



Log - expo Transformation Flexible Weibull Three Parameter Distribution LET- FW

By

Dr. Mohamed Mohamed Abdelkader

Lecturer of Statistics and Mathematics

Faculty of Commerce, Al Azhar University

Mkader77@azhar.edu.eg

***Scientific Journal for Financial and Commercial Studies and Research
(SJFCR)***

Faculty of Commerce – Damietta University

Vol.4, No.2, Part 1., July 2023

APA Citation:

Abdelkader, M M. (2023). Log - expo transformation Flexible weibull three parameter distribution LET- FW, ***Scientific Journal for Financial and Commercial Studies and Research***, Faculty of Commerce, Damietta University, 4(2)1, 599- 620.

Website: <https://cfdj.journals.ekb.eg/>

Dr. Mohamed Mohamed Abdelkader

Log - expo Transformation Flexible Weibull Three Parameter Distribution LET- FW

Dr. Mohamed Mohamed Abdelkader

Abstract:

This paper introduces the LET-FW three parameter distribution. Some mathematical properties of this distribution are studied. Density distribution, Reliability and hazard rate functions are obtained. The ordinary moments, quintile function, mean residual life, Renyi entropy are given. Four methods of estimation of the LET-FW distribution based on complete sampling and the MLE estimates based on censoring type | and || are given. Squared Bias and variances of the estimates via a Mont Carlo simulation study are computed.

Keyword: Flexible weibull, LET-FW, Quantile function, Renyi Entropy

1- Introduction

The Weibull distribution [19] is often used in the modeling of lifetimes of components of engineering applications, physical systems and many different fields. In previous years, many authors provided many extensions for the Weibull distribution and their applications. **Mark** (2007) proposed a new two-parameter ageing distribution (flexible Weibull) which is a generalization of the Weibull [12]. **M. R. mahmoud** (2011) Based on type II censored sample, the maximum likelihood estimators of the parameters of an extension of the Weibull distribution referred to as the flexible Weibull distribution [11]. **Sinjay** (2013) developed the Bayesian estimation procedure for flexible Weibull distribution under Type-II censoring scheme [17]. **Sinjay** (2015). discussed classical and Bayes estimation procedures for estimating the unknown parameters as well as the reliability and hazard functions of the flexible Weibull distribution [18]. **A.El-Gohary** (2015). introduced a new three parameters model. he called it the exponentiated a flexible Weibull extension (EFW) distribution [1]. **Sangun** (2016). Proposed a general class of flexible Weibull distribution functions which includes some well-known modified Weibull distributions [15].

Abdelfattah (2016) introduced a new four parameters model called the Weibull Generalized Flexible Weibull extension [2]. **Zubair** (2017). Proposed a new model. This model is called new extended flexible Weibull distribution [21]. **Zubair** (2017). introduced a four-parameter modification of new flexible Weibull distribution [20]. **El-Desouky** (2017). devoted to study a new generalization of the flexible Weibull with three parameters. This model is referred to as the exponential flexible Weibull extension [5]. **Khaleel** (2020). Introduced the Gompertz flexible Weibull distribution as an extension of the flexible Weibull distribution [10]. **NihadSh** (2022) developed The Topp Leone Flexible Weibull distribution: An extension of the Flexible Weibull distribution [14].

2- transformation the log-expo transformation (LET): LET-FW.

Aslam et al. (2020) [4] developed a generator to propose new continuous lifetime distributions defined as:

Let $F(x; z)$ be the cdf of a given random variable depending on some real-valued parameter (s) z . Our approach in this paper consists in enriching this cdf by transforming it into:

$$G(X; \xi) = \frac{\log(2 - e^{-\lambda F(x)})}{\log(2 - e^{-\lambda})} \dots (1)$$

where $\xi = (\lambda, \zeta)$ for some positive real-valued shape parameter λ and the parameter ζ from the baseline distribution. We call this transformation the log-expo transformation (LET).

The probability density function (pdf) corresponding to Eq (1) is given by

$$g(X; \xi) = \frac{\lambda f(x; \nu) e^{-\lambda F(x; \nu)}}{\log(2 - e^{-\lambda})(2 - e^{-\lambda F(x; \nu)})} x > 0 \dots (2)$$

$f(\cdot)$ and $F(\cdot)$ are the PDF and the CDF of flexible weibull distribution, where:

$$f(x) = (\alpha + \frac{\beta}{x^2}) \exp(\alpha x - \frac{\beta}{x}) \exp(-e^{\alpha x - \frac{\beta}{x}}), \alpha, \beta, x > 0 \dots (3)$$

$$F(x) = 1 - \exp(-e^{\alpha x - \frac{\beta}{x}}) \dots (4)$$

Dr. Mohamed Mohamed Abdelkader

We obtain the PDF and the CDF of LET-flexible weibull (LET-FW) by putting (3) and (4) in (1) and (2) as:

$$g(x) = \frac{\lambda z (\alpha + \frac{\beta}{x^2}) e^{-[z + \lambda(1 - e^{-z})]}}{\log(2 - e^{-\lambda})(2 - e^{-\lambda[1 - e^{-z}]})} \dots (5)$$

where : $z = \exp(\alpha x - \frac{\beta}{x})$

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

$$G(x) = \frac{\log(2 - e^{-\lambda[1 - e^{-z}]})}{\log(2 - e^{-\lambda})} \dots (6)$$

where : $z = \exp(\alpha x - \frac{\beta}{x})$

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

Where $x = 0 \rightarrow G(0) = 0 \& x = \infty \rightarrow G(\infty) = 1$

By the PDF (5) and the CDF (6) we can write the survival function $s(x)$ and the hazard function $h(x)$ as:

$$s(x) = 1 - G(x)$$

$$\therefore s(x) = 1 - \frac{\log(2 - e^{-\lambda[1 - e^{-z}]})}{\log(2 - e^{-\lambda})}$$

where : $z = \exp(\alpha x - \frac{\beta}{x})$

Dr. Mohamed Mohamed Abdelkader

$$h(x) = \frac{g(x)}{s(x)}$$

$$h(x) = \frac{\lambda z (\alpha + \frac{\beta}{x^2}) e^{-[z + \lambda(1 - e^{-z})]}}{\log[(2 - e^{-\lambda}) / (2 - e^{-\lambda[1 - e^{-z}]})] (2 - e^{-\lambda[1 - e^{-z}]})}$$

