



Estimation and Prediction of Logistic Nadarajah-Haghighi distribution

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Summary

This study explores four estimation methods for the Logistic Nadarajah-Haghighi (LNH) distribution, utilizing complete sampling and Maximum Likelihood Estimation (MLE) based on two censoring types: | & ||. The study assesses the squared bias and variances of these estimates through Monte Carlo simulations. Additionally, it provides insights into ordinary moments, the quintile function, mean residual life, and Renyi entropy.

Keywords: Logistic Nadarajah-Haghighi - Renyi entropy - mean residual life - Progressive Type-II Censoring

1. Introduction

The Nadarajah-Haghighi (NH) distribution, proposed as a generalized form of the exponential distribution by Nadarajah and Haghighi (2011) [18], offers an alternative to conventional distributions like gamma, Weibull, and exponentiated exponential. The distribution has seen successful extensions for more accurate statistical modelling and inference.

The parent Nadarajah-Haghighi distribution (with parameters $\alpha, \beta > 0$) has pdf given by:

$$g(x; \alpha, \beta) = \alpha\beta(1 + \beta x)^{\alpha-1}e^{1-(1+\beta x)^\alpha}, \quad (1)$$

and cdf given by:

$$G(x) = 1 - e^{1-(1+\beta x)^\alpha} \quad \text{where } x > 0, \alpha, \beta > 0 \quad (2)$$

The research builds upon previous work in this domain. Ziyad (2017) [21] focused on statistical inferences for the exponentiated Nadarajah-Haghighi (ENH) distribution with progressively type-II censoring. Cícero (2018a) [2] proposed the beta Nadarajah-Haghighi distribution as a generalization. Hilany (2018b) [4] derived ordinary differential equations (ODE) for the probability functions of the Marshall-Olkin Nadarajah-Haghighi distribution using differentiation. Morad (2018c) [15] introduced the Extended Exponentiated-Nadarajah-Haghighi (EENH) distribution as a four-parameter model. Hisham (2019a) [5] proposed the Burr X Nadarajah-Haghighi

distribution, expanding the original distribution. Ms.Sana (2019b) [16] delved into maximum likelihood and Bayesian estimation of the two unknown parameters of the Nadarajah and Haghghi distribution. Fernando (2020a) [3] presented the logistic Nadarajah–Haghghi distribution, a three-parameter model, and proposed a parametric regression model. Marija (2020b) [12] estimated shape and scale parameters of Nadarajah-Haghghi based on simple random samples (SRS) and ranked set sampling (RSS). Sanku (2021) [20] presented estimation methods for parameters and acceleration factor in Nadarajah–Haghghi distribution based on constant-stress partially accelerated life tests. Almarashi (2022a) [1] focused on maximum likelihood and Bayesian estimation methods for the unknown parameters, reliability, and hazard rate functions of the Nadarajah–Haghghi (NH) distribution, employing adaptive type-I progressive hybrid censoring (ATIPHC) scheme. Muhammad (2022b) [17] proposed and studied a generalization of the inverted Nadarajah–Haghghi distribution.

2.Logistic-X Family

M. A. Aljarrah. (2014) [13] introduced a comprehensive approach for constructing distribution families. Their method involves utilizing a probability density function (PDF) denoted as $r(\cdot)$ for a continuous random variable. By applying a function $W(G(x))$, which adheres to specified conditions, they systematically create the T-X family. The cumulative distribution function (CDF) of this T-X family is explicitly defined as part of their innovative methodology as follows:

$$F(x) = \int_a^{w[G(x)]} r(t)dt , \tag{3}$$

where

$W [G(x)]$ is differentiable and monotonically non-decreasing, and $W [G(x)] \rightarrow a$ as $x \rightarrow -\infty$ and $W [G(x)] \rightarrow b$ as $x \rightarrow \infty$. The pdf corresponding to (3) is given by:

$$f(x) = \left\{ \frac{d}{dx} w[G(x)] \right\} r \{ w[G(x)] \} \tag{4}$$

M. H. Tahir (2016) [11] introduced the Logistic-X Family, a novel family of distributions. This family is characterized by T, a random variable that follows a logistic distribution with a specified shape parameter.

Let $G(x; \varphi)$ be the baseline cdf on a parameter vector φ . we define the cdf of the LX family by

$$F(x; \lambda, \varphi) = [1 + \{-\log[\bar{G}(x; \varphi)]\}^{-\lambda}]^{-1}. \quad (5)$$

The Lx family pdf is expressed as

$$f(x; \lambda, \varphi) = \frac{\lambda g(x; \varphi)}{\bar{G}(x; \varphi)} \{-\log[\bar{G}(x; \varphi)]\}^{-\lambda-1} [1 + \{-\log[\bar{G}(x; \varphi)]\}^{-\lambda}]^{-2}. \quad (6)$$

3. Logistic Nadarajah-Haghighi distribution (LNH).

By replacing (1) and (2) in (5) and (6) the cdf and pdf of the Logistic Nadarajah-Haghighi distribution (LNH) distribution are given by:

$$F(x; \alpha, \beta, \lambda) = [1 + \{(1 + \beta x)^\alpha - 1\}^{-\lambda}]^{-1}, \quad (7)$$

for $x > 0; \alpha, \beta, \lambda > 0$

and

$$f(x; \alpha, \beta, \lambda) = \alpha\beta\lambda(1 + \beta x)^{\alpha-1} [(1 + \beta x)^\alpha - 1]^{-\lambda-1} [1 + \{(1 + \beta x)^\alpha - 1\}^{-\lambda}]^{-2}. \quad (8)$$

The survival function and the hazard function of the LNH distribution are given by

$$s(x) = 1 - [1 + \{(1 + \beta x)^\alpha - 1\}^{-\lambda}]^{-1}, \quad (9)$$

and

$$h(x) = \frac{\alpha\beta\lambda(1 + \beta x)^{\alpha-1} [(1 + \beta x)^\alpha - 1]^{-\lambda-1} [1 + \{(1 + \beta x)^\alpha - 1\}^{-\lambda}]^{-2}}{1 - [1 + \{(1 + \beta x)^\alpha - 1\}^{-\lambda}]^{-1}}. \quad (10)$$

