Some Exponentiated Distributions with Various Applications

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Article History Article Received: 25 March 2022 Revised: 30 April 2022 Accepted: 15 June 2022 Publication: 19 August 2022 Abstract The expansion of weibull exponentiated, exponential exponentiated, lognormal exponentiated, gumble exponentiated and exponentiated exponential were discussed. Weibull exponentiated embellishes to match unimodel, monotone and hazardous functions unlike the weibull model. Both the shape and the scale parameter of exponential exponentiated are similar to the gamma and weibull distribution. Specific lognormal (three parameters) and exponentiated gumble (two parameters) are unimodel distributions and can show better equilibrium. The exponential exponentiated distribution provides a highly flexible model for lifetime data. The parameter estimation were performed with the same probability and equal efficiency. The applications were defined by three data sets. Keywords-Exponentiated weibull, Exponentiated exponential, Exponentiated lognormal, Exponentiated gumble, Extended exponentiated exponential, Maximum likelihood estimators, Goodness of fit.

INTRODUCTION

Evaluation of lifetime data sets are usually done by gamma and weibull. The gamma distribution is not so much perceived as weibull distribution as in the case of gamma distribution the survival function cannot be detected in a closed way unless the shape parameter is a whole number. Data derived from the engineering and technical trainings often find a place in survival data. Mudhokar and Srivastava (1993) and Mudhokar et al (1995) confirmed in their study various sets of data time failures for the proposed weibull distribution. A Marshall and I. Olkin (1997) introduced a new way to add a parameter to a distribution family by utilizing descriptive and weibull families. The enhanced weibull distribution has a unique feature of the standard weibull class described by Gupta et al (1998). Gupta and Kundu (2001) presented a life-time data and noted that the distribution may be substituted. Nadarajah (2005) presented gumble distribution of survival work in clarifying rain data from Orland, Florida. Real-life data sets were also studied by Kakade and Shirke (2006) and found that enhanced lognormal distribution is well matched compared to weibull and descriptive distribution. Raja and Mir (2011) discussed the expansion of other distributions by distinct applications. Bagheri et al (2014) has been very active in the effective pdf estimation and cdf of gumble distribution s. Abu-Youssef et al (2015) introduced a descriptive extension that provides a comparatively flexible model for lifetime data sets in most cases. Suresh and Usha (2016) performed a reduced health trial on a descriptive dose. Raja and Maqbool (2019) also extended application of Poisson and Poisson type distributions. Malik Mansoor and Kumar Devendra (2020) studied exponential weibull model. However the exponentiated gumble distribution is a well fit and can be used in place of weibull. Here exponentiated exponential distribution gives comparatively better fit than three parameter weibull and exponentiated gumble.

Three data sets were utilized by exploiting these distributions together and comparisons were explained.

1. Exponentiated Weibull Distribution

Probability density function

Probability density function (p.d.f) of exponentiated weibull(EW) distribution as considered by Mudhokar et al(1995) with parameter α , θ , and σ is given as

$$f(t;\alpha,\theta,\sigma) = \frac{\alpha\theta}{\sigma} \left[1 - \exp\left(-\left(\frac{t}{\sigma}\right)^{\alpha}\right) \exp\left[-\left(\frac{t}{\sigma}\right)^{\alpha}\right] \left(\frac{t}{\sigma}\right)^{\alpha-1}, \nabla t > 0....(1)$$

Where $\alpha >0$, $\theta >0$ are shape parameters and $\sigma >0$ is a scale parameter.

Specifies the weibull distribution when $\theta = 1$ and the descriptive distribution when $\alpha = 1$ and $\theta = 1$.

Survival work associated with random T variance and weibull exponentiated is provided as

Maximum Likelihood Estimators

Maximum likelihood estimators for a three parameter EW are given as.