where $z = \exp(\alpha x - \frac{\beta}{x^2})$

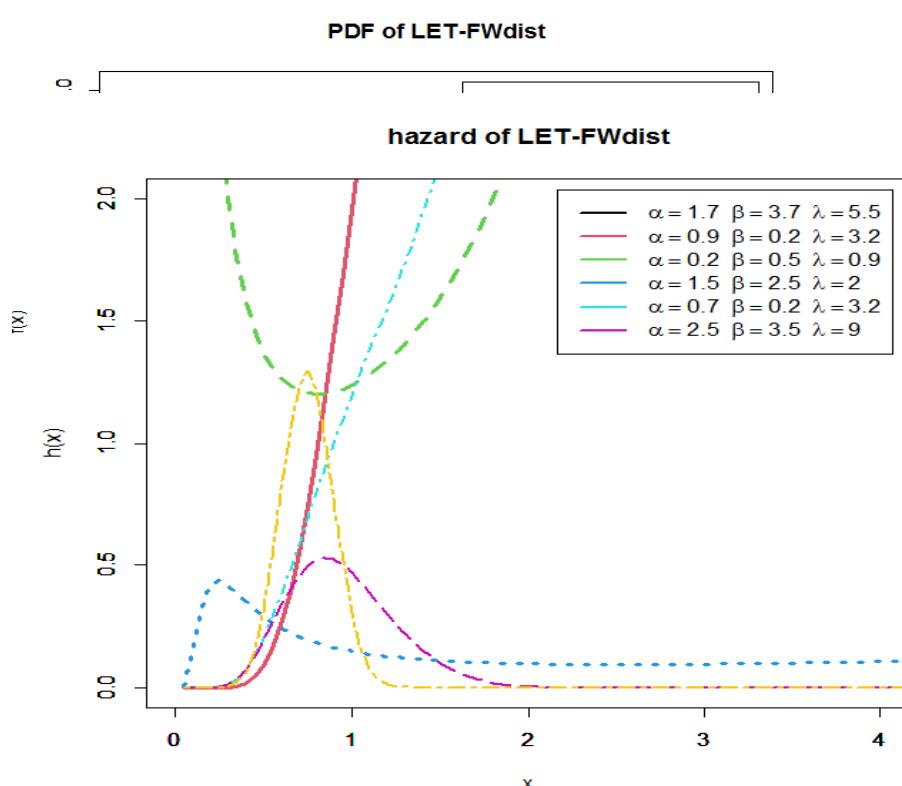


Figure 2. Hazard of LET-FW distribution

3-Quantile function

The Quantile function $Q(p)$ or Q of the LET-FW distribution is the solution of the equation: $G(Q)=P$. then the quantile function Q at a vector p of percentiles is:

Dr. Mohamed Mohamed Abdelkader

$$\text{Where } t = \log\left\{-\log\left[1 + \frac{\log(2 - \exp(P \log(2 - e^{-\lambda})))}{\lambda}\right]\right\}$$

We can obtain the generating function of the LET-FW distribution from equation (7) by writing x_u instead of Q and u instead of p, Where u is the uniform random variable (0,1) then:

$$\therefore x_u = \frac{t + \sqrt{t^2 - 4\alpha\beta}}{2\alpha}, \alpha, \beta, \lambda > 0$$

$$\text{Where } t = \log\left\{-\log\left[1 + \frac{\log(2 - \exp(u \log(2 - e^{-\lambda})))}{\lambda}\right]\right\}$$

The Bowley Skewness measure Bsk [9] and the Moor's Kurtosis measure Mkur [13] are defined by

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

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

Then the skewness and kurtosis of LET-FW for different parameter values are given in the following table.

table. 1 Quantile

λ, α, β	$Q_{0.25}$	$Q_{0.5}$	$Q_{0.75}$	$Q_{0.125}$	$Q_{0.375}$	$Q_{0.625}$	$Q_{0.875}$	Bsk	Mkur
0.5,0.7,0.9	0.2192	0.3255	0.4799	0.1679	0.2696	0.3924	0.6121	0.1847	0.4525
0.9,1.2,1.5	0.3562	0.5193	0.7675	0.2773	0.4332	0.6247	0.9969	0.2069	0.5258
1.2,1.5,0.9	0.5261	0.7811	1.1516	0.4029	0.6470	0.9418	1.4690	0.1847	0.4525
1.5,1.2,2	0.5546	0.7958	1.1678	0.4368	0.6687	0.9522	1.5273	0.2134	0.5597
1.5,2.5,2	0.5546	0.7958	1.1678	0.4368	0.6687	0.9522	1.5273	0.2134	0.5597
1.7,3.7,5.5	0.4811	0.6389	0.8628	0.3965	0.5578	0.7347	1.0786	0.1728	0.4785
0.9,0.2,3.2	0.2945	0.4084	0.5814	0.2368	0.3488	0.4809	0.7553	0.2060	0.5659

From Table 1. drawn above it can be deduced that the LET-FW distribution can be used to model data that are positively skewed.

4-Raw Moments

the r-th raw moment of the LET-FW variable x is

$$\mu'_r = E(x^r)$$

$$= \int_a^b x^r \frac{\lambda z (\alpha + \frac{\beta}{x^2}) \exp\{-z - \lambda(1 - e^{-z})\}}{\log(2 - e^{-\lambda})(2 - e^{-\lambda[1 - e^{-z}]})} dx$$

$$where : z = \exp\{\alpha x + \frac{\beta}{x}\}$$

The mean of x corresponds to r = 1. The mean, variance, skewness and kurtosis of the distribution for various values of the parameters are shown in Table 1. Table 1 indicates that if a, b and λ are fixed, the mean and variance of the LET-FW distribution

λ, α, β	μ'_1	μ'_2	μ'_3	μ'_4	μ_2	CV	sk	kur
0.5,0.7,0.9,4	0.1813	0.2535	0.4964	1.1882	0.2206	2.5901	3.5760	14.9794
0.9,1.2,1.5,4	0.2566	0.2551	0.3111	0.4441	0.1893	1.6954	1.8032	2.9315
1.2,1.5,0.9,4	0.1868	0.1883	0.2160	0.2747	0.1534	2.0971	2.0552	3.3333
1.5,1.2,2,4	0.2322	0.1645	0.1353	0.1261	0.1106	1.4324	1.2422	0.6708

5-Renyi Entropy:

Entropy has been appeared by Alfred Renyi [3] as a logarithmic measure of variation of uncertainty.

