

The two component generalized finite Erlang mixture and its properties and special cases

Abstract: This research proposes construction of the two component generalized finite Erlang mixture with four parameters. Three cases of the mixture have been presented, their differences being the mixing weights applied and corresponding component probability (Erlang) distributions. Their special cases, the one, two and three parameter finite Erlang mixtures, have also been derived. Statistical properties investigated for the mixtures are the distribution function, survival function, hazard function, moment generating function, raw and central moments, mean, variance, coefficient of skewness, coefficient of kurtosis, and order statistics. Method of moments and maximum likelihood estimation were used in parameter estimation of the finite Erlang mixtures. Additionally, the 4-parameter mixed Erlang distributions have been fitted to a real data set to assess their goodness of fit.

Key Words: Finite Erlang mixture, generalization, component, moments, skewness, kurtosis

1. Introduction

The gamma distribution is a probability density function with numerous applications, including modeling time between events. It has two parameters, the shape and rate (scale). A number of distributions are its special cases, attributable to its adaptable shape parameter. They include, the exponential distribution when the shape parameter is 1, and the Erlang distribution when the shape parameter is an integer. The Erlang distribution is a more preferred alternative to the gamma distribution, owing to its increased flexibility due to its discretized shape parameter. Its applications are extensive and include queuing systems and stochastic processes. Generalization is a method of devising a new distribution with additional parameters, which is intended to increase the scope and applicability of the distribution.

When there are two or more sub-populations in a population, mixed distributions can be used to model the population, such that components of the mixture will suit the sub-populations. Thus, mixture distributions are used to model data that the basic distributions may fail to fit. Pearson[7] introduced mixed distributions in 1894, when he constructed a finite mixture using two normal distributions with different means and variances. Finite mixtures are among the three types of mixtures, the other two being continuous and discrete. Finite mixtures are defined by the number of components which can be ≥ 2 , and the number of parameters which can be at least one. Lindley[3] introduced finite Erlang mixtures when he presented the Lindley distribution, a two component mixture, which he applied in studying fiducial distributions and Bayes' theorem. There since have been innumerable work on finite Erlang mixtures. Shanker et al.[22], Shanker[19], Shanker et al.[20], Shanker et al.[21], Mussie and Shanker[17], Tesfay and Shanker[23], Tesfay and Shanker[24], and Nwikpe and Iwok[18] are among authors who studied three component finite Erlang mixtures, while Shanker[26], Shanker[27] and Rashid et al.[25] presented four component finite Erlang mixtures. Shanker[28] and Shanker[29] defined five and six component finite Erlang mixtures respectively.

The focus of this paper is on two component four parameter generalized finite Erlang mixtures, and their special cases, the one, two and three parameter finite Erlang mixtures.