Let $x_1, x_2, x_3, \dots, x_n$ be a random sample from EW and the log likelihood can be worked out as

L(α, θ, σ)=n. log ($\alpha\theta/\sigma$)+

$$(\theta-1).\sum_{i=1}^{n}\log(g(Ti)) - \sum_{i=1}^{n}(Ti/\sigma)^{\alpha} + (\alpha-1).\sum_{i=1}^{n}\log(Ti/\sigma)....(1.3)$$

Where $g(Ti)=g(Ti;\alpha,\theta)=1-exp(-T/\sigma)^{\alpha}$

Differentiate (1.1) with respect to three parameters.

$$\frac{\partial L}{\partial \alpha} = \frac{n}{\alpha} + (\theta - 1) \sum_{i=1}^{n} g_{\alpha} (Ti) / g(Ti) - \sum_{i=1}^{n} (Ti / \sigma)^{\alpha} \cdot \log(Ti / \sigma) + \sum_{i=1}^{n} \log(T / \sigma) = 0 \dots (1.4)$$

$$\frac{\partial L}{\partial \theta} = \frac{n}{\theta} + \sum_{i=1}^{n} \log(g(Ti)) = 0....(1.5)$$

$$\frac{\partial L}{\partial \sigma} = -\left(\frac{n\alpha}{\sigma}\right) + (\theta - 1) \sum_{i=1}^{n} g_{\sigma}(T_{i}) / g(T_{i}) + (\alpha / \sigma) \sum_{i=1}^{n} (T_{i} / \sigma)^{\alpha} \dots (1.6)$$

where

$$g_{\alpha}(Ti) = \exp(-(Ti/\sigma)^{\alpha} . (Ti/\sigma)^{\alpha} . \log(Ti/\sigma),$$

$$g_{\sigma}(Ti) = -\left[\alpha . \exp(-(Ti/\sigma)^{\alpha}) . (Ti/\sigma)^{\alpha}\right]/\sigma$$

From (1.4), (1.5) and (1.6) we obtain the ML Estimates.

2. Exponentiated Exponential

Probability density function

The Probability density function of exponentiated exponential is defined by

Gupta and Kunda (2001) with parameters α and λ as

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

Here α is the shape parameter and λ is the scale parameter. For $\alpha=1$ it signify

the exponential family.

The survival function corresponding with exponentiated-exponential density is given as

The exponentiated exponential represents a parallel system.

Maximum Likelihood Estimators:-

Let $x_1, x_2, x_3, \dots, x_n$ be a random sample from EE the log likelihood can be as

$$L(\alpha, \lambda) = n \ln \alpha + n \ln \lambda + (\alpha - 1) \sum_{i=1}^{n} In(1 - e^{-\lambda xi}) - \lambda \sum_{i=1}^{n} x_i \dots (2.3)$$

The MLE's of α and λ can be directly maximized $\frac{\partial L}{\partial \alpha} = \frac{n}{\alpha} + \sum_{i=1}^{n} In(1 - e^{-\lambda x}) = 0.....$

$$\frac{\partial L}{\partial \lambda} = \frac{n}{\lambda} + (\alpha - 1) \sum_{i=1}^{n} \frac{x_i e^{-\lambda x_i}}{1 - e^{-\lambda x_i}} - \sum_{i=1}^{n} x_i = 0....(2.5)$$

From (2.4), we obtain the MLE of α as a function of λ , say $\alpha(\lambda^{2})$, as

For a known scale parameter, MLE of the standard parameter α^{\uparrow} , can be obtained directly from (2.6) .If both parameters are unknown, first the scale parameter measurement can be obtained by directly increasing L($\alpha(\lambda^{\uparrow})$, λ) in relation to λ . Once λ^{\uparrow} is detected α^{\uparrow} can be obtained from (2.6) as $\alpha^{\uparrow}(\lambda^{\uparrow})$, .

3. Exponentiated Lognormal Distribution

Probability density function

Probability density function (P.d.f) of exponential Lognormal distribution is

defined by three parameters (α, μ, σ) as

$$f(x; (\alpha, \mu, \sigma)) = \alpha \big(\varphi(In(x); \mu, \sigma) \big)^{\alpha - 1} \cdot \phi \big(In(x); \mu, \sigma \big) x^{-1}, \dots \dots (3.1)$$

x, $\alpha > 0, -\infty < \mu < \infty$

where $\varphi(In(x);\mu,\sigma)$ and $\phi(In(x);\diamond)$ are the c.d.f and p.d.f of the normal distribution with mean and standard deviation as μ and σ .