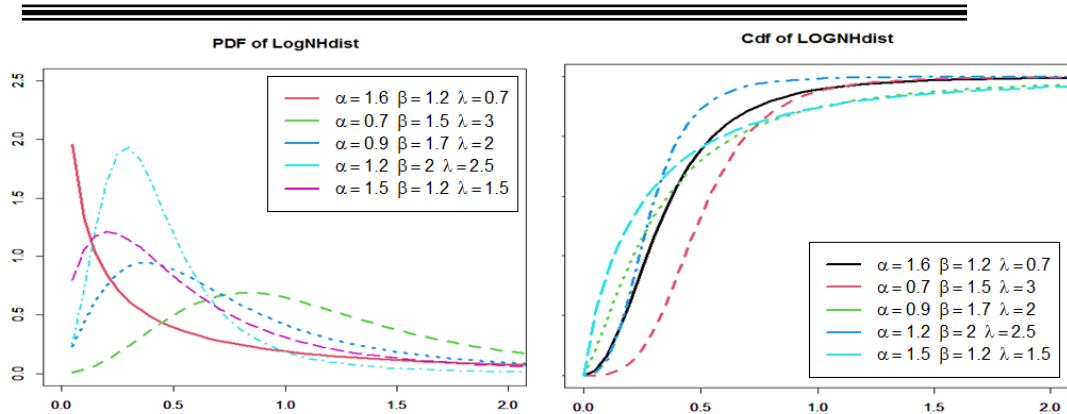


Fig. 1: Plots of the pdf $f(x)$ and cdf $F(x)$ of the LNH distribution.

Based on Figure 1, we can observe that the LNH distribution displays three distinct shapes: decreasing, bathtub, and unimodal. Furthermore, the newly proposed model exhibits similarities to other well-known distributions, such as Weibull, Gamma, and Exponential. These resemblances emerge when specific parameter values are chosen.

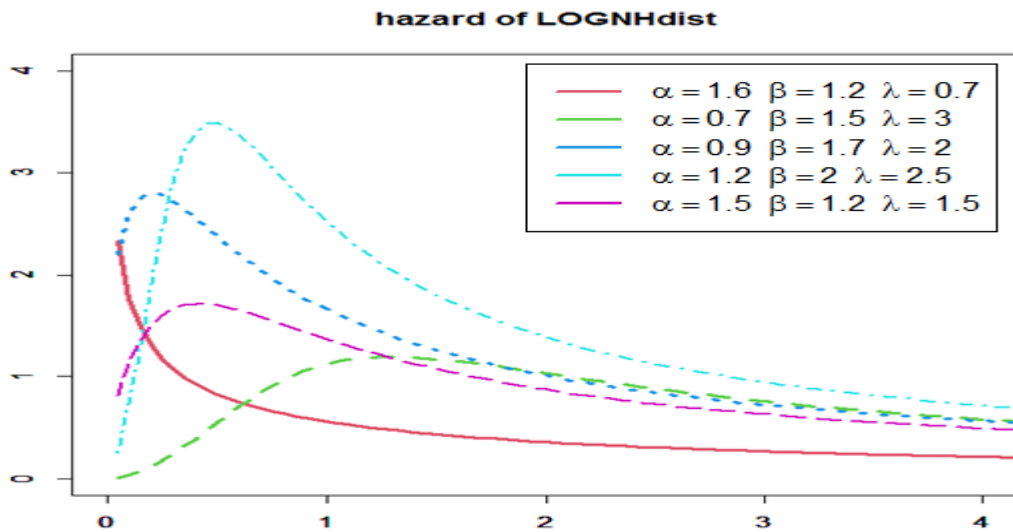


Fig. 2: Hazard Rate Function Plot of the LNH distribution.

4. Quantile function

The quantile function, denoted as $Q(p)$ or Q for the logistic Nadarajah-Haghighi distribution, is determined by solving the equation $G(Q) = P$, where G represents the cumulative distribution function. The quantile function Q , when evaluated at a vector p of percentiles, provides the corresponding values that satisfy this equation:

$$Q = \frac{[1 + (\frac{1}{p} - 1)^{\frac{-1}{\lambda}}]^{\frac{1}{\alpha}}}{\beta} - \frac{1}{\beta} \quad \alpha, \beta, \lambda > 0 \quad (11)$$

The r th moment of the logistic Nadarajah-Haghighi distribution can be derived from equation (11) by replacing Q by the variable x and replacing p by u. Here, p represents a uniform random variable in the range (0,1) as follows:

$$x_u = \frac{[1 + (\frac{1}{u} - 1)^{\frac{-1}{\lambda}}]^{\frac{1}{\alpha}}}{\beta} - \frac{1}{\beta} \quad \alpha, \beta, \lambda > 0 \quad (12)$$

The Bowley Skewness measure (Bsk) and the Moor's Kurtosis measure (Mkur) [14] are defined by:

$$Bsk = \frac{Q_{0.75} - 2Q_{0.5} + Q_{0.25}}{Q_{0.75} - Q_{0.25}},$$

$$Mkur = \frac{Q_{0.875} - 2Q_{0.625} - 2Q_{0.375} + Q_{0.125}}{Q_{0.75} - Q_{0.25}}.$$

Table 1 presents the skewness and kurtosis values for the logistic Nadarajah-Haghighi distribution under different parameter settings.

Table.1 Quantile for different parameter value.