If we assume that the events $X = \{x_1, x_2, \dots, x_N\}$ have different probability $\{p_1, p_2, \dots, p_N\}$. And each deliver $I(p) = \sum_{k=1}^N p_k I_k$ bits of information, then the total amount of information for the set is

$$Applying the definition to the I(p) we got $I(p) = g^{-1}(\sum_{k=1}^N p_k g(I_k))$$$

When the postulate of additively for independent events is applied, we get just two possible g(x):

$$g(x) = cx$$

$$g(x) = c^{-2(1-\alpha)x}$$

The first form gives Shannon information and the second gives

$$I_\alpha(p) = \frac{1}{1-\alpha} \log \sum_{k=1}^N p_k^\alpha$$

Dr. Mohamed Mohamed Abdelkader

$$I_\alpha(p) = \frac{1}{1-\alpha} \log \int_0^\infty g^p(x) dx, \alpha > 0, \alpha \neq 0$$

In continuous distribution

Hence,

$$I_\alpha(p) = \frac{1}{1-\alpha} \log \int_0^\infty \left\{ \frac{\lambda z (\alpha + \frac{\beta}{x^2}) \exp\{-z - \lambda(1-e^{-z})\}}{\log(2-e^{-\lambda})(2-e^{-\lambda[1-e^{-z}]})} \right\}^p dx$$

$$\text{where } z = \exp\{\alpha x + \frac{\beta}{x}\}$$

The following Table below gives the values of Renyi Entropy of LET-FW distribution for different values of the parameters.

table .3 Renyi Entropy

λ, α, β	p=2	p=3	p=4
0.9,0.7,0.5	3.387055	2.465451	2.119736
0.9,1.2,1.5	3.246222	2.415173	2.118701
1.5,0.9,1.2	2.397793	1.750885	1.509868
2, 1.5, 2.5	1.9248	1.381453	1.180555
2, 1.5, 1.2	1.689384	1.135174	0.928305
5.5,1.7, 3.7	1.250535	0.808847	0.64208
3.2, 0.9, 0.2,	0.105591	-0.46075	-0.68114
4.5, 0.7, 0.4	-0.31782	-0.31782	-0.31782

It should be noted that the higher the value of the Renyi entropy the greater the level of uncertainty in the system.

6-The mean Residual life:

The mean Residual life (MRL) or the life expectancy at age t is the expected additional life length for a unit, which is alive at age t. the MRL is given by:

$$m(t) = \left(\frac{1}{1-F(x)} \int_t^\infty x g(x) dx \right) - t$$

$$= \left(\frac{1}{\exp\{-z - \lambda(1-e^{-z})\}} \int_t^\infty \frac{\lambda z (\alpha x + \frac{\beta}{x^2}) \exp\{-z - \lambda(1-e^{-z})\}}{\log(2-e^{-\lambda})(2-e^{-\lambda[1-e^{-z}]})} dx \right) - t$$

$$\text{where, } z = e^{\alpha x + \frac{\beta}{x}}$$

The following Table below gives the values of MRL of LET-FW distribution for a fixed value of t.

TABLE.4 Mean residual life, $\alpha=0.5, \beta=0.7, \lambda=0.9$

NO.	Death. Time	EMRL	NO.	Death. Time	EMRL
1	0.091065	0.256272	11	0.212294	0.177682
2	0.12218	0.229848	12	0.216801	0.177732
3	0.126223	0.230609	13	0.222688	0.176489
4	0.162771	0.19828	14	0.225212	0.178798
5	0.182556	0.182462	15	0.225859	0.183241
6	0.191661	0.177296	16	0.232166	0.182138
7	0.193951	0.179076	17	0.233552	0.186229
8	0.199815	0.177336	18	0.235976	0.189549
9	0.206831	0.174474	19	0.240115	0.191391
10	0.212165	0.173369	20	0.240906	0.196954

EMRL decreases with increasing death time

7-Methods of Estimation

In this section we estimate the parameters of the LET-FW distribution by 5 different methods using complete sample technique. These methods are: Maximum likelihood (MLE), Least-squares (LS), weighted least squares, Maximum Product of spacing (MPS) and percentile-based estimation (PE). The performance of all methods is studied by the R software.

7.1-Maximum likelihood estimation (MLE):

The MLE method is a general method, and its estimators have some optimum properties such as consistency, asymptotic efficiency and invariance property.

Let x_1, x_2, \dots, x_n be a random sample from LET-FW population with PDF $g(x)$ given in (5) with unknown parameters α , β , and λ and the log-likelihood function is $\ell(\alpha, \beta, \lambda)$ then the MLE estimates of α , β , and λ are the simultaneously solution of the following equations:

$$\frac{\partial \ell(\alpha, \beta, \lambda, \theta)}{\partial \alpha} = 0, \quad \frac{\partial \ell(\alpha, \beta, \lambda, \theta)}{\partial \beta} = 0, \quad \frac{\partial \ell(\alpha, \beta, \lambda, \theta)}{\partial \lambda} = 0$$

We derive sample estimates of the unknown parameters of the LET model by using the maximum likelihood estimation technique. Let x_1, x_2, \dots, x_n be the observations of a random sample of size n from the LET model. The likelihood function is given by [4]

Dr. Mohamed Mohamed Abdelkader

$$L(\Omega) = \prod_{i=1}^n \frac{\lambda f(x_i; \Omega) \exp\{-\lambda F(x_i; \Omega)\}}{\log[2 - e^{-\lambda}][2 - \exp\{-\lambda F(x_i; \Omega)\}]}$$

and the log-likelihood function by

For obtaining the partial derivatives, differentiating (8) for α and β we get,

$$\begin{aligned} \frac{\partial \ell(\lambda)}{\partial \lambda} &= \frac{n}{\lambda} - \sum 1 - e^{-e^{\alpha x - \beta x}} - \frac{n e^{-\lambda}}{(2 - e^{-\lambda}) \log(2 - e^{-\lambda})} \\ - \sum \frac{(1 - e^{-e^{\alpha x - \beta x}}) \exp\{-\lambda[1 - e^{-e^{\alpha x - \beta x}}]\}}{2 - \exp\{-\lambda[1 - e^{-e^{\alpha x - \beta x}}]\}} &= 0 \dots \dots \dots (9) \end{aligned}$$

$$\begin{aligned} \frac{\partial \ell(\Omega)}{\partial \alpha} &= \sum \frac{x^2(1 - e^{-e^{\alpha x - \beta x^{-1}}})}{\alpha} (\alpha + \beta x^{-2})^{-1} - \lambda \sum x e^{\alpha x - \beta x^{-1}} e^{-e^{\alpha x - \beta x^{-1}}} \\ &\quad - \sum \frac{x e^{\alpha x - \beta x^{-1}} e^{-e^{\alpha x - \beta x^{-1}}} \exp\{-\lambda[1 - e^{-e^{\alpha x - \beta x^{-1}}}\}] }{2 - \exp\{-\lambda[1 - e^{-e^{\alpha x - \beta x^{-1}}}\]}\} = 0. \end{aligned} \quad (10)$$

$$\begin{aligned} \frac{\partial \ell(\Omega)}{\partial \beta} &= \sum x (1 - e^{\alpha x - \beta x^{-1}}) + \lambda \sum x^{-1} e^{\alpha x - \beta x^{-1}} e^{-e^{\alpha x - \beta x^{-1}}} \\ &+ \sum \frac{x^{-1} e^{\alpha x - \beta x^{-1}} e^{-e^{\alpha x - \beta x^{-1}}} \exp\{-\lambda[1 - e^{-e^{\alpha x - \beta x^{-1}}}\}] }{2 - \exp\{-\lambda[1 - e^{-e^{\alpha x - \beta x^{-1}}}\]}\} = 0. \dots \quad (11) \end{aligned}$$

Setting (9), (10) and (11) to zero and solving these equations simultaneously gives the MLE of θ i.e., and. However, solving these equations to get the estimates of the unknown parameter is quite difficult. Therefore, a numerical technique such as the newton-raphson method may be used to solve these non-linear equations.

