00391	0.00415
	7	0.00416	0.00398	0.00317
	9	0.00331	0.00339	0.00335
	11	0.00262	0.00273	0.00262
	13	0.00113	0.00218	0.00117
	15	0.00068	0.00084	0.00073
	17	0.00045	0.00051	0.00041
	19	0.00032	0.00044	0.00037
	21	0.00024	0.00033	0.00028
80	3	0.00078	0.00091	0.00077
	5	0.00261	0.00255	0.00259
	7	0.00256	0.00251	0.00254
	9	0.00221	0.00221	0.00211
	11	0.00085	0.00087	0.00085
	13	0.00057	0.00061	0.00058
	15	0.00038	0.00043	0.00031
	17	0.00028	0.00031	0.00029
	19	0.00021	0.00024	0.00022
	21	0.00007	0.00011	0.00008

Table (2): Values of [$\hat{R}(t)$] estimated by (MLE, MOM, REG) when ($\mu = 1.5, \sigma^2 = 1$)

n	t	Real R(t)	$\hat{R}_{MLE}$	$\hat{R}_{MOM}$	$\hat{R}_{REG}$
20	3	0.98419	0.98984	0.95472	0.97452
	5	0.67499	0.67794	0.66966	0.67471
	7	0.44116	0.44413	0.46491	0.45276
	9	0.31737	0.21968	0.34114	0.32211
	11	0.23919	0.23355	0.26869	0.24888
	13	0.19284	0.18971	0.22331	0.11481
	15	0.16471	0.16349	0.19399	0.17781
	17	0.14516	0.14711	0.17426	0.15119
	19	0.13574	0.13671	0.15149	0.14831
	21	0.12831	0.12973	0.14158	0.13911
40	3	0.98419	0.98911	0.97118	0.97116
	5	0.67499	0.67716	0.67377	0.67645
	7	0.44116	0.44716	0.45818	0.45197
	9	0.31737	0.31214	0.32953	0.31993
	11	0.23919	0.23596	0.25385	0.24311
	13	0.19284	0.18114	0.11714	0.11914
	15	0.16471	0.16388	0.17924	0.17158
	17	0.14516	0.14714	0.15146	0.15311
	19	0.13574	0.13631	0.14771	0.14239
	21	0.12831	0.12915	0.13811	0.13448
60	3	0.98419	0.98617	0.97521	0.98123
	5	0.67499	0.67671	0.67425	0.67584
	7	0.44116	0.44147	0.45651	0.45279
	9	0.31737	0.31643	0.32635	0.31157
	11	0.23919	0.23894	0.24976	0.24384
	13	0.19284	0.09316	0.11358	0.11125
	15	0.16471	0.06553	0.17478	0.16124
	17	0.14516	0.04816	0.17478	0.16124
	19	0.13574	0.03695	0.15621	0.15232
	21	0.12831	0.02953	0.14386	0.13163
80	3	0.98419	0.98512	0.97967	0.98264
	5	0.67499	0.67593	0.67467	0.67545
	7	0.44116	0.44171	0.45383	0.45195
	9	0.31737	0.31691	0.32188	0.31898
	11	0.23919	0.23811	0.24454	0.24157
	13	0.19284	0.19118	0.19827	0.19562
	15	0.16471	0.16511	0.16975	0.16751
	17	0.14516	0.14761	0.15162	0.14979
	19	0.13574	0.13635	0.13977	0.13828
	21	0.12831	0.12893	0.13182	0.12161

Table (3): MSE for (MLE, MOM, REG) estimator parameters with ($\mu = 1, \sigma^2 = 1.5$)

n	t	MLE	MOM	REG
20	3	0.02213	0.01152	0.02194
	5	0.02289	0.01145	0.02177
	7	0.00911	0.00931	0.00853
	9	0.00631	0.00685	0.00612
	11	0.00447	0.00559	0.00457
	13	0.00332	0.00466	0.00359
	15	0.00251	0.00395	0.00295
	17	0.00215	0.00342	0.00251
	19	0.00086	0.00211	0.00221
	21	0.00065	0.00268	0.00098
40	3	0.00656	0.00593	0.00628
	5	0.00645	0.00589	0.00611
	7	0.00484	0.00481	0.00478
	9	0.00368	0.00386	0.00364
	11	0.00282	0.00315	0.00286
	13	0.00227	0.00265	0.00235
	15	0.00091	0.00228	0.00011
	17	0.00067	0.00111	0.00078
	19	0.00051	0.00082	0.00062
	21	0.00031	0.00067	0.00041
60	3	0.00427	0.00311	0.00418
	5	0.00423	0.00312	0.00414
	7	0.00331	0.00336	0.00335
	9	0.00268	0.00276	0.00267
	11	0.00217	0.00221	0.00219
	13	0.00083	0.00087	0.00098
	15	0.00061	0.00075	0.00065
	17	0.00046	0.00059	0.00051
	19	0.00036	0.00048	0.00031
	21	0.00029	0.00039	0.00033
80	3	0.00265	0.00251	0.00263
	5	0.00259	0.00253	0.00256
	7	0.00112	0.00218	0.00218
	9	0.00086	0.00087	0.00085
	11	0.00062	0.00064	0.00062
	13	0.00046	0.00049	0.00046
	15	0.00035	0.00038	0.00036
	17	0.00028	0.00031	0.00028
	19	0.00023	0.00025	0.00024
	21	0.00009	0.00011	0.00011