α, β, λ	$Q_{0.125}$	$Q_{0.25}$	$Q_{0.325}$	$Q_{0.5}$	$Q_{0.625}$	$Q_{0.75}$	$Q_{0.875}$	skewn	kurtosis
2.5,3,2.4	0.05283	0.07221	0.08913	0.10650	0.12667	0.15370	0.20076	0.15845	0.46373
2,1.5,2.3	0.13030	0.18192	0.22797	0.27614	0.33304	0.41084	0.54996	0.17682	0.52094
2.5,3,2	0.04561	0.06666	0.08596	0.10650	0.13106	0.16495	0.22590	0.18923	0.55435
0.9,1.7,1.4	0.16491	0.30491	0.46853	0.68242	0.99684	1.54771	2.94027	0.39248	1.31944
2.5,1.7,0.9	0.02620	0.06409	0.11576	0.18795	0.29518	0.47472	0.87082	0.39675	1.18373
1.2,1.5,0.9	0.06335	0.16028	0.30260	0.52120	0.88879	1.62027	3.75747	0.50558	1.80099
0.5,1,0.7	0.12794	0.45965	1.19641	3.00000	8.45294	32.68626	291.99005	0.84234	8.76507

5.Raw moment

the 1-st raw moment of the Random variable X is [9]:

$$\mu_{x=E(x)} = \int_0^{\infty} xf(x) dx,$$

and the r-th raw moment of the LNH Random variable X is

$$\mu_r = E(x^r) = \alpha\beta\lambda \int_0^{\infty} x^r (1 + \beta x)^{\alpha-1} [(1 + \beta x)^{\alpha} - 1]^{-\lambda-1} [1 + \{(1 + \beta x)^{\alpha} - 1\}^{-\lambda}]^{-2} dx. \quad (13)$$

We can calculate skewness and kurtoses from moments as:

$$sk = \frac{\mu_3^2}{\mu_2^3},$$

$$ku = \frac{\mu_4}{\mu_2^2}.$$

Table 2 presents the moment, mean, variance, skewness, and kurtosis values for the logistic Nadarajah-Haghighi distribution under different parameter settings.

Table.2 moment, mean, variance, skewness and kurtosis

α, β, λ	0.6,1.3,2.8	1.4,1.1,0.9	0.8,1.6,2.1	1,1.8,2.3
Mean (μ)	2.053321	1.151684	1.228858	0.750808
m2 (μ_2')	6.814764	4.206815	3.126969	1.122327
m3 (μ_3')	32.39307	23.68192	13.65019	3.405697
m4 (μ_4')	195.4822	161.8371	81.328	16.96168
Variance (μ_2)	2.598637	2.880439	1.616877	0.558615
CV	0.785084	1.473656	1.034753	0.995468
sk	1.844917	2.49605	2.837484	4.129757
kur	4.181049	6.755639	10.66426	27.68829

6. Mean residual life

Reliability analysts, statisticians, and other professionals have demonstrated increased interest in the concept of mean residual life (MRL) [10]. When considering an entity with an age of t , the remaining life beyond time t is a stochastic variable. The mean residual life at time t is corresponding to the expected value of this random residual life.

Let F be a life distribution (i.e., $F(t) = 0$ for $t < 0$) with a finite first moment. Let $\bar{F}(t) = 1 - F(t)$. X is the random life with distribution F . The MRL function is defined as:

$$m(t) = E(x - t / x > t)$$

When $\bar{F}(t) > 0$, We can express $m(t)$ in the form:

$$m(t) = \int_0^{\infty} u f(u) du / \bar{F}(t) - t.$$

Like the failure rate function (recall that it is defined as $r(t) = f(t) / \bar{F}(t)$ when $\bar{F}(t) > 0$), the MRL function is a conditional concept. Both functions are conditioned on survival to time t .

The mean residual life at time t of the LNH Random variable X is

$$m(t) = \frac{1}{1 - [1 + \{(1 + \beta t)^\alpha - 1\}^{-\lambda}]^{-1}} \int_t^\infty [1 + \{(1 + \beta t)^\alpha - 1\}^{-\lambda}]^{-1} dt \dots\dots\dots(14)$$

Table 3 presents the Empirical Mean Residual life values for the logistic Nadarajah-Haghighi distribution under different parameter settings.

Table.3. Empirical Mean Residual life. $\alpha = 1.6, \beta = 1.2, \lambda = 0.7, n = 50$

No	Death. Time	EMRL	No	Death. Time	EMRL
1	0.000681	2.195853	11	0.09163	2.654152
2	0.005547	2.236633	12	0.099936	2.715474
3	0.00678	2.282961	13	0.111459	2.777031
4	0.027444	2.311478	14	0.116634	2.848852
5	0.047444	2.342399	15	0.117984	2.928859
6	0.059083	2.383732	16	0.131646	3.000939
7	0.062266	2.435911	17	0.13477	3.088657
8	0.070895	2.485074	18	0.140341	3.179433
9	0.08215	2.534157	19	0.150173	3.271845
10	0.0914	2.588029	20	0.152099	3.378917

As observed, the Empirical Mean Residual Life value needs to significantly increase with sample size to enable powerful procedures.

7. Renyi Entropy

It is possible to show that Entropy measure [19] extends to case of continuous random variable as follows:

$$R_\alpha(x) = \lim_{n \rightarrow \infty} (I_\alpha(p_n) - \log n) = \frac{1}{1 - \alpha} \log \int p^\alpha(x) dx ,$$

and the quadratic entropy takes the form:

$$R_2(x) = -\log \int p^2(x) dx .$$

Notice, however, that now entropy is no longer positive, in fact it can become arbitrarily large negative.

Entropy measure of the LNH Random variable X is

$$R_\alpha(x) = \frac{1}{1 - \alpha} \log \int (\alpha\beta\lambda(1 + \beta x)^{\alpha-1} [(1 + \beta x)^\alpha - 1]^{-\lambda-1} [1 + \{(1 + \beta x)^\alpha - 1\}^{-\lambda}]^{-2})^\alpha dx \dots(15)$$

Table 4 presents the Renyi Entropy values for the logistic Nadarajah-Haghighi distribution under different parameter settings.

Table. 4. Renyi Entropy

parameter	v = 1.5	v = 2	v = 3
(0.9,1.7,2)	0.954233	0.844134	0.72618
(1.5,1.2,1.8)	0.704143	0.573664	0.438247
(1.2,2,2.5)	0.33635	0.223088	0.101986
(0.9,1.2,0.7)	1.189355	0.520089	-0.5375
(1.6,1.2,0.7)	0.408512	-0.12698	-1.11977
(0.7,1.5,3)	-0.10747	-0.20814	-0.31834

It's important to recognize that as the Renyi entropy value increases, the level of uncertainty in the system also grows.