The survival function corresponding with exponentiated lognormal distribution density is given as

 $S(x, \mu \sigma, \alpha) = 1 - (\varphi(In(x); \mu, \sigma))^{\alpha}$ where x>0

Maximum Likelihood Estimators

Let $x_1, x_2, x_3, \dots, x_n$ be a random sample from EL distribution the log likelihood function can be as

$$L(\alpha, \mu, \sigma / x) = n \ln \alpha - \sum_{i=1}^{n} \ln(xi) + (\alpha - 1) \sum_{i=1}^{n} \ln \varphi(\ln(xi); \mu, \sigma) + \sum_{i=1}^{n} \ln \phi(\ln(xi); \mu, \sigma) ...(3.2)$$

To find the values of the parameters α, μ, σ that maximize $L(\alpha, \mu, \sigma/x)$ we can solve the equations which are as follows:-

$$\frac{\partial L}{\partial \alpha} = \frac{n}{\alpha} + \sum_{i=1}^{n} \ln \varphi(\ln(xi); \mu, \sigma) = 0......$$
(3.3)

$$\frac{\partial L}{\partial \mu} = (\alpha - 1) \sum_{i=1}^{n} \frac{\varphi_{\mu}^{-1}(In(xi); \mu, \sigma)}{\varphi(In(xi); \mu, \sigma)} + \sum_{i=1}^{n} \frac{\varphi_{\mu}^{-1}(In(xi); \mu, \sigma)}{\varphi(In(xi); \mu, \sigma)} = 0.....(3.4)$$
$$\frac{\partial L}{\partial \sigma} = (\alpha - 1) \sum_{i=1}^{n} \frac{\varphi_{\sigma}^{-1}(In(xi); \mu, \sigma)}{\varphi(In(xi); \mu, \sigma)} + \sum_{i=1}^{n} \frac{\varphi_{\sigma}^{-1}(In(xi); \mu, \sigma)}{\varphi(In(xi); \mu, \sigma)} = 0.....(3.5)$$

From (3.3), (3.4) and (3.5) MLE of α , μ and σ is obtained.

4. Exponential Gumble Distribution

Probability density function

The Probability density function (Pd.f) of exponential gumble distribution was led by Nadarajah(2005) with parameters α and σ as

Where α and $\sigma > 0$ and $-\infty < x < \infty$

Where α is a shape parameter and σ is scale parameter.

Here when $\alpha=1$ it reduces to standard gumble distribution.

The survival function corresponding with exponentiated-gumble density is given as

The survival function of the exponentiated gumble distribution is the α th power of the survival function of the gumble distribution.

Maximum Likelihood Estimators

Let $x_1, x_2, x_3, \dots, x_n$ be a random sample from EG distribution the log likelihood function can be as

L (
$$\alpha$$
, σ)=n ln α - nln σ - $\frac{1}{\sigma}\sum_{i=1}^{n} x_i - \alpha \sum e^{\frac{-xi}{\sigma}}$(4.3)

Therefore to obtain the MLE's of α and σ we can directly maximize (4.3) with respect to α and σ or we can solve the non-linear normal equations which are as follows:-

$$\frac{\partial L}{\partial \alpha} = \frac{n}{\alpha} - \sum_{i=1}^{n} e^{-\frac{x_i}{\sigma}} = 0.....(4.4)$$

$$\frac{\partial L}{\partial \sigma} = -\frac{n}{\sigma} + \frac{1}{\sigma^2} \sum_{i=1}^{n} x_i - \frac{\alpha}{\sigma^2} \sum_{i=1}^{n} x_i .e^{\frac{-x_i}{\sigma}} = 0....(45)$$

From (4.4) and (4.5) MLE of α , and σ is obtained.

5. Extended Exponentiated Exponential Distribution:-

Assume that X is a random variable with a given survival function $F^-(x)$, the Marshall-Olkin extension of the real family is defined as a distribution family with survival function as:

 $G^{-}(x) = \lambda F^{-}(x) / (1 - \lambda^{-}F^{-}(x)), \qquad -\infty < x < \infty, \ \lambda > 0, \ \lambda^{-} = 1 - \lambda.$ (5.1)

Abu-Youssef et al (2015)

Presented a new alternative of the Marshall-Olkin extended family of distributions by selecting in (5.1) the exponentiated exponential distribution with survival function 1 which shows

 $G(x) = \lambda - \lambda(1 - e - \beta x) \alpha \lambda + \lambda(1 - e - \beta x) \alpha, x > 0, \alpha > 0, \lambda > 0, \beta > 0...(5.2)$