Zakerzadeh and Dolati[16] defined the generalized Lindley distribution with three parameters as a mixture of $\text{gamma}(\alpha, \theta)$ and $\text{gamma}(\alpha + 1, \theta)$, with respective mixing weights $\frac{\theta}{\theta + \gamma}$ and $\frac{\gamma}{\theta + \gamma}$. Nadarajah et al.[5] demonstrated that the cdf of the two parameter generalized Lindley distribution they proposed, was the α^{th} order statistic of the Lindley distribution. A two parameter Lindley distribution was studied by Shanker et al.[14] as the sum of $\frac{\theta}{\theta + \alpha}$ $\text{gamma}(1, \theta)$ and $\frac{\alpha}{\theta + \alpha}$ $\text{gamma}(2, \theta)$, and Shanker and Mishra[15] presented it as the sum of $\frac{\alpha\theta}{\alpha\theta + 1}$ $\text{gamma}(1, \theta)$ and $\frac{1}{\alpha\theta + 1}$ $\text{gamma}(2, \theta)$. Shanker and Mishra[13] defined a Quasi Lindley distribution with two parameters as $\frac{\alpha}{\alpha + 1}$ $\text{gamma}(1, \theta) + \frac{1}{\alpha + 1}$ $\text{gamma}(2, \theta)$, and Shanker and Amanuel[12] expressed a new Quasi Lindley distribution with two parameters as $\frac{\theta^2}{\theta^2 + \alpha}$ $\text{gamma}(1, \theta) + \frac{\alpha}{\theta^2 + \alpha}$ $\text{gamma}(2, \theta)$. The cdf of the Transmuted Lindley distribution with two parameters was expressed by Merovci[4] as the sum of the cdf the Lindley distribution and the squared cdf of the Lindley distribution, with respective weights $(1 + \lambda)$ and $-\lambda$. They also presented the Lindley distribution as a special case of the Transmuted Lindley distribution. Elbatal et al.[2] proposed a new generalized Lindley distribution with three parameters as $\frac{\theta}{\theta + 1}$ $\text{gamma}(\alpha, \theta) + \frac{1}{\theta + 1}$ $\text{gamma}(\beta, \theta)$. The Lindley, gamma and exponential distributions were expressed as special cases of the distribution. The cdf of a four parameter beta-generalized Lindley (BGL) distribution was expressed in terms of the cdf of the generalized Lindley distribution by Oluyede[6]. A new generalized Lindley distribution with five parameters was presented by Abouammoh[1] as the sum of $\text{gamma}(\tau, \theta)$ and $\text{gamma}(\eta, \theta)$, with respective mixing weights $\frac{\theta\rho}{\gamma + \theta\rho}$ and $\frac{\gamma}{\gamma + \theta\rho}$. Shanker[9] proposed a one parameter Shanker distribution as $\frac{\theta^2}{\theta^2 + 1}$ $\text{gamma}(1, \theta) + \frac{1}{\theta^2 + 1}$ $\text{gamma}(2, \theta)$. The Akash distribution with one parameter, $\frac{\theta^2}{\theta^2 + 2}$ $\text{gamma}(1, \theta) + \frac{2}{\theta^2 + 2}$ $\text{gamma}(3, \theta)$, was presented by Shanker[8]. Shanker[10] studied a one parameter Rama distribution, $\frac{\theta^3}{\theta^3 + 6}$ $\text{gamma}(1, \theta) + \frac{6}{\theta^3 + 6}$ $\text{gamma}(4, \theta)$. Shanker[11] defined a one parameter Suja distribution as $\frac{\theta^4}{\theta^4 + 24}$ $\text{gamma}(1, \theta) + \frac{24}{\theta^4 + 24}$ $\text{gamma}(5, \theta)$. The structure of this research is outlined as follows: The mixed Erlang distribution and its properties have been presented in section 2. The three cases of the two component four parameter generalized finite Erlang mixture, and their properties and special cases have been presented in sections 3, 4 and 5. In section 6, the three cases of the generalized finite Erlang mixture have been fitted to a data set alongside other distributions to assess their goodness of fit, and the conclusion of the paper is provided in section 7.

2. The two component finite Erlang mixture and its properties.

- The gamma (α, θ) distribution is given by;

$$f(x; \alpha, \theta) = \frac{\theta^\alpha}{\Gamma(\alpha)} e^{-\theta x} x^{\alpha-1}, \quad x > 0; \alpha > 0, \theta > 0 \quad (2.1)$$

- The exponential (θ) distribution,

$$f(x; \theta) = \theta e^{-\theta x}, \quad x > 0; \theta > 0 \quad (2.2)$$

is a special case of the gamma distribution when $\alpha = 1$.

- The Erlang (n, θ) distribution,

$$f(x; n, \theta) = \frac{\theta^n}{\Gamma(n)} e^{-\theta x} x^{n-1}, \quad x > 0; \theta > 0, n = 1, 2, 3, \dots \quad (2.3)$$

is a special case of the gamma distribution when $\alpha = n$ is a positive integer.

Properties of the Erlang (n, θ) distribution

1. The distribution function (CDF) of the Erlang distribution is given by

$$F(x; n, \theta) = 1 - e^{-\theta x} \sum_{t=0}^{n-1} \frac{(\theta x)^t}{t!} = \frac{\gamma(n, \theta x)}{\Gamma(n)} \quad (2.4)$$

2. Its survival and hazard functions are, respectively,

$$S(x; n, \theta) = 1 - F(x; n, \theta) = e^{-\theta x} \sum_{t=0}^{n-1} \frac{(\theta x)^t}{t!} = \frac{\Gamma(n, \theta x)}{\Gamma(n)}$$

and
$$h(x; n, \theta) = \frac{f(x; n, \theta)}{S(x; n, \theta)} = \frac{\theta^n}{\Gamma(n, \theta x)} e^{-\theta x} x^{n-1} \quad (2.5)$$