8.Methods of Estimation

This section involves the estimation of parameters for the Logistic Nadarajah-Haghighi (LNH) distribution using a complete sample technique. Five distinct methods are employed for this estimation: Maximum Likelihood (MLE), Least-Squares (LS), Weighted Least Squares, Maximum Product of Spacing (MPS), and Percentile-Based Estimation (PE). The effectiveness of each method is evaluated using the R software.

8.1-Maximum Likelihood Estimation

let x_1, \dots, x_n be a random sample of size n from X . Here, we obtain the MLEs of the unknown parameters of the LX family from complete samples only. The total log-likelihood function for Θ is given by

$$\ell(\Theta) = n \log \lambda + \sum_{i=1}^n \log[h_g(x; \varphi)] - (\lambda + 1) \sum_{i=1}^n \log[H_g(x; \varphi)] - 2 \sum_{i=1}^n \log(1 + [H_g(x; \varphi)]^{-\lambda})$$

In LNH is given by :

$$\ell(\Theta) = n \log \lambda + \sum_{i=1}^n \log[\alpha \beta (1 + \beta x)^{\alpha-1}] - (\lambda + 1) \sum_{i=1}^n \log[(1 + \beta x)^{\alpha} - 1] - 2 \sum_{i=1}^n \log(1 + [(1 + \beta x)^{\alpha} - 1]^{-\lambda}), \quad (16)$$

For obtaining the partial derivatives, differentiating (18) with respect to α, β and λ , we get:

$$U_{\lambda} = \frac{n}{\lambda} - \sum_{i=1}^n \log[(1 + \beta x)^{\alpha} - 1] + 2 \sum_{i=1}^n \log(1 + [(1 + \beta x)^{\alpha} - 1]^{-\lambda})^{-1} \{ \log[(1 + \beta x)^{\alpha} - 1]$$

$$U_{\alpha} = \sum_{i=1}^n \left[\frac{\beta(1+\beta x)^{\alpha-1}(\alpha \log(1+\beta x) + 1)}{\alpha\beta(1+\beta x)^{\alpha-1}} \right] - (\lambda + 1) \sum_{i=1}^n \left[\frac{(1+\beta x)^{\alpha} \log(1+\beta x)}{(1+\beta x)^{\alpha} - 1} \right] + 2\lambda \sum_{i=1}^n \left[\frac{(1+\beta x)^{\alpha} - 1}{((1+\beta x)^{\alpha} - 1)\{1 + [(1+\beta x)^{\alpha} - 1]^{\lambda}\}} \right],$$

and

$$U_{\beta} = \sum_{i=1}^n \left[\frac{\alpha(1+\beta x)^{\alpha}(1+\alpha\beta x)}{\alpha\beta(1+\beta x)^{\alpha-1}} \right] - (\lambda + 1) \sum_{i=1}^n \left[\frac{\alpha x(1+\beta x)^{\alpha-1}}{(1+\beta x)^{\alpha} - 1} \right] + 2\lambda \sum_{i=1}^n \left[\frac{\alpha x(1+\beta x)^{\alpha-1}}{((1+\beta x)^{\alpha} - 1)\{1 + [(1+\beta x)^{\alpha} - 1]^{\lambda}\}} \right].$$

8.2-Method of Ordinary Least Squares (L):

The best estimates according to LS method [6] are those which minimize the following quantity:

$$Q_1 = \sum_{i=1}^n \left(G(x_{(i)}) - \frac{i}{n+1} \right)^2,$$

with respect to α , β and λ . $x_{(i)}$ is the i -th order statistic of LNH

Similarly, these estimators are also obtained by solving the following equation (for $k = 1, 2, 3, 4$) (see [6]) as:

$$Q_1 = \{ [1 + \{(1 + \beta(x_i - \frac{i}{n+1}))^{\alpha} - 1\}^{-\lambda}]^{-1} \} \psi_k(x_{(i)} / \Omega) = 0$$

Where

$$\psi_1(x_{(i)} / \Omega) = \frac{\partial G(x)}{\partial \lambda} = -(w^{\alpha} - 1)^{-\lambda} [1 + (w^{\alpha} - 1)^{-\lambda}]^{-2} \log(w^{\alpha} - 1),$$

$$\psi_2(x_{(i)} / \Omega) = \frac{\partial G(x)}{\partial \alpha} = \lambda w^{\alpha} \log w (w^{\alpha} - 1)^{-\lambda-1} [1 + (w^{\alpha} - 1)^{-\lambda}]^{-2},$$

$$\psi_3(x_{(i)} / \Omega) = \frac{\partial G(x)}{\partial \beta} = \alpha \lambda \left(x_i - \frac{i}{n+1} \right) w^{\alpha-1} (w^{\alpha} - 1)^{-\lambda-1} [1 + (w^{\alpha} - 1)^{-\lambda}]^{-2}.$$

where $w = 1 + \beta(x_i - \frac{i}{n+1})$. The solution of ψ_k for $k = 1, 2, 3, 4$ may be obtained numerically.

8.3-Method of Weighted Least Squares (WLS):

The WLS estimators of α , β and λ . of LNH distribution can be obtained by minimizing the quantity:

$$Q_2 = \sum_{i=1}^n \frac{(n+1)^2(n+2)}{n-i+1} \left(G(x_{(i)} - \frac{i}{n+1})\right)^2$$

with respect to α , β , and λ In LNH Q_2 is given by

$$Q_2 = \sum_{i=1}^n \frac{(n+1)^2(n+2)}{n-i+1} \left([1 + \{(1 + \beta(x_i - \frac{i}{n+1}))^\alpha - 1\}^{-\lambda}]^{-1}\right)^2.$$

8.4-Method of Percentile Estimation (PCE) :

This method has been introduced by kao [7, 8]. The PCEs estimators of α , β , and λ of LNH distribution can be obtained by minimizing the quantity:

$$Q_3 = \sum_{i=1}^n \left[x_{(i)} - \frac{[1 + (\frac{1}{p} - 1)^{\frac{1}{\lambda}}]^{\frac{1}{\alpha}}}{\beta} + \frac{1}{\beta} \right]^2$$

9.Simulation Study

To assess the performance of the proposed estimation methods, a simulation study is conducted through Monte Carlo analysis. This involves generating 5000 random data points from the Logistic Nadarajah-Haghighi (LNH) distribution under specific conditions:

1. Sample sizes are $n = 50, 100, 150, 300$
2. Assuming the following selected cases of parameters α, β and λ of the LNH distribution:
 - a. $\alpha = 0.9, \beta = 1.7, \lambda = 2$
 - b. $\alpha = 0.7, \beta = 1.5, \lambda = 3$
 - c. $\alpha = 1.2, \beta = 2, \lambda = 2.5$
 - d. $\alpha = 1.5, \beta = 1.2, \lambda = 1.7$

Utilizing the generated data and employing diverse estimation methods, Tables (5) to (8) present the results of the Mean Square Error (MSE) and Relative Biases (BIAS) for each of the five estimation methods.