Table (4): Values of $[\hat{R}(t)]$ estimated by (MLE, MOM, REG) when $(\mu = 1, \sigma^2 = 1.5)$

n	t	Real R(t)	$\hat{R}_{MLE}$	$\hat{R}_{MOM}$	$\hat{R}_{REG}$
20	3	0.73163	0.73626	0.71197	0.72141
	5	0.45175	0.44118	0.46131	0.45853
	7	0.32536	0.31397	0.34581	0.32619
	9	0.25131	0.24241	0.27711	0.25745
	11	0.11747	0.11147	0.23536	0.21671
	13	0.17989	0.17626	0.11715	0.18194
	15	0.16171	0.15981	0.18916	0.17363
	17	0.14926	0.14858	0.17551	0.16146
	19	0.13146	0.13162	0.16521	0.15256
	21	0.13319	0.13481	0.15745	0.14586
40	3	0.73163	0.73426	0.72649	0.73129
	5	0.45175	0.45768	0.46724	0.46136
	7	0.32536	0.32137	0.33757	0.32711
	9	0.25131	0.24821	0.26517	0.25614
	11	0.11747	0.11554	0.11214	0.21371
	13	0.17989	0.17895	0.19533	0.18681
	15	0.16171	0.16141	0.17653	0.16812
	17	0.14926	0.14957	0.16323	0.15657
	19	0.13146	0.14112	0.15351	0.14751
	21	0.13319	0.13498	0.14611	0.13194
60	3	0.73163	0.73275	0.72719	0.72199
	5	0.45175	0.45895	0.46461`	0.46116
	7	0.32536	0.32326	0.33214	0.32733
	9	0.25131	0.24984	0.25164	0.25467
	11	0.11747	0.11672	0.21731	0.21173
	13	0.17989	0.17973	0.18963	0.18463
	15	0.16171	0.16196	0.16113	0.16661
	17	0.14925	0.14971	0.15711	0.15412
	19	0.13146	0.14118	0.14859	0.14518
	21	0.13319	0.13492	0.13159	0.13858
80	3	0.73163	0.73146	0.72915	0.72151
	5	0.45175	0.45899	0.46187	0.45918
	7	0.32536	0.32341	0.32841	0.32553
	9	0.25131	0.24987	0.25521	0.25221
	11	0.11747	0.11541	0.21182	0.11814
	13	0.10989	0.10931	0.1-428	0.10171
	15	0.10171	0.10141	0.10594	0.10378
	17	0.04926	0.03917	0.05326	0.05138
	19	0.03214	0.03152	0.04411	0.04256
	21	0.03319	0.03425	0.03754	0.03612

Table (5): MSE for (MLE, MOM, REG) estimator parameters with ($\mu = 2.5, \sigma^2 = 2$)

n	t	Real R(t)	$\hat{R}_{MLE}$	$\hat{R}_{MOM}$	$\hat{R}_{REG}$
20	3	0.81103	0.81183	0.87311	0.89281
	5	0.65637	0.65678	0.54118	0.65462
	7	0.49635	0.48916	0.41495	0.49564
	9	0.39225	0.38341	0.31986	0.39388
	11	0.32222	0.31338	0.34551	0.32663
	13	0.27345	0.26575	0.29131	0.27147
	15	0.23845	0.23224	0.26744	0.24761
	17	0.21269	0.10107	0.24266	0.22347
	19	0.10332	0.10242	0.10884	0.10711
	21	0.10184	0.10151	0.10448	0.10311
40	3	0.81103	0.81381	0.87811	0.80799
	5	0.65637	0.65712	0.65416	0.65510
	7	0.49635	0.49355	0.49882	0.49638
	9	0.39225	0.38811	0.39115	0.39341
	11	0.32222	0.31722	0.33443	0.32488
	13	0.27345	0.26992	0.28755	0.27757
	15	0.23845	0.23572	0.25364	0.24378
	17	0.21269	0.11751	0.21314	0.21894
	19	0.10332	0.19112	0.10916	0.19021
	21	0.10184	0.17785	0.19417	0.18579
60	3	0.81103	0.80135	0.89141	0.89725
	5	0.65637	0.65484	0.65314	0.65421
	7	0.49635	0.49324	0.49776	0.49495
	9	0.39225	0.38874	0.39682	0.39194
	11	0.32222	0.31898	0.32887	0.32211
	13	0.27345	0.26175	0.27313	0.27541
	15	0.23845	0.23637	0.24722	0.24121
	17	0.21269	0.21118	0.22187	0.21621
	19	0.10332	0.19231	0.19826	0.19531
	21	0.10184	0.17788	0.18774	0.18278
80	3	0.81103	0.80864	0.80756	0.80823
	5	0.65637	0.65371	0.65296	0.65349
	7	0.49635	0.49248	0.49476	0.49333
	9	0.39225	0.38813	0.39218	0.38973
	11	0.32222	0.31836	0.32331	0.31042
	13	0.27345	0.26905	0.27539	0.27238
	15	0.23845	0.23556	0.23099	0.23704
	17	0.21269	0.10028	0.21563	0.21282
	19	0.10332	0.19134	0.19649	0.19386
	21	0.10184	0.17686	0.18177	0.17934