3. The moment generating function (MGF) is

$$M_x(t) = E(e^{tx}) = \frac{\theta^n}{\Gamma(n)} \int_0^\infty e^{-(\theta-t)x} x^{n-1} dx = \left(\frac{\theta}{\theta-t} \right)^n \quad (2.6)$$

4. The r^{th} raw moment of the Erlang distribution is given by

$$E(X^r) = \frac{\theta^n}{\Gamma(n)} \int_0^\infty e^{-\theta x} x^{r+n-1} dx = \frac{\Gamma(r+n)}{\theta^r \Gamma(n)} \quad (2.7)$$

and hence, the first four raw moments are

$$E(X) = \frac{n}{\theta}, \quad E(X^2) = \frac{n(n+1)}{\theta^2}, \quad E(X^3) = \frac{n(n+1)(n+2)}{\theta^3},$$

and
$$E(X^4) = \frac{n(n+1)(n+2)(n+3)}{\theta^4} \quad (2.8)$$

Remark: The above properties of the Erlang distribution will be applied in obtaining properties of the finite Erlang mixtures, since the component probability distributions are Erlang distributions.

5. The central moments are thus

i. Variance

$$Var(X) = E(X^2) - [E(X)]^2 = \frac{n(n+1)}{\theta^2} - \frac{n^2}{\theta^2} = \frac{n}{\theta^2} \quad (2.9)$$

ii. Coefficient of skewness

$$\frac{\mu_3}{\sigma^3} = \frac{1}{\sigma^3} \{E(X^3) - 3E(X)E(X^2) + 2[E(X)]^3\} = \frac{1}{\sigma^3} \left\{ \frac{n(n+1)(n+2)}{\theta^3} - \frac{3n^2(n+1)}{\theta^3} + \frac{3n^3}{\theta^3} \right\} \quad (2.10)$$

iii. Coefficient of kurtosis

$$\begin{aligned} \frac{\mu_4}{\sigma^4} &= \frac{1}{\sigma^4} \{E(X^4) - 4[E(X)][E(X^3)] + 6[E(X)]^2[E(X^2)] - 3[E(X)]^4\} \\ &= \frac{1}{\sigma^4} \left\{ \frac{n(n+1)(n+2)(n+3)}{\theta^4} - \frac{4n^2(n+1)(n+2)}{\theta^4} + \frac{6n^3(n+1)}{\theta^4} - \frac{3n^4}{\theta^4} \right\} \end{aligned} \quad (2.11)$$

6. The probability function of the k^{th} order statistic is

$$\begin{aligned} f_k(x) &= \frac{n!f(x)}{(k-1)!(n-k)!} \sum_{i=0}^{n-k} \binom{n-k}{i} (-1)^i [F(x)]^{i+k-1} \\ &= \frac{n!\theta^n e^{-\theta x} x^{n-1}}{(k-1)!(n-k)!\Gamma(n)} \sum_{i=0}^{n-k} \binom{n-k}{i} (-1)^i \left[\frac{\gamma(n, \theta x)}{\Gamma(n)} \right]^{i+k-1} \end{aligned} \quad (2.12)$$

7. The method of moments estimators for the Erlang distribution parameters are given by

$$\hat{\eta} = \frac{n\bar{x}^2}{\sum_{i=1}^n (x_i - \bar{x})^2}, \quad \text{and} \quad \hat{\theta} = \frac{n\bar{x}}{\sum_{i=1}^n (x_i - \bar{x})^2} \quad (2.13)$$

and the maximum likelihood estimators are

$$\hat{\theta} = \frac{\hat{\eta}}{\bar{x}}, \quad \text{and} \quad \frac{\delta}{\delta \hat{\eta}} \log \Gamma(\hat{\eta}) - \log \hat{\eta} + \log \bar{x} - \frac{1}{n} \sum_{i=1}^n \log x_i = 0 \quad (2.14)$$

- A k-component finite mixture $f(x)$ is given by;

$$f(x) = \sum_{j=1}^k \omega_j f_j(x) \quad (2.15)$$

where $f_j(x)$ is the j^{th} component probability distribution which can be discrete or continuous, and ω_j is the weighted j^{th} mixing weight for $j = 1, 2, 3, \dots, k$, with the following properties; $\omega_j > 0$ and $\sum_{j=1}^k \omega_j = 1$. Hence, $f_j(x)$ is given by (2.3) in (2.15) for a k-component finite Erlang mixture, and for two components, the mixtures will thus be of the form;

$$g(x) = \omega g_1(x) + (1 - \omega) g_2(x) \quad (2.16)$$

where $g_i(x)$ is an Erlang distribution.