Table.5 The MSE and BIAS for different estimates of the LNH distribution with different values

Estimation	parm	$\alpha = 0.7$	$\beta = 1.5$	$\lambda = 3$	parm	$\alpha = 0.7$	$\beta = 1.5$	$\lambda = 3$
		n = 50				n = 150		
MLE	Bias	1.300111	2.32581	0.238748	Bias	0.474887	1.208663	0.122511
	MSE	6.243952	42.41076	2.794604	MSE	1.453568	19.58916	1.381536
MPS	Bias	1.680944	2.46109	0.327444	Bias	0.591814	1.354937	0.161187
	MSE	8.333252	44.09193	3.651898	MSE	1.839232	21.92581	1.698615
LSE	Bias	0.337176	0.769023	0.081114	Bias	0.239378	0.405721	0.044964
	MSE	0.539617	6.541684	0.880223	MSE	0.279419	2.966477	0.518669
WLSE	Bias	0.437686	1.043156	0.116244	Bias	0.296363	0.528444	0.059113
	MSE	0.85452	10.77633	1.208418	MSE	0.405863	4.601454	0.666113
PE	Bias	0.976288	2.056061	0.029938	Bias	0.630759	2.240984	0.042397
	MSE	2.756773	36.62246	1.091939	MSE	1.992241	40.09295	1.129633
		n = 100				n = 300		
MLE	Bias	0.771949	1.543055	0.160362	Bias	0.12158	0.80965	0.09743
	MSE	2.921254	25.72089	1.882993	MSE	0.20373	10.40272	0.88347
MPS	Bias	1.059836	1.669283	0.204111	Bias	0.14244	0.95882	0.12739
	MSE	4.474894	28.8205	2.275575	MSE	0.24921	12.86450	1.09661
LSE	Bias	0.27465	0.479312	0.050318	Bias	0.14038	0.32109	0.04316
	MSE	0.327075	3.797982	0.621231	MSE	0.16372	1.96643	0.37393
WLSE	Bias	0.388808	0.629964	0.069554	Bias	0.13139	0.42016	0.05812
	MSE	0.608648	5.90818	0.836142	MSE	0.17866	2.94994	0.46487
PE	Bias	0.708949	2.446648	0.048272	Bias	0.35397	2.38321	0.10739
	MSE	2.245572	43.03393	1.184109	MSE	1.13059	38.40531	1.25764

Table.6 The MSE and BIAS for different estimates of the LNH distribution with different values

Estimation	parm	$\alpha = 0.9$	$\beta = 1.7$	$\lambda = 2$	parm	$\alpha = 0.9$	$\beta = 1.7$	$\lambda = 2$
		n = 50			n = 150			
MLE	Bias	1.077475	2.309147	0.224001	Bias	0.235602	0.994046	0.098974
	MSE	9.548177	88.58781	1.37842	MSE	0.973982	32.49193	0.478773
MPS	Bias	1.52575	2.74883	0.312691	Bias	0.361047	1.217011	0.142958
	MSE	13.3383	112.6092	1.891631	MSE	1.683738	43.87294	0.708559
LSE	Bias	0.588411	1.123808	0.107173	Bias	0.303019	0.542196	0.060359
	MSE	2.23715	19.1187	0.51515	MSE	0.789763	6.744807	0.260763
WLSE	Bias	0.677901	1.34998	0.126737	Bias	0.260243	0.572598	0.064027
	MSE	3.146453	28.23972	0.634019	MSE	0.760585	8.333041	0.268867
PE	Bias	1.536274	2.162142	0.059034	Bias	0.808543	2.500032	0.014497
	MSE	10.55131	63.1215	0.707779	MSE	4.652092	67.59279	0.869434
		n = 100			n = 300			
MLE	Bias	0.521898	1.56595	0.150527	Bias	0.082806	0.340718	0.041075
	MSE	3.283916	58.46077	0.836739	MSE	0.164558	7.695085	0.165054
MPS	Bias	0.811676	1.73783	0.200792	Bias	0.123931	0.383874	0.056317
	MSE	5.380803	66.65809	1.100255	MSE	0.225051	9.650466	0.218034
LSE	Bias	0.397763	0.779637	0.088331	Bias	0.182143	0.32318	0.038309
	MSE	1.182111	11.15774	0.385945	MSE	0.389433	3.398002	0.155515
WLSE	Bias	0.393477	0.923255	0.102025	Bias	0.119471	0.276183	0.034995
	MSE	1.390203	16.22352	0.457169	MSE	0.267075	3.04711	0.133463
PE	Bias	1.077184	2.479614	0.002934	Bias	0.433132	2.579345	0.068891
	MSE	6.955389	71.64537	0.831405	MSE	2.154259	72.11955	0.956934

Table.7 The MSE and BIAS for different estimates of the LNH distribution with different values