Maximum Likelihood Estimators:-

Suppose x1, x2, ..., xn is a random sample size n from Marshall Olkin extended descriptive distribution and the function of likelihood will be

and the log-likelihood function is

 $Ln = \sum_{i=1}^{n} (\alpha - 1) (\log(1 - e - \beta xi)) - \beta xi - 2 \log((\lambda (1 - e - \beta xi) \alpha + \lambda)))$

 $+ n \log (\alpha \beta \lambda)$(5.4)

The Maximum Likelihood Estimation (MLE) of α , β and λ are attained as the result of $\partial L / \partial \alpha = 0$,

$$\partial \operatorname{Ln} (\alpha, \beta, \lambda) / \partial \alpha = \partial / \partial \alpha \prod_{i=1}^{n} g(\operatorname{xi}, \alpha, \beta, \lambda) = \prod \frac{\alpha \beta \lambda (1 - e - \beta \operatorname{xi}) \cdot \alpha - 1 \cdot e - \beta \operatorname{xi}}{(\lambda^{-} (1 - e - \beta \operatorname{xi}) \cdot \alpha + \lambda) \cdot 2} \dots (5.5)$$
$$\partial L / \partial \beta = 0,$$

 $\partial \operatorname{Ln} (\alpha, \beta, \lambda) / \partial \beta = \partial / \partial \beta \prod_{i=1}^{n} g(\operatorname{xi}, \alpha, \beta, \lambda) = \prod \frac{\alpha \beta \lambda (1 - e - \beta \operatorname{xi}) \cdot \alpha - 1 \cdot e - \beta \operatorname{xi}}{(\lambda^{-} (1 - e - \beta \operatorname{xi}) \cdot \alpha + \lambda) \cdot 2} \dots (5.6)$

and

$$\partial L / \partial \lambda = 0.$$

 $\partial \operatorname{Ln}(\alpha,\beta,\lambda)/\partial \lambda = \partial/\partial \lambda \prod_{i=1}^{n} g(\operatorname{xi},\alpha,\beta,\lambda) = \prod \frac{\alpha\beta\lambda(1-e-\beta\operatorname{xi}).\alpha-1.e-\beta\operatorname{xi}}{(\lambda^{-}(1-e-\beta\operatorname{xi})\alpha+\lambda)2}...(5.7)$

From (5.1),(5.6) and (5.7) we can have MLE.

Goodness of Fit

Nine models namely gamma, weibull, lognormal, gumble, exponentiated weibull, exponentiated exponential, exponentiated lognormal, exponentiated gumble and extended exponentiated exponential have been fitted to three real data sets. The distributions along with Probability density function are given as under:-

Distribution P.d. f

Gamma

$$f(x, \alpha, \lambda) = \frac{\lambda^{\alpha}}{\Gamma \alpha} x^{\alpha - 1} \cdot e^{-\lambda \cdot x}; \qquad \alpha, \lambda, x > 0$$

Weibull

$$\mathbf{f}(\mathbf{x}, \alpha, \lambda) = \alpha \lambda (x\lambda)^{\alpha-1} \cdot e^{(-\lambda x)^{\alpha}}; \alpha, \lambda, x > 0$$

Lognormal
$$f(x, \mu, \sigma) = \frac{\exp\left(-\frac{1}{2}\left(\frac{In(x) - \mu}{\sigma}\right)^2\right)}{x \cdot \sigma \cdot \sqrt{2\lambda}} ; -\infty < \mu < \infty, \sigma > 0$$

Gumble
$$f(x, \sigma) = \frac{1}{\sigma} \exp^{\frac{-x}{\sigma}} . \exp\left(-e^{\frac{-x}{\sigma}}\right) ; \sigma > 0$$

Exponentiated weibull
$$f(t; \alpha, \theta, \sigma) = \frac{\alpha \theta}{\sigma} \left[1 - \exp(-\left(\frac{t}{\sigma}\right)^{\alpha} \right] \exp\left[-\left(\frac{t}{\sigma}\right)^{\alpha}\right] \left(\frac{t}{\sigma}\right)^{\alpha-1}, t > 0$$

Exponentiated exponential $f(x, \alpha, \lambda) = \alpha \lambda (1 - e^{-\lambda x})^{\alpha - 1} \cdot e^{-\lambda x}, \quad \alpha, \lambda, x > 0$