7.2-Method of Ordinary Least Squares (L):

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

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

Dr. Mohamed Mohamed Abdelkader

With respect to α , β and λ .

Where $x_{(i)}$ is the i th orders statistic of LET-FW

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

$$Q = \left[\frac{\log(2 - \exp\{-\lambda[1 - e^{-\alpha x_{(i)} - \beta x_{(i)}^{-1}}]\})}{\log(2 - e^{-\lambda})} - \frac{i}{n+1} \right] \Psi_k(x_{(i)} / \Omega) = 0$$

Where

$$\Psi_1(x_{(i)} / \Omega) = \frac{\partial G(x)}{\partial \lambda} = \frac{\lambda e^{-\lambda} \{ [\log(2 - e^{-\lambda})]^2 e^{(1-w)} + [\log(2 - e^{-\lambda(1-w)})]^2 \}}{\log(2 - e^{-\lambda}) \log(2 - e^{-\lambda(1-w)})}$$

$$\Psi_2(x_{(i)} / \Omega) = \frac{\partial G(x)}{\partial \alpha} = \frac{-(\lambda / x) w (\log w) e^{-\lambda(1-w)}}{\log(2 - e^{-\lambda(1-w)})}$$

$$\Psi_3(x_{(i)} / \Omega) = \frac{\partial G(x)}{\partial \beta} = \frac{\lambda x w (\log w) e^{-\lambda(1-w)}}{\log(2 - e^{-\lambda(1-w)})}$$

where $w = \exp\{-e^{\alpha x_{(i)} - \beta x_{(i)}^{-1}}\}$. The solution of Ψ_k for $k = 1, 2, 3, 4$ may be obtained numerically.

7.3-Method of Weighted Least Squares (WLS):

The WLS estimators of α , β , and λ of LET-FW 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

7.4-Method of Percentile Estimation (PCE) :

This method introduced by kao [7, 8] the PCEs estimators of α , β , and λ of LET-FW distribution can be obtained by minimizing the quantity:

$$Q = \sum_{i=1}^n \left[x_{(i)} - \frac{t + \sqrt{t^2 - 4\alpha\beta}}{2\alpha} \right]^2$$

$$\text{Where } t = \log\left\{-\log\left[1 + \frac{\log(2 - \exp(P \log(2 - e^{-\lambda})))}{\lambda}\right]\right\}$$

7.5-Simulation Study and Data Analysis

The aim of this section is to compare the performance of the methods of estimation, namely: MLE, MPS, LS, WLS, and PE for the LET-FW distribution which discussed in the previous section. A Monte Carlo study is

Dr. Mohamed Mohamed Abdelkader

employed to check the behavior of the proposed methods of estimation. Also, a real data set is analyzed for illustrative purpose. R-statistical programming language will be used for calculation.

7.5.1-Simulation Study

A simulation study is employed to compare the performance of proposed methods of estimation using Monte Carlo. The Monte Carlo process is carried by generating 5000 random data from the LET-FW distribution with the following assumptions:

1. Sample sizes are $n = 50, 100, 150, 200$
2. Assume the following selected cases of parameters α and β of the LET-FW 3rd distribution:
 - a. $\alpha = 1.2, \beta = 2, \lambda = 4$
 - b. $\alpha = 0.5, \beta = 0.7, \lambda = 0.9$

Based on the generated data and applying different methods of estimation. All the means square error (MSE) and relative biases (BIAS) are reported from Table (5) to Table (8) for five different methods of estimation.

Table (5): The MSE and BIAS for different estimates of the LET-FW distribution with n= 200

Parameters	MLE		MPS		LSE		WLSE		PE	
	MSE	Bias								
case 										
$\alpha = 1.2$	0.616496	0.64932	0.13364	0.186632	0.480028	0.360602	0.343588	0.348281	0.012991	0.00286
$\beta = 2$	0.434049	0.327603	0.671499	0.405988	0.662265	0.397548	0.647193	0.395986	1.990717	0.257411
$\lambda = 4$	8.380159	0.690051	2.759733	0.059395	14.45506	0.245171	7.004066	0.157858	1.007737	0.005931
case 										
$\alpha = 0.5$	0.122319	0.684559	2.517458	3.154277	2.201844	2.911553	2.243438	2.965425	0.003342	0.037965
$\beta = 0.7$	0.003187	0.052026	0.040197	0.274817	0.046604	0.289153	0.044598	0.287616	0.252265	0.108033
$\lambda = 0.9$	16.33434	4.477	0.217618	0.01616	0.534472	0.096433	0.323855	0.054066	0.409235	0.214932

Table (6): The MSE and BIAS for different estimates of the LET-FW distribution with n= 150

Parameters	MLE		MPS		LSE		WLSE		PE	
	MSE	Bias								
case 										
$\alpha = 1.2$	0.619616	0.649224	0.152874	0.163355	0.540322	0.367439	0.394422	0.359114	0.015762	0.000207
$\beta = 2$	0.432702	0.326477	0.677594	0.406638	0.676602	0.399485	0.653944	0.396233	2.936521	0.285161
$\lambda = 4$	8.904842	0.70012	3.795244	0.061588	19.09814	0.288819	9.447946	0.195857	1.26137	0.016602
case 										
$\alpha = 0.5$	0.123488	0.682512	2.574445	3.183128	2.171876	2.859347	2.218424	2.933811	0.005248	0.053862
$\beta = 0.7$	0.003971	0.053644	0.03994	0.26991	0.049121	0.28997	0.04615	0.287522	0.407575	0.087416
$\lambda = 0.9$	16.52208	4.49738	0.291019	0.038525	0.873238	0.155786	0.489165	0.091305	0.637385	0.303331

Table (7): The MSE and BIAS for different estimates of the LET-FW distribution with n= 100