Estimation	parm	$\alpha = 1.2$	$\beta = 2$	$\lambda = 2.5$	parm	$\alpha = 1.2$	$\beta = 2$	$\lambda = 2.5$
		n = 50				n = 150		
MLE	Bias	2.048544	2.584501	0.23496	Bias	0.622489	0.98395	0.097447
	MSE	32.31082	139.3048	2.016919	MSE	7.275323	38.83006	0.659646
MPS	Bias	2.481319	2.475248	0.293049	Bias	0.832926	1.105539	0.120776
	MSE	36.82994	130.3489	2.36914	MSE	8.141455	49.79035	0.825268
LSE	Bias	0.447452	0.822037	0.085451	Bias	0.254086	0.471465	0.055207
	MSE	2.141436	15.27939	0.522638	MSE	1.036212	6.461698	0.281876
WLSE	Bias	0.607032	1.109656	0.116071	Bias	0.284597	0.604212	0.071086
	MSE	3.841619	26.04498	0.701835	MSE	1.433278	10.16354	0.361773
PE	Bias	0.929867	3.039848	0.108791	Bias	0.353617	3.121066	0.203658
	MSE	9.25213	133.9141	0.930158	MSE	4.751573	127.9829	1.19168
		n = 100				n = 300		
MLE	Bias	1.184055	1.405043	0.130911	Bias	0.214544	0.320322	0.032726
	MSE	14.74861	65.68415	1.086904	MSE	1.079685	9.411566	0.221032
MPS	Bias	1.582826	1.407527	0.159611	Bias	0.32885	0.287066	0.03831
	MSE	19.54527	67.86216	1.253358	MSE	1.805999	9.50374	0.245948
LSE	Bias	0.330301	0.611735	0.072778	Bias	0.176109	0.280537	0.033161
	MSE	1.473181	9.715541	0.409583	MSE	0.596345	3.420197	0.173005
WLSE	Bias	0.443582	0.735379	0.086148	Bias	0.182102	0.261039	0.030256
	MSE	2.410766	14.31737	0.505934	MSE	0.660381	3.725273	0.1685
PE	Bias	0.732264	2.742931	0.140044	Bias	0.151266	3.124965	0.236574
	MSE	7.902465	114.8551	1.019721	MSE	2.549177	131.3992	1.369404

Table.8 The MSE and BIAS for different estimates of the LNH distribution with different values

Estimation	parm	$\alpha = 1.5$	$\beta = 1.2$	$\lambda = 1.7$	parm	$\alpha = 1.5$	$\beta = 1.2$	$\lambda = 1.7$
		n = 50				n = 150		
MLE	Bias	1.261234	0.711381	0.193167	Bias	0.448107	0.2182	0.036413
	MSE	31.75934	13.69002	0.901951	MSE	6.760806	2.118448	0.126457
MPS	Bias	2.08034	0.898023	0.276312	Bias	0.718639	0.154253	0.0494
	MSE	54.33612	21.81064	1.246787	MSE	11.00418	3.068382	0.167521
LSE	Bias	0.684094	1.366326	0.120121	Bias	0.402178	0.503662	0.050081
	MSE	7.81408	14.47074	0.339786	MSE	3.169429	3.542477	0.134185
WLSE	Bias	0.761294	1.535991	0.136809	Bias	0.368159	0.401837	0.041625
	MSE	10.97051	19.75357	0.419214	MSE	3.482594	3.238734	0.11597
PE	Bias	1.276058	2.691017	0.118891	Bias	0.458773	2.809125	0.203946
	MSE	27.93761	45.04055	0.632478	MSE	10.5055	45.35784	0.808819
		n = 100				n = 300		
MLE	Bias	0.76266	0.553253	0.081685	Bias	0.169144	0.082635	0.009967
	MSE	14.96444	9.046802	0.314395	MSE	1.119374	0.685829	0.036673
MPS	Bias	1.233162	0.447662	0.113765	Bias	0.273288	0.022872	0.012322
	MSE	24.77268	9.044879	0.436126	MSE	2.013819	0.676378	0.039449
LSE	Bias	0.557835	0.710482	0.068445	Bias	0.246013	0.223297	0.02055
	MSE	4.891234	5.904778	0.203016	MSE	1.345576	1.393142	0.067892
WLSE	Bias	0.577662	0.729071	0.07229	Bias	0.176916	0.143822	0.014259
	MSE	6.639498	7.44816	0.211996	MSE	0.999635	0.850889	0.048241
PE	Bias	0.80343	2.546393	0.145503	Bias	0.209403	2.592269	0.233742
	MSE	17.21377	41.98287	0.69574	MSE	6.137387	39.49215	0.892119

-Analysis of Data

The tabulated findings above reveal several noteworthy observations:

The Mean Square Errors (MSEs) exhibit a decreasing trend with an increase in sample size.

Upon comparing various estimation methods, it is evident that the Least Squares Estimation (LSE) method consistently yields superior results for estimating the parameters θ and λ .

Regarding the performance ranking of estimators for θ , the order from best to worst is LSE, Maximum Likelihood Estimation (MLE), and Weighted Least Squares Estimation (WLSE). Similarly, for λ , the ranking is LSE and WLSE. These insights provide valuable information about the efficiency and reliability of the different estimation methods under consideration.

10. Order statistics

Order statistics play a crucial role in non-parametric statistics and inference, serving as fundamental tools. The probability density function of the i th order statistic, denoted as $f_{i:n}(x)$, in a random sample of size n drawn from the distribution proposed distribution is provided by:

$$f_{i:n}(x) = \frac{n!}{(i-1)!(n-i)!} f(x) F(x)^{i-1} [1 - F(x)]^{n-i}.$$

Using the binomial expansion, $f_{i:n}(x)$ can be reduced to:

$$f_{i:n}(x) = \sum_{m=0}^{\infty} t_{m+i} v_{m+i}(x; \lambda, \varphi),$$

where

$$t_{m+i} = \frac{(-1)^m n!}{(m+i)m!(n-i-m)!(i-1)!},$$

and $v_{m+i}(x) = (m+i) f(x; \lambda, \varphi) F(x; \lambda, \varphi)^{m+i-1}$ is the LNH density function with power parameter $m+i$. So, $f_{i:n}(x)$ is a linear combination of LNH densities.