Properties of the k-component finite mixture

1. The distribution function (CDF) of the finite mixture can be expressed as,

$$\begin{aligned} F(x) &= \int_0^x f(t) dt = \sum_{j=1}^k \omega_j \int_0^x f_j(t) dt = \sum_{j=1}^k \omega_j F_j(x) \\ &= \sum_{t=0}^x f(t) dt = \sum_{j=1}^k \omega_j \sum_{t=0}^x f_j(t) dt = \sum_{j=1}^k \omega_j F_j(x) \end{aligned} \quad (2.17)$$

where $F_j(x)$'s are the respective continuous and discrete j^{th} component CDFs.

2. The survival function is given by

$$\begin{aligned} S(x) &= \int_x^\infty f(t) dt = \sum_{j=1}^k \omega_j \int_x^\infty f_j(t) dt = \sum_{j=1}^k \omega_j S_j(x) \\ &= \sum_{t=x}^\infty f(t) dt = \sum_{j=1}^k \omega_j \sum_{t=x}^\infty f_j(t) dt = \sum_{j=1}^k \omega_j S_j(x) \end{aligned} \quad (2.18)$$

where $S_j(x)$'s are the continuous and discrete j^{th} component survival functions respectively.

3. The hazard function of the mixture is given by

$$h(x) = \frac{f(x)}{S(x)} \quad (2.19)$$

4. The moment generating function (MGF) of the finite mixture is

$$\begin{aligned} M_x(t) &= E(e^{tx}) = \int_0^{\infty} e^{tx} f(x) dx = \sum_{j=1}^k \omega_j \int_0^{\infty} e^{tx} f_j(x) dx = \sum_{j=1}^k \omega_j M_x(t)_j \\ &= \sum_{x=0}^{\infty} e^{tx} f(x) = \sum_{j=1}^k \omega_j \sum_{x=0}^{\infty} e^{tx} f_j(x) = \sum_{j=1}^k \omega_j M_x(t)_j \end{aligned} \quad (2.20)$$

for the continuous and discrete component distributions respectively, where $M_x(t)_j$ is the j^{th} component MGF.

5. The r^{th} raw moment of the mixture is given by

$$\begin{aligned} E(X^r) &= \int_0^{\infty} x^r f(x) dx = \sum_{j=1}^k \omega_j \int_0^{\infty} x^r f_j(x) dx = \sum_{j=1}^k \omega_j E_j(X^r) \\ &= \sum_{x=0}^{\infty} x^r f(x) = \sum_{j=1}^k \omega_j \sum_{x=0}^{\infty} x^r f_j(x) = \sum_{j=1}^k \omega_j E_j(X^r) \end{aligned} \quad (2.21)$$

for the continuous and discrete component distributions respectively, where $E_j(X^r)$ is the r^{th} raw moment of the j^{th} component.

The first four raw moments of the mixture will thus be

$$\begin{aligned} E(X) &= \sum_{j=1}^k \omega_j E_j(X), \quad E(X^2) = \sum_{j=1}^k \omega_j E_j(X^2), \quad E(X^3) = \sum_{j=1}^k \omega_j E_j(X^3), \\ \text{and } E(X^4) &= \sum_{j=1}^k \omega_j E_j(X^4) \end{aligned} \quad (2.22)$$