Exponentiated lognormal
$$f(x, (\alpha, \mu, \sigma)) = \alpha (\varphi(In(x); \mu, \sigma))^{\alpha - 1} \cdot \phi (In(x); \mu, \sigma) x^{-1},$$

 $x, \alpha > 0, -\infty < \mu < \infty$

Exponentiated gumble
$$f(x; \alpha, \sigma) = \frac{\alpha}{\sigma} \left[\exp\left(-e^{-\frac{x}{\sigma}}\right) \right]^{\alpha} \cdot e^{-\frac{x}{\sigma}}, \alpha, \sigma > 0$$

Extended Exponentiated exponential $f(x) = \alpha\beta\lambda(1 - e - \beta x) \alpha - 1 e - \beta x (\lambda^{-}(1 - e - \beta x) \alpha + \lambda) 2, x > 0.$

Data Set1:-The data pertaining to failure times of the conditioning system of an aero plane.

12,120,11,3, 14, 71,11,14,11,16, 90, 1,16,52,95.

| Distribution | MLE'S | Log likelihood | Anderson's Value |
|---------------------------|---|----------------|------------------|
| Gamma | $\alpha^{-}=0.8119, \ \lambda^{-}=0.0136$ | -152.167 | 0.078 |
| Weibull | $\alpha^{-}=0.8536, \ \lambda^{-}=0.0183$ | -151.9.70 | 0.069 |
| Lognormal | $\mu^{=}3.358, \lambda^{=}1.3190$ | -151.621 | 0.065 |
| Gumble | $\alpha^{-27.792}, \lambda^{-55.106}$ | -151.256 | 0.062 |
| Exponentiated weibull | $\alpha^{-}=$ 3.824, $\theta^{-}=$ | -149.567 | 0.057 |
| | 0.1732 σ [^] =82.235 | | |
| Exponentiated exponential | $\alpha^{-}=0.8093, \ \lambda^{-}=0.0145$ | -152.206 | 0.079 |
| Exponentiated lognormal | $\alpha^{-}_{=} 0.1543 \mu^{-}_{=}$ | -148.659 | 0.055 |
| | 3.1353 σ [^] =0.3648 | | |
| Exponentiated gumble | $\alpha^{-1.9881, \lambda^{-49.0638}}$ | -148.537 | 0.054 |
| Extended exponentiated | $\alpha^{*}=0.8119, \beta=1.46$ | 1381.572 | 0.051 |
| exponential | λ^=0.0136 | | |

Table1:- Distribution with MLE'S, Log-likelihood and Anderson's value.

Data Set 2:-The data pertains to runs scored by a cricketer in 27 innings at national level:-

28,20,6,4,23,127,25,45,41,67,68,3,17,2,

105,98,55,68,15,3,42,45,7,20, 34,9,6,

Table2:- Distribution with MLE'S, Log-likelihood and Anderson's value.

| Distribution | MLE'S | Log likelihood | Anderson's Value |
|---------------------------|---|----------------|------------------|
| Gamma | $\alpha^{-}=0.7235$, $\lambda^{-}=0.0127$ | -125.654 | 0.956 |
| Weibull | $\alpha^{-1.040, \lambda^{-36.985}}$ | -124.021 | 0.716 |
| Lognormal | $\mu^{=}3.053, \lambda^{=}1.174$ | -125.022 | 0.916 |
| Gumble | $\alpha^{2} = 21.432$, $\lambda^{2} = 25.944$ | -124.059 | 0.702 |
| Exponentiated weibull | $\alpha_{=}^{2}$ 3.521, $\theta_{=}^{2}$ | -125.078 | 0.928 |
| | 0.1452 σ [^] =67.235 | | |
| Exponentiated exponential | $\alpha^{2} = 0.8126, \ \lambda^{2} = 0.0153$ | -125.945 | 0.959 |
| Exponentiated lognormal | $\alpha^{-}=0.578, \ \mu^{-}=3.836$ | -125.965 | 0.961 |
| | σ [^] =0.7834 | | |
| Exponentiated gumble | $\alpha^{^{}}_{= 1.873}, \lambda^{^{}}_{= 45.264}$ | -124.843 | 0.843 |
| Extended exponentiated | $\alpha^{^{}}=0.8119, \beta=1.46$ | -121.784 | 0.827 |
| exponential | λ^=0.0136 | | |