$f_{i:n}(x)$, the i th order statistic of LNH distribution is given by:

$$f_{i:n}(x) = \sum_{m=0}^{\infty} t_{m+i} \alpha \beta \lambda (1 + \beta x)^{\alpha-1} [(1 + \beta x)^{\alpha} - 1]^{-\lambda-1} [1 + \{(1 + \beta x)^{\alpha} - 1\}^{-\lambda}]^{-2} [1 + \{(1 + \beta x)^{\alpha} - 1\}^{-\lambda}]^{1-m-i},$$

Table. 9. MLE Estimation under type-I censoring scheme. n=25,50

	n= 25			n= 50		
	a = 1.2	b =2	$\lambda = 2.5$	a = 1.2	b =2	$\lambda = 2.5$
Time of censoring (%) 30						
Bias	0.649668	4.926434	0.60923	0.36796	4.786571	0.48561
MSE	9.937075	252.6143	4.964276	6.458349	224.4373	3.006853
CP	92.99	94.9	97.6	94.2	94.79	98
Time of censoring (%) 60						
Bias	1.178346	5.06619	0.522384	1.008053	4.300733	0.368676
MSE	16.54518	270.9567	3.948463	11.66566	217.9167	2.455779
CP	93.6	97.3	97.9	94.5	94.3	97.5
Time of censoring (%) 90						
Bias	1.883939	4.843844	0.466951	1.722957	3.148915	0.279291
MSE	31.26156	275.6015	3.870508	23.25247	173.1045	2.28072
CP	92.7	97.5	98.1	92.7	91.5	96
Time of censoring (%) 99.99						
Bias	3.02046	3.259536	0.33233	1.749798	2.193454	0.208957
MSE	48.89261	198.5864	3.257292	24.06855	119.4353	1.908957
CP	93.17	92.4	96.4	93.1	90.3	94.3

Table. 10. MLE Estimation under type-I censoring scheme. n=75,100

	n= 75			n= 100		
	a = 1.2	b =2	$\lambda = 2.5$	a = 1.2	b =2	$\lambda = 2.5$
Time of censoring (%) 30						
Bias	0.427144	4.447768	0.385735	0.445588	3.944125	0.327314
MSE	5.237462	212.1619	2.153511	4.732963	181.4919	1.743009
CP	93.3	94.1	97.9	94.1	93.67	97.5
Time of censoring (%) 60						
Bias	0.926301	4.224687	0.338311	0.765755	3.309591	0.268514
MSE	11.02658	212.048	2.096333	6.995857	150.6801	1.586327
CP	95.1	94.6	98	92.7	93.6	96.6
Time of censoring (%) 90						
Bias	1.165455	2.634399	0.220286	0.673126	2.350916	0.220129
MSE	12.92989	133.8139	1.681694	7.016888	103.9434	1.421902
CP	93.99	90.5	94.8	94.4	92.3	94
Time of censoring (%) 99.99						
Bias	1.355785	1.874996	0.182617	1.124943	1.679063	0.147696
MSE	18.51045	91.40019	1.458482	13.49209	80.17721	1.174893
CP	93.6	92.1	91.9	93.3	92.4	92

Table 11. MLE Estimation under type-I censoring scheme. n=25,50

	n= 25			n= 50		
	a = 0.7	b =1.5	$\lambda = 3$	a = 0.7	b =1.5	$\lambda = 3$
Time of censoring (%) 30						
Bias	0.287533	5.119673	0.590579	0.253107	4.465618	0.473634
MSE	1.794882	110.2303	6.307976	1.410951	91.98796	4.279184
CP	94	98.2	99	95	98.4	97.9
Time of censoring (%) 60						
Bias	0.58528	4.069458	0.472594	0.567348	3.365379	0.351993
MSE	2.833577	77.881	4.933781	1.885304	62.20015	3.404274
CP	94.5	98.7	98.1	94.1	99.1	98.8
Time of censoring (%) 90						
Bias	1.119589	3.401549	0.400968	0.829607	2.764668	0.309253
MSE	5.3892	62.79687	4.35316	3.299092	48.62101	3.218999
CP	93.7	98.4	98.1	95	97.6	99.4
Time of censoring (%) 99.99						
Bias	1.752244	2.571771	0.28201	1.052161	2.231204	0.238137
MSE	7.787667	51.35312	3.764009	3.828153	41.67167	2.858282
CP	93.1	97.1	98.2	94.7	96.8	98.6

Table 12. MLE Estimation under type-I censoring scheme. n=75,100

	n= 75			n= 100		
	a = 0.7	b =1.5	$\lambda = 3$	a = 0.7	b =1.5	$\lambda = 3$
Time of censoring (%) 30						
Bias	0.30419	3.878214	0.373808	0.214556	3.482151	0.33849
MSE	1.065539	79.1608	3.128471	0.811364	67.30136	2.731215
CP	94.5	98.5	98.9	94.5	97.8	98.4
Time of censoring (%) 60						
Bias	0.466985	2.854431	0.298177	0.398496	2.745943	0.277565
MSE	1.40391	50.85458	2.636724	1.164411	48.28711	2.438393
CP	95.1	98	99	94.6	98.1	98.9
Time of censoring (%) 90						
Bias	0.644375	2.431623	0.247722	0.436571	2.304572	0.247457
MSE	2.012367	43.16993	2.525183	1.54027	37.62998	2.311934
CP	93.9	98.2	99.2	94	97.3	99.6
Time of censoring (%) 99.99						
Bias	0.623556	1.943982	0.204284	0.531608	1.778257	0.190045
MSE	1.885022	33.45876	2.219914	1.651643	29.28222	1.986813
CP	94.5	96.3	98	95	95.5	97.8

Table 13. MLE Estimation under type-II censoring scheme. n=25,50

	n= 25			n= 50		
	a = 1.2	b =2	$\lambda = 2.5$	a = 1.2	b =2	$\lambda = 2.5$
Time of censoring (%) 30						
Bias	2.084741	2.551816	0.493283	1.604249	2.984072	0.363348
MSE	24.63218	130.9428	3.626362	16.60021	143.9592	2.100432
CP	94.7	92.6	97.1	94.9	92.8	97.2
Time of censoring (%) 60						
Bias	2.572791	3.222154	0.414318	1.896524	3.464295	0.320033
MSE	35.84274	171.0519	3.066956	23.69069	177.5908	2.155219
CP	94.1	93.1	97.6	94.6	92.8	97.4
Time of censoring (%) 90						
Bias	3.000692	3.359583	0.334707	2.060485	2.704569	0.251161
MSE	49.23146	194.3237	2.944403	27.84157	143.3958	2.023756
CP	93.1	92.8	96.5	93.9	91.4	95.6
Time of censoring (%) 99.99						
Bias	2.861621	3.051454	0.312589	1.798465	2.479311	0.233297
MSE	50.42647	178.2683	3.042994	28.99403	129.3269	1.989734
CP	91.3	91.2	96.3	91.8	91	94.3