Parameters .	MLE		MPS		LSE		WLSE		PE	
	MSE	Bias								
case 										
$\alpha = 1.2$	0.62717	0.648928	0.208926	0.129269	0.678321	0.382291	0.503767	0.37089	0.020819	0.001967
$\beta = 2$	0.427403	0.322943	0.684219	0.405584	0.704576	0.402034	0.673211	0.397538	2.368339	0.306453
$\lambda = 4$	10.674	0.731419	7.075583	0.035797	36.70636	0.42247	19.69992	0.295698	1.754424	0.017292
case 										
$\alpha = 0.5$	0.131423	0.693565	2.729861	3.264185	2.166979	2.787758	2.216589	2.894623	0.007711	0.068609
$\beta = 0.7$	0.005658	0.059692	0.040613	0.263337	0.054306	0.290954	0.050294	0.289081	0.509271	0.065401
$\lambda = 0.9$	16.88202	4.532799	0.495875	0.050664	1.983776	0.268424	1.096127	0.152403	0.923971	0.372343

Table (8): The MSE and BIAS for different estimates of the LET-FW distribution with n= 50

Parameters .	MLE		MPS		LSE		WLSE		PE	
	MSE	Bias								
case 										
$\alpha = 1.2$	0.637864	0.642906	0.387293	0.040868	0.983082	0.412819	0.787634	0.406681	0.033822	0.006683
$\beta = 2$	0.420285	0.315911	0.698617	0.401638	0.782257	0.410949	0.732183	0.402658	3.026804	0.337227
$\lambda = 4$	16.75231	0.815134	20.44738	0.062346	94.63256	0.717014	60.02438	0.575011	3.236457	0.036112
case 										
$\alpha = 0.5$	0.150411	0.711585	3.154388	3.466396	2.1749	2.595215	2.173154	2.738738	0.011845	0.089169
$\beta = 0.7$	0.010357	0.070355	0.04145	0.243577	0.067525	0.294601	0.060576	0.290315	0.758217	0.029168
$\lambda = 0.9$	17.89873	4.629399	1.049375	0.11494	4.712268	0.556691	2.871747	0.376766	1.236915	0.443736

7.5.2 -Data Analysis

From the above tabulated results, one can indicate that:

The MSEs decrease as sample size increases.

Comparing the different methods of estimation, the results show that the MLE produces the best results for estimating the parameter β and the PE produces the best results for parameters (α, λ) .

The ordering performance of the estimators in terms of LSs (from best to worst) for α PE and MPS. For β is MLE and PE. While the ordering performance for λ is PE and MLE.

8-Censored samples and types of censoring

In life testing experiments, items drawn from a population are put to test and their times to failure are noted. The test is usually terminated after a fixed time or after a fixed number of failures is observed, giving a censored sample.

The situation in which we observe the lifetimes of all the items is called uncensored data, but such data will rarely arise in reliability testing even under controlled conditions. It is often necessary to terminate the test before all failure items have been observed because of limited budget or time.

An observation is said to be right censored at L in the exact value of the observation is not known but it is known only that it is greater than or equal to L . similarly, an observation is said to be left censored at M if it is known only that the observation is less than or equal to M. right censoring is very common in lifetime data, but left censoring is fairly rare.

Some methods by which the data may be censored are:

Type I censored data

Suppose that a random sample of n units from $G(x, \Omega)$ is processed for a predefined time x_c and then the process terminates. We observed the lifetime of δ observations before terminating the process and the remaining $n - \delta$ observations will be censored. Thus, the lifetimes are observed only if $x_i < x_c$ for $i = 1, 2, \dots, n$.

$$\text{Defining } I_i = \begin{cases} 1, & \text{if } x_i \leq x_c \\ 0, & \text{if } x_i > x_c \end{cases} \text{ and } \delta = \sum_{i=1}^n I_i$$

the likelihood function can be written as

Dr. Mohamed Mohamed Abdelkader

$$L(\Omega) = \left[\prod_{i=1}^n g(x_i; \Omega)^{I_i} \right] S(x_n; \Omega)^{n-\delta} \quad [4]$$

and the log-likelihood function is given by

$$\ell(\Omega) = (n - \delta) \log \left[1 - \frac{\log(2 - e^{-\lambda F(x_c; \Omega)})}{\log(2 - e^{-\lambda})} \right] + \sum_{i=1}^n I_i \log \left[\frac{\lambda f(x_i; \Omega) e^{-\lambda F(x_i; \Omega)}}{\log(2 - e^{-\lambda})(2 - e^{-\lambda F(x_i; \Omega)})} \right]$$

then

$$\begin{aligned} \ell\ell(\Omega) &= (n - \delta) \log \left[1 - \frac{\log(2 - e^{-\lambda[1 - \exp\{-e^{\alpha x_c - \beta x_c^{-1}\}}]})}{\log(2 - e^{-\lambda})} \right] + \sum_{i=1}^n I_i \log \left[\frac{\lambda(\alpha + \beta x_i^{-2}) e^{\alpha x_i - \beta x_i^{-1}} \exp\{-e^{\alpha x_i - \beta x_i^{-1}}\} e^{-\lambda[1 - \exp\{-e^{\alpha x_i - \beta x_i^{-1}}\}]} }{\log(2 - e^{-\lambda})(2 - e^{-\lambda[1 - \exp\{-e^{\alpha x_i - \beta x_i^{-1}}\}]})} \right] \end{aligned}$$

Type II censored data

In case of Type-II right censoring, t observations out of the n are censored from the right side. The likelihood function then becomes

$$L(\Omega) = \frac{n!}{t!} \left[\prod_{i=1}^{n-t} g(x_i; \Omega) \right] [S(x_{n-t}; \Omega)]^t$$

where x_i is the order statistic of order i , and the log-likelihood function, expressed in terms of the original baseline distribution, reads

$$\ell(\Omega) = \log \left(\frac{n!}{t!} \right) + t \log \left[1 - \frac{\log(2 - e^{-\lambda F(x_{n-t}; \Omega)})}{\log(2 - e^{-\lambda})} \right] + \sum_{i=1}^{n-t} I_i \log \left[\frac{\lambda f(x_i; \Omega) e^{-\lambda F(x_i; \Omega)}}{\log(2 - e^{-\lambda})(2 - e^{-\lambda F(x_i; \Omega)})} \right]$$