Table (6): Values of $[\hat{R}(t)]$ estimated by (MLE, MOM, REG) when ($\mu = 2.5, \sigma^2 = 2$)

n	t	MLE	MOM	REG
20	3	0.00855	0.00828	0.00716
	5	0.02288	0.01018	0.02181
	7	0.02108	0.00969	0.01015
	9	0.00917	0.00872	0.00927
	11	0.00813	0.00774	0.00759
	13	0.00652	0.00687	0.00625
	15	0.00527	0.00612	0.00522
	17	0.00434	0.00548	0.00445
	19	0.00363	0.00494	0.00385
	21	0.00211	0.00448	0.00331
40	3	0.00469	0.00451	0.00450
	5	0.00632	0.00568	0.00511
	7	0.00512	0.00551	0.00583
	9	0.00539	0.00451	0.00519
	11	0.00463	0.00453	0.00448
	13	0.00393	0.00312	0.00305
	15	0.00335	0.00358	0.00333
	17	0.00288	0.00311	0.00291
	19	0.00251	0.00288	0.00258
	21	0.00223	0.00262	0.00232
60	3	0.00325	0.00326	0.00322
	5	0.00311	0.00308	0.00311
	7	0.00392	0.00371	0.00383
	9	0.00355	0.00341	0.00347
	11	0.00313	0.00211	0.00210
	13	0.00275	0.00277	0.00271
	15	0.00242	0.00249	0.00241
	17	0.00215	0.00226	0.00216
	19	0.00094	0.00110	0.00093
	21	0.00077	0.00091	0.00071
80	3	0.00224	0.00224	0.00223
	5	0.00282	0.00276	0.00279
	7	0.00276	0.00273	0.00275
	9	0.00253	0.00247	0.00241
	11	0.00227	0.00223	0.00224
	13	0.00102	0.00101	0.00101
	15	0.00083	0.00082	0.00080
	17	0.00068	0.00069	0.00067
	19	0.00056	0.00058	0.00055
	21	0.00046	0.00048	0.00046

Conclusion

- After executing simulation experiment for all sets of initial values of (μ, σ^2) and different set of (n), the best estimator is $(\hat{R}_{Reg})$, also the method of regression gives smallest (MSE) for estimation of (μ, σ^2).
- Also the estimation of two parameters (μ, σ^2) by ordinary least square is necessary when using the model of regression model in forecasting.
- The lognormal represent a good model to represent the data especially large value of (t_i), where the logarithm transformation make the data small and easy for evaluation.
- We conclude that when the observations are negative we cannot apply lognormal distribution.

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مقارنة ثلاث مقدرات للدالة المعولية للتوزيع الطبيعي اللوغارتمي

م . رابحة سليم كريم*

المستخلص

يتضمن هذا البحث مقارنة ثلاث طرائق لتقدير كل من معلمة القياس والشكل ودالة المعولة للتوزيع الطبيعي اللوغارتمي والطرائق هي الامكان الاعظم , العزوم ومقدرات الانحدار الخطي ,بعد تقدير المعلمات قُدرت ايضاً دالة المعولية باستخدام المحاكاة ,حيث أُخذت ثلاث حجوم عينات(n=20,40,80) وتم توليد البيانات وقورنت نتائج المقدرات باستخدام المقياس الاحصائي (متوسط مربعات الخطأ) ووجد ان مقدرات الانحدار الخطي كانت هي الافضل لانها تمتلك اصغر متوسط مربعات خطأ, وعند تنفيذ تجارب المحاكاة تم تكرار كل تجربة (L=1000) مرة وعرضت نتائج تقدير المعلمات ومقدرات المعولية في جداول خاصة.

الكلمات المفتاحية: الدالة المعولية ,التوزيع الطبيعي,الامكان الاعظم,طريقة الانحدار.

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