Table 14. MLE Estimation under type-II censoring scheme. n=100, 75

	n= 100			n= 75		
	a = 1.2	b =2	$\lambda = 2.5$	a = 1.2	b =2	$\lambda = 2.5$
Time of censoring (%) 30						
Bias	1.35176	3.079558	0.297115	1.327378	2.663802	0.241741
MSE	12.50296	145.6913	1.638181	10.96793	123.6279	1.269024
CP	95.2	92.8	97.1	95.1	92.6	96.8
Time of censoring (%) 60						
Bias	1.671424	2.935675	0.253907	1.441978	2.574743	0.21595
MSE	17.07926	146.5809	1.674127	13.54311	119.2073	1.345503
CP	95.7	92.3	96.3	94.7	92.2	95.5
Time of censoring (%) 90						
Bias	1.675032	2.547646	0.224217	1.259407	1.973118	0.174527
MSE	22.64548	128.519	1.70453	15.23907	91.61826	1.296694
CP	93.7	91.8	93.7	93.5	92.5	93
Time of censoring (%) 99.99						
Bias	1.625018	1.536477	0.147488	1.232104	1.14944	0.105827
MSE	22.95176	72.99336	1.264841	14.85007	51.08049	0.914206
CP	92.4	91.6	91.6	93.7	93.4	91.9

Table 15. MLE Estimation under type-II censoring scheme. n=25,50

	n= 25			n= 50		
	a = 0.7	b =1.5	$\lambda = 3$	a = 0.7	b =1.5	$\lambda = 3$
Time of censoring (%) 30						
Bias	1.816447	2.730621	0.499595	1.480692	2.758956	0.361672
MSE	7.265226	60.94906	5.902773	5.044278	59.43761	3.28162
CP	94.1	94.4	98.2	95	95.6	98.3
Time of censoring (%) 60						
Bias	2.194529	2.606784	0.334392	1.623432	2.632783	0.294152
MSE	10.28213	51.98401	3.562091	6.396382	48.97948	2.920658
CP	93.8	96.7	98.8	94.8	97.3	98.5
Time of censoring (%) 90						
Bias	2.36241	2.799715	0.316273	1.618352	2.413075	0.257377
MSE	12.79473	55.87062	3.902538	7.504111	43.31698	2.964913
CP	92.1	97.4	98.5	93.8	98.2	98.8
Time of censoring (%) 99.99						
Bias	2.298949	2.398637	0.259408	1.450915	2.192598	0.232355
MSE	13.15698	47.4648	3.625283	7.475958	39.2485	2.741396
CP	92.4	96.8	98.6	93.1	97.1	98.9

Table 16. MLE Estimation under type-II censoring scheme. n=100, 75

	n= 100			n= 75		
	a = 0.7	b =1.5	$\lambda = 3$	a = 0.7	b =1.5	$\lambda = 3$
Time of censoring (%) 30						
Bias	1.254841	2.629106	0.28642	1.143134	2.511262	0.265355
MSE	3.684308	52.9904	2.473688	3.175733	48.12521	2.312511
CP	94.2	95.5	97.9	94.6	95	98.5
Time of censoring (%) 60						
Bias	1.206677	2.496348	0.276813	1.218319	2.05215	0.211143
MSE	4.444362	43.98303	2.581589	4.100263	34.98315	2.064838
CP	94.2	97.3	99.2	93.8	96.1	99.1
Time of censoring (%) 90						
Bias	1.334895	2.052657	0.213719	1.101739	1.755144	0.180545
MSE	5.605285	36.08629	2.428999	4.380492	29.58061	2.013796
CP	93.7	96	99	93.1	95.4	98.4
Time of censoring (%) 99.99						
Bias	0.910486	1.942925	0.213947	0.595874	1.690169	0.183638
MSE	3.949319	32.8467	2.28624	2.268045	27.6933	1.973701
CP	94.7	95.9	98.5	95.2	94.6	98.2

Conclusion

- the Empirical Mean Residual Life value needs to significantly increase with sample size.
- the Renyi entropy value increases, the level of uncertainty in the system also grows.
- Upon comparing various estimation methods, it is evident that the Least Squares Estimation (LSE) method consistently yields superior results for estimating the parameters θ and λ .

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تقدير معالم توزيع لوجيستك نادراج - حقيقي Nadarajah-Haghighi

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الملخص

تقدم الدراسة توزيع نادراج حقيقي اللوجيستي كإمتداد لتوزيع Nadarajah-Haghighi الذي اقترحه Haghighi وآخرون في عام ٢٠١١، مما يوفر بديلا قيما للتوزيعات التقليدية مثل توزيعات γ , Weibull, exponentiated exponential.

تعرض هذه الدراسة لأربع طرق لتقدير معالم توزيع نادراج حقيقي اللوجستي Logistic Nadarajah-Haghighi (LNH) هي: الامكان الأعظم (MLE) والمربعات الصغرى (LS) والمربعات الصغرى الموزونة (WLS) بالإضافة لطريقة التقدير المئوي (PCE)، وذلك باستخدام العينات الكاملة تارة والعينات المراقبة أخرى بناءً على نوعين من الرقابة: | & . تقوم الدراسة بالمفاضلة بين هذه الطرق باستخدام التحيز التربيعي والتباينات لهذه التقديرات من خلال عمليات محاكاة مونت كارلو. بالإضافة إلى ذلك، فإن الدراسة تعرض لخصائص التوزيع وبعض المقاييس الأخرى مثل متوسط الحياة المتبقية، وريبي انتروبيا.

الكلمات المفتاحية: دالة الوسيط - العزوم - متوسط الحياة المتبقية - ريني انتروبيا - الاحصاءات الترتيبية