Data Set 3:- Nichols and Padgett data set consisting of 100 observations on breaking stress of carbon fibers (in gba):-

3.72.742.732.53.63.113.272.871.473.114.422.413.193.221.693.283.091.873.154.93.752.432.952.973.392.962.532.672.933.22

| 3.15 | 2.35 | 2.55 | 2.59 | 2.38 | 2.81 | 4.2 | 3.33 | 2.55 3.39 |
|------|------|--------|--------|--------|--------|------|------|-----------|
| 3.31 | 3.31 | 2.85 | 2.56 | 3.56 | 2.81 | 2.77 | 2.17 | 2.83 1.92 |
| 1.41 | 3.68 | 2.97 | 1.36 | 0.98 | 2.76 | 4.91 | 3.68 | 1.84 1.59 |
| 2.17 | 1.17 | 5.08 | 2.48 | 1.18 | 3.19 | 1.57 | 0.81 | 5.56 1.73 |
| 1.59 | 2.0 | 1.22 | 2 1.12 | 2 1.71 | 1.84 | 3.65 | 2.05 | 0.39 3.68 |
| 2.48 | 0.85 | 5 1.61 | 2.79 | 9 4.7 | 3.51 | 2.17 | 1.69 | 1.25 4.38 |
| 2.03 | 1.8 | 1.57 | 1.08 | 3 2.03 | 3 1.61 | 2.12 | 1.89 | 2.88 2.82 |
| | | | | | | | | |

Table3:- Distribution with MLE'S, Log-likelihood and Anderson's value.

| Distribution | MLE'S | Log likelihood | Anderson's Value |
|---------------------------|---|----------------|------------------|
| Gamma | α =0.6754 , λ=0.1324 | -134.976 | 0.743 |
| Weibull | $\alpha_{=0.9678, \lambda=5.678}^{\circ}$ | -115.763 | 0.843 |
| Lognormal | $\mu^{2}=2.609, \lambda^{2}=2.419$ | -117.046 | 0.744 |
| Gumble | $\alpha^{^{}}=17.435$, $\lambda^{^{}}=19.865$ | -116.052 | 0.789 |
| Exponentiated weibull | $\alpha_{=}^{2}$ 4.564, $\theta_{=}^{2}$ | -117.078 | 0.710 |
| | 0.1432 σ [^] =67.235 | | |
| Exponentiated exponential | $\alpha^{^{}}=0.984, \lambda^{^{}}=0.0453$ | -117.956 | 0.783 |
| Exponentiated lognormal | $\alpha^{-}=0.436, \ \mu^{-}=2.342$ | -117.893 | 0.776 |
| | σ^=0.6753 | | |
| Exponentiated gumble | $\alpha^{^{^{^{^{^{^{^{^{^{^{^{^{^{^{^{^{^^{^^$ | -115.67 | 0.734 |
| Extended exponentiated | $\alpha^{^{}}=0.763, \beta=1.45 \lambda^{^{}}=0.0125$ | -114.31 | 0.713 |
| exponential | | | |

The following table gives a comparison between the MLE's Loglikelihood, and Anderson's Value and can be interpreted as :-

Conclusion

The probability density function of exponentiated weibull, exponentiated exponential, exponentiated lognormal, exponentiated gumble and extended exponentiated exponential distributions and its applications for three data sets were discussed. It appears that the weibull defined by the two parameters is more suitable to fit the unimodel, monotone and risk functions. The exponential has a framework and scale similar to the gamma and weibull distribution and can be considered as an alternative and equally superior to the weibull and gamma in most cases. Three parameter extended exponentiated exponential distribution offers more flexible model for real time data sets. The initial set of data relates to the failure times of the flight status suspension system. The exponential exponentiated and gamma provides the best balance followed by Weibull. Thus the gamma weibull and the extended exponentiated exponential can be exchanged with each other in a particular case. In second data set regarding runs scored by a cricketer extended exponentiated exponential, exponentiated lognormal and exponentiated exponential gives better fit followed by gamma.

replaced as an alternative with each other. In third data set extended exponentiated exponential followed by exponentiated weibull gives better fit. One can fit other distributions and can look for flexibility and advancement.

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