$$\begin{aligned} \ell(\Omega) &= \log \left(\frac{n!}{t!} \right) + t \log \left[1 - \frac{\log(2 - e^{-\lambda[1 - \exp\{-e^{\alpha x_{n-t} - \beta x_{n-t}^{-1}\}}]})}{\log(2 - e^{-\lambda})} \right] \\ &\quad + \sum_{i=1}^{n-t} I_i \log \left[\frac{\lambda(\alpha + \beta x_i^{-2}) e^{\alpha x_i - \beta x_i^{-1}} \exp\{-e^{\alpha x_i - \beta x_i^{-1}}\} e^{-\lambda[1 - \exp\{-e^{\alpha x_i - \beta x_i^{-1}\}]}}{\log(2 - e^{-\lambda})(2 - e^{-\lambda[1 - \exp\{-e^{\alpha x_i - \beta x_i^{-1}\}\}]})} \right] = 0 \end{aligned}$$

$$\begin{aligned} \frac{\partial \ell(\Omega)}{\partial \lambda} &= \frac{n-t}{\lambda} - k_1(k_2 - k_3) \\ &\quad - \sum_{i=1}^{n-t} \left[1 - \exp\{-e^{\alpha x_i - \beta x_i^{-1}}\} + \frac{e^{-\lambda}}{(2 - e^{-\lambda}) \log(2 - e^{-\lambda})} + \frac{(1 - \exp\{-e^{\alpha x_i - \beta x_i^{-1}}\}) e^{-\lambda[1 - \exp\{-e^{\alpha x_i - \beta x_i^{-1}}\}]}}{2 - e^{-\lambda[1 - \exp\{-e^{\alpha x_i - \beta x_i^{-1}}\}]}} \right] = 0 \end{aligned}$$

Where:

Dr. Mohamed Mohamed Abdelkader

$$\begin{aligned}
 k_1 &= \frac{t}{\log(2-e^{-\lambda})[\log(2-e^{-\lambda})-\log(2-e^{-\lambda[1-\exp\{-e^{\alpha x_{n-t}-\beta x_{n-t}^{-1}\}}]})]} \\
 k_2 &= \frac{\log(2-e^{-\lambda})[1-\exp\{-e^{\alpha x_{n-t}-\beta x_{n-t}^{-1}}\}]e^{-\lambda[1-\exp\{-e^{\alpha x_{n-t}-\beta x_{n-t}^{-1}}\}]}}{2-e^{-\lambda[1-\exp\{-e^{\alpha x_{n-t}-\beta x_{n-t}^{-1}}\}]}} \\
 k_3 &= \frac{\log(2-e^{-\lambda[1-\exp\{-e^{\alpha x_{n-t}-\beta x_{n-t}^{-1}}\}]}e^{-\lambda}}{2-e^{-\lambda}} \\
 \frac{\partial \ell \ell(\Omega)}{\partial \alpha} &= \frac{-t \lambda x_{n-t} e^{\alpha x_{n-t}-\beta x_{n-t}^{-1}} e^{-e^{\alpha x_{n-t}-\beta x_{n-t}^{-1}}} e^{-\lambda[1-\exp\{-e^{\alpha x_{n-t}-\beta x_{n-t}^{-1}}\}]}}{(2-e^{-\lambda[1-\exp\{-e^{\alpha x_{n-t}-\beta x_{n-t}^{-1}}\}]})(\log(2-e^{-\lambda})-\log(2-e^{-\lambda[1-\exp\{-e^{\alpha x_{n-t}-\beta x_{n-t}^{-1}}\}]}))} + \sum_{i=1}^{n-t} \left[\frac{x_i^2 (1-e^{\alpha x_i-\beta x_i^{-1}})}{\alpha} + (\alpha + \beta x_i^{-2})^{-1} \right] \\
 &- \lambda \sum_{i=1}^{n-t} \left[\frac{x_i e^{\alpha x_i-\beta x_i^{-1}} e^{-e^{\alpha x_i-\beta x_i^{-1}}}}{1-\exp\{-e^{\alpha x_i-\beta x_i^{-1}}\}} \right] - \lambda \sum_{i=1}^{n-t} \left[\frac{x_i e^{\alpha x_i-\beta x_i^{-1}} e^{-e^{\alpha x_i-\beta x_i^{-1}}} e^{-\lambda[1-\exp\{-e^{\alpha x_i-\beta x_i^{-1}}\}]}}{2-e^{-\lambda[1-\exp\{-e^{\alpha x_i-\beta x_i^{-1}}\}]}} \right] = 0 \\
 \frac{\partial \ell \ell(\Omega)}{\partial \beta} &= \frac{-t \lambda x_{n-t}^{-1} e^{\alpha x_{n-t}-\beta x_{n-t}^{-1}} e^{-e^{\alpha x-\beta x^{-1}}} e^{-\lambda[1-\exp\{-e^{\alpha x_{n-t}-\beta x_{n-t}^{-1}}\}]}}{(2-e^{-\lambda[1-\exp\{-e^{\alpha x_{n-t}-\beta x_{n-t}^{-1}}\}]})(\log(2-e^{-\lambda})-\log(2-e^{-\lambda[1-\exp\{-e^{\alpha x_{n-t}-\beta x_{n-t}^{-1}}\}]}))} + \sum_{i=1}^{n-t} [x_i (1-e^{\alpha x-\beta x^{-1}})] \\
 &- \lambda \sum_{i=1}^{n-t} \left[\frac{x_i^{-1} e^{\alpha x_i-\beta x_i^{-1}} e^{-e^{\alpha x_i-\beta x_i^{-1}}}}{1-\exp\{-e^{\alpha x_i-\beta x_i^{-1}}\}} \right] - \lambda \sum_{i=1}^{n-t} \left[\frac{x_i^{-1} e^{\alpha x_i-\beta x_i^{-1}} e^{-e^{\alpha x_i-\beta x_i^{-1}}} e^{-\lambda[1-\exp\{-e^{\alpha x_i-\beta x_i^{-1}}\}]}}{2-e^{-\lambda[1-\exp\{-e^{\alpha x_i-\beta x_i^{-1}}\}]}} \right] = 0
 \end{aligned}$$

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

Name	$\alpha=0.5$	$\beta=0.7$	$\lambda=0.9$	$\alpha=0.5$	$\beta=0.7$	$\lambda=0.9$
Time of censoring (% 30)				Time of censoring (% 60)		
Bias	18.66094	0.368929	7.310087	5.469342	0.201593	6.788221
MSE	183.9349	0.217024	49.65025	19.45356	0.108474	43.32669
AIL	38.59205	1.520234	9.895382	13.56835	1.166825	9.606604
CP	100	97.25	94.38776	100	94.1	94.14536
Time of censoring (% 90)				Time of censoring (% 99.99)		
Bias	0.502595	0.106925	5.684782	0.736369	0.09749	4.959587
MSE	0.781198	0.034759	30.33054	0.214299	0.023833	21.80851
AIL	3.322486	0.669505	7.99143	1.100228	0.542951	5.382554
CP	99.6	96.15	94.93136	97.1	96.6	95.98394

Dr. Mohamed Mohamed Abdelkader

Table.10. MLE Estimation under type-I censoring scheme (n=50)

Name	$\alpha=0.5$	$\beta=0.7$	$\lambda=0.9$	$\alpha=0.5$	$\beta=0.7$	$\lambda=0.9$
Time of censoring (% 30)				Time of censoring (% 60)		
Bias	13.1507	0.167236	7.465081	3.53562	0.069969	6.768525
MSE	80.68157	0.083021	50.75216	6.292838	0.028787	42.42405
AIL	23.99338	1.032298	9.290721	6.978429	0.636934	9.040172
CP	99.9	93.1	93.42533	100	95.9	93.75355
Time of censoring (% 90)				Time of censoring (% 99.99)		
Bias	0.252295	0.060709	5.357527	0.697425	0.066563	4.617337
MSE	0.19266	0.010372	24.97674	0.146293	0.010034	17.78777
AIL	1.648401	0.362897	5.153031	0.616127	0.347676	2.823951
CP	98.7	96.45	96.42677	96.4	97.05	95.7

Table.11. MLE Estimation under type-I censoring scheme (n=75)

Name	$\alpha=0.5$	$\beta=0.7$	$\lambda=0.9$	$\alpha=0.5$	$\beta=0.7$	$\lambda=0.9$
Time of censoring (% 30)				Time of censoring (% 60)		
Bias	10.97393	0.103652	7.445455	2.941758	0.027718	6.533631
MSE	54.47567	0.050209	49.70957	3.337862	0.012275	37.99613
AIL	19.35551	0.831234	8.597914	4.249037	0.427686	7.249638
CP	99.95	93.55	94.44856	99.8	95.95	95.62433
Time of censoring (% 90)				Time of censoring (% 99.99)		
Bias	0.233561	0.047731	5.208587	0.698732	0.065513	4.591746
MSE	0.111507	0.006442	22.94296	0.136544	0.007128	17.3837
AIL	1.226618	0.286128	3.857996	0.471936	0.277946	2.16734
CP	98.65	96.7	96.94847	96.65	97.1	95.95

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

Name	$\alpha=0.5$	$\beta=0.7$	$\lambda=0.9$	$\alpha=0.5$	$\beta=0.7$	$\lambda=0.9$
Time of censoring (% 30)				Time of censoring (% 60)		
Bias	9.553252	0.053174	7.549929	2.740278	0.012746	6.557685
MSE	38.72291	0.030942	51.00367	2.478933	0.005986	38.08188
AIL	15.63787	0.674081	8.620099	3.041303	0.301327	7.067776
CP	100	93.6	93.7415	99.65	95.85	95.46392
Time of censoring (% 90)				Time of censoring (% 99.99)		
Bias	0.190914	0.046368	5.11259	0.692779	0.061839	4.536351
MSE	0.077407	0.00479	21.65912	0.130586	0.00584	16.89286
AIL	1.024661	0.239683	2.735885	0.40369	0.246946	1.856921
CP	98.1	96.7	96.49825	96.45	96.4	96.15

Dr. Mohamed Mohamed Abdelkader

Table.13. MLE Estimation under type-II censoring scheme (n=25)

Name	$\alpha=1.2$	$\beta=2.0$	$\lambda=2.5$	$\alpha=1.2$	$\beta=2.0$	$\lambda=2.5$
Time of censoring (% 30)				Time of censoring (% 60)		
Bias	1.848557	0.07224	2.875782	1.472882	0.148814	2.9256
MSE	15.96578	0.427464	107.627	5.341196	0.353655	120.6223
AIL	13.03079	2.500143	29.32829	5.838452	2.018687	32.1261
CP	97.8	95.3	93.96067	99.4	94.45	93.17102
Time of censoring (% 90)				Time of censoring (% 99.99)		
Bias	0.810813	0.224332	2.014976	0.664566	0.243463	1.587606
MSE	1.078529	0.295409	51.11129	0.675635	0.294768	22.48834
AIL	1.42371	1.202825	19.89089	0.781311	0.942143	10.18154
CP	98.8	96.75	95.8523	96.53465	97.0297	95.54455

Table.14. MLE Estimation under type-II censoring scheme (n=50)

parm	$\alpha=1.2$	$\beta=2.0$	$\lambda=2.5$	$\alpha=1.2$	$\beta=2.0$	$\lambda=2.5$
Time of censoring (% 30)				Time of censoring (% 60)		
Bias	2.406791	0.151269	2.966659	1.356629	0.221778	2.878048
MSE	15.93513	0.321378	110.0101	3.562864	0.286987	106.917
AIL	10.80473	1.879785	29.0817	3.745704	1.177875	29.11774
CP	99.5	93.6	93.45037	99.55	94.95	94.04117
Time of censoring (% 90)				Time of censoring (% 99.99)		
Bias	0.847804	0.250531	1.796532	0.682449	0.258561	1.401501
MSE	1.093698	0.282949	29.23044	0.68484	0.294122	14.18583
AIL	0.949684	0.700151	11.80084	0.466909	0.640752	5.418167
CP	98.25	96.25	96.63655	96.45	96.55	95.7979

Table.15. MLE Estimation under type-II censoring scheme (n=75)

parm	$\alpha=1.2$	$\beta=2.0$	$\lambda=2.5$	$\alpha=1.2$	$\beta=2.0$	$\lambda=2.5$
Time of censoring (% 30)				Time of censoring (% 60)		
Bias	2.376767	0.17592	3.034973	1.34692	0.238462	2.810155
MSE	14.38871	0.298831	111.929	3.247861	0.287813	95.76949
AIL	9.805498	1.640416	28.91083	3.125487	0.963277	26.71252
CP	99.8	94.1	93.86139	99.9	95.45	94.60318
Time of censoring (% 90)				Time of censoring (% 99.99)		
Bias	0.846121	0.26167	1.671403	0.685401	0.261656	1.346967
MSE	1.061074	0.292488	21.74019	0.684942	0.289962	12.317
AIL	0.680791	0.534784	8.11189	0.36077	0.497621	3.876557
CP	98.55	96.25	96.8	96.25	97.1	96.4

Dr. Mohamed Mohamed Abdelkader

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

parm	$\alpha=1.2$	$\beta=2.0$	$\lambda=2.5$	$\alpha=1.2$	$\beta=2.0$	$\lambda=2.5$
Time of censoring (% 30)				Time of censoring (% 60)		
Bias	2.36531	0.200833	3.127899	1.321521	0.248773	2.736617
MSE	13.13739	0.297286	116.4435	2.978365	0.288643	88.81589
AIL	8.838175	1.445693	29.15808	2.669453	0.794797	25.41343
CP	99.95	93.3	93.97208	99.85	95.5	94.27083
Time of censoring (% 90)				Time of censoring (% 99.99)		
Bias	0.854554	0.261174	1.670675	0.686349	0.264133	1.310204
MSE	1.077274	0.286352	20.94553	0.684174	0.291005	11.31658
AIL	0.628526	0.455637	7.336199	0.299279	0.428453	3.005628
CP	98.4	96.15	97	96.15385	97.12821	95.79487

Reference

- 1- A. El-Gohary, A. H. El-Bassiouny, M.El-Morshedy (2015), Exponentiated Flexible Weibull Extension, <https://www.researchgate.net/publication/272677857>
- 2- Abdelfattah Mustafa, Beih S. El-Desouky, Shamsan AL-Garash, (2016), THE WEIBULL GENERALIZED FLEXIBLE WEIBULL EXTENSION DISTRIBUTION, Journal of Data Science 14, 453-478
- 3- Alfred Renyi, On Measures of entropy and information, 1961
- 4- Aslam M, Ley C, Hussain Z, Shah SF, Asghar Z (2020) A new generator for proposing flexible lifetime distributions and its properties. PLoS ONE 15(4): e0231908.<https://doi.org/10.1371/journal.pone.0231908> doi: org/10.1080/00949658808811068.
- 5- El-Desouky, B.S., Mustafa, A. and Al-Garash, S. (2017) The Exponential Flexible Weibull Extension Distribution. Open Journal of Modelling and Simulation,5,83-97. <http://dx.doi.org/10.4236/ojmsi.2017.51007>
- 6- J. J. Swain, S. Venkatraman, J.R. Wilson, Least-squares estimation of distribution functions in johnson's translation system, J. Stat. Comput. Simul., 29 (1988),271–297.
- 7- Kao, j. H. (1958) computer methods for estimating weibull parameters in reliability studies, trans. IRE Reliab. Qual. Control 13, pp. 15-22.
- 8- Kao, j. H. (1959) A graphical estimation of mixed weibull parameters in life testing electron tube, technometrics 1, pp. 389-407
- 9- Kenney, j. F. and E. S. (1962). Mathematics of statistics. 3rd ed. Princeton, NJ: Chapman and Hall, pp. 101-102.

Dr. Mohamed Mohamed Abdelkader

-
-
- 10- Khaleel M.A. & Oguntunde P.E. & Ahmed,M.T. & Ibrahim N.A. , and Loh,Y.F. (2020), The Gompertz Flexible Weibull Distribution and its Applications, Malaysian Journal of Mathematical Sciences 14(1): 169–190
 - 11- M. R. mahmoud Reyad, Soad El-gendy, Eman M. Sewilam, Amira Albadwy, (2011), Maximum Likelihood Estimation of the Flexible Weibull Distribution Based on Type II censored Data, Academy of Business Journal, Al-Azhar University, vol-9.
 - 12- Mark Bebbingtona, Chin-Diew Lai, Ricardas Zitikis, (2007) A flexible Weibull extension, Reliability Engineering and System Safety 92 719–726
 - 13- Moors, J. J. (1988). A quantile alternative for kurtosis. J. Royal statist. Soc. D, vol. 37, pp. 25-32
 - 14- NihadSh.Khalaf, Moudher Kh. Abdul Hameedb, Mundher A. Khaleel, Zeyad M. Abdullahe, (2022) The Topp Leone Flexible Weibull distribution: An extension of the Flexible Weibull distribution, Int .J. Nonlinear Anal. Appl.13 ,1,2999-3010, <http://dx.doi.org/10.22075/ijnaa.2022.6031>
 - 15- Sangun Park & Jiwhan Park (2016): A general class of flexible Weibull distributions, Communications in Statistics - Theory and Methods, DOI: 10.1080/03610926.2015.1118509
 - 16- Sangun Parka, Jihwan Park, Youngsik Choi, (2016) , A new flexible Weibull distribution, Communications for Statistical Applications and Methods, Vol.23, No.5, 399–409
 - 17- Sanjay Kumar Singh, Umesh Singh, and Vikas Kumar Sharma (2013), Bayesian Estimation and Prediction for Flexible Weibull Model, Journal of Probability and Statistics, Volume, Article ID 146140,16pages. <http://dx.doi.org/10.1155/2013/146140>
 - 18- Sanjay Kumar Singh, Umesh Singh, Vikas Kumar Sharma, Manoj Kumar, (2015), Estimation for flexible Weibull extension under progressive Type-II censoring, Journal of Data Science 13, 21-42
 - 19- Weibull,W.A. (1951)."Statistical distribution function of wide applicability". Journal of Applied Mechanics,18,293-6.
 - 20- Zubair Ahmad, Zawar Hussain (2017), Modified New Flexible Weibull Distribution, Circulation in Computer Science, Vol.2, No.6, pp: (7-13)
 - 21- Zubair Ahmad, Zawar Hussain. (2017), The New Extended Flexible Weibull Distribution and Its Applications. International Journal of Data Science and Analysis. Vol. 3, No. 3, pp. 18-23. doi: 10.11648/j.ijdsa.20170303.11

تحويلة Log – expo لتوزيع وايل المرن ذي المعالم الثلاث

د. محمد محمد عبد القادر

ملخص البحث

هناك طريقة جديدة لتوليد توزيعات الحياة تسمى بطريقة تحويلة Log – expo ، هذه الدراسة تقدم توزيعاً جديداً باستخدام هذه الطريقة هو توزيع وايل المرن باستخدام هذه التحويلة LET-FW. وقد تمت دراسة بعض الخصائص الرياضية لهذا التوزيع كما تم ايجاد دالة كثافة الاحتمال ودالتي البقاء والخطر. وتم الحصول على العزوم العادية ودالة الوسيط ومتوسط البقاء على قيد الحياة و Rényi entropy . تم تقدير معالم التوزيع باستخدام خمس طرق للتقدير كما تمك ايجاد أفضل تقدير عن طريق المقارنة بين نتائج هذه الطرق. وقد تمت المقارنة باستخدام المعيار MSE (متوسط مربعات الخطأ) عن طريق تجارب المحاكاة بالاعتماد على برنامج R باختيار أحجام عينات مختلفة وقيم معلومات أولية مختلفة. وأخيراً تقدير معالم التوزيع في حالات البيانات غير الكاملة والبيانات المراقبة وذلك بالنسبة للنوعين الأول والثاني للبيانات.

المصطلحات الرئيسية للبحث: وايل المرن، دالة الوسيط، LET-FW، Rényi entropy