6. The central moments of the mixed distribution are

i. Variance

$$\mu_2 = E(X^2) - [E(X)]^2 = \sum_{j=1}^k \omega_j E_j(X^2) - \left[\sum_{j=1}^k \omega_j E_j(X) \right]^2 \quad (2.23)$$

ii. Coefficient of skewness

$$\begin{aligned} \frac{\mu_3}{\sigma^3} &= \frac{1}{\sigma^3} \{ E(X^3) - 3E(X)E(X^2) + 2[E(X)]^3 \} \\ &= \frac{1}{\sigma^3} \left\{ \sum_{j=1}^k \omega_j E_j(X^3) - 3 \left[\sum_{j=1}^k \omega_j E_j(X) \right] \left[\sum_{j=1}^k \omega_j E_j(X^2) \right] + 2 \left[\sum_{j=1}^k \omega_j E_j(X) \right]^3 \right\} \end{aligned} \quad (2.24)$$

iii. Coefficient of kurtosis

$$\begin{aligned} \frac{\mu_4}{\sigma^4} &= \frac{1}{\sigma^4} \{ E(X^4) - 4[E(X)][E(X^3)] + 6[E(X)]^2[E(X^2)] - 3[E(X)]^4 \} \\ &= \frac{1}{\sigma^4} \left\{ \left[\sum_{j=1}^k \omega_j E_j(X^4) \right] - 4 \left[\sum_{j=1}^k \omega_j E_j(X) \right] \left[\sum_{j=1}^k \omega_j E_j(X^3) \right] + 6 \left[\sum_{j=1}^k \omega_j E_j(X) \right]^2 \right. \\ &\quad \left. \left[\sum_{j=1}^k \omega_j E_j(X^2) \right] - 3 \left[\sum_{j=1}^k \omega_j E_j(X) \right]^4 \right\} \end{aligned} \quad (2.25)$$

7. The probability function of the k^{th} order statistic for the finite mixture is given by

$$\begin{aligned}
 f_k(x) &= \frac{n!}{(k-1)!(n-k)!} [F(x)]^{k-1} [1-F(x)]^{n-k} f(x) \\
 &= \frac{n!f(x)}{(k-1)!(n-k)!} \sum_{i=0}^{n-k} \binom{n-k}{i} (-1)^i [F(x)]^{i+k-1} \\
 &= \frac{n!f(x)}{(k-1)!(n-k)!} \sum_{i=0}^{n-k} \binom{n-k}{i} (-1)^i \left[\sum_{j=1}^k \omega_j F_j(x) \right]^{i+k-1} \tag{2.26}
 \end{aligned}$$

where $f(x)$ is the mixture distribution and $F_j(x)$ is the j^{th} component distribution function in the mixed distribution.

8. Parameter estimation

Method of moments estimation (MME)

The r^{th} sample moments have been equated to the r^{th} moments of the mixed distributions to obtain parameter estimates of the finite mixtures, that is,

$$\frac{1}{n} \sum_{i=1}^n x_i^r = x_i^r = E(X^r), \quad r = 1, 2, 3, \dots \tag{2.27}$$

Maximum likelihood estimation (MLE)

The parameters of the finite mixtures have also been estimated using MLE. The log-likelihood functions obtained from the likelihood functions have been differentiated with respect to the parameters, and the resulting equations solved simultaneously using the Newton-Raphson method to obtain the numerical estimates of the parameters.

3. The two component four parameter finite Erlang mixture: Case 1

Let $g_1(x) = \text{Gamma}(\alpha, \theta)$, $g_2(x) = \text{Gamma}(\alpha + 1, \theta)$, $\omega = \frac{\theta}{\theta + s}$ and $(1 - \omega) = \frac{s}{\theta + s}$

$$\begin{aligned} \text{Then, } g(x) &= \frac{\theta}{\theta + s} \frac{\theta^\alpha}{\Gamma(\alpha)} e^{-\theta x} x^{\alpha-1} + \frac{s}{\theta + s} \frac{\theta^{\alpha+1}}{\Gamma(\alpha + 1)} e^{-\theta x} x^\alpha = \frac{\theta^{\alpha+1}}{\theta + s} e^{-\theta x} \left(\frac{x^{\alpha-1}}{\Gamma(\alpha)} + \frac{s x^\alpha}{\Gamma(\alpha + 1)} \right) \\ &= \frac{\theta^{\alpha+1}}{\theta + s} \frac{x^{\alpha-1}}{\Gamma(\alpha + 1)} e^{-\theta x} (\alpha + s x) \\ \text{let } s &= \frac{\delta}{\beta} \\ g(x) &= \frac{\theta^{\alpha+1}}{\theta + \frac{\delta}{\beta}} e^{-\theta x} \frac{x^{\alpha-1}}{\Gamma(\alpha + 1)} \left(\alpha + \frac{\delta}{\beta} x \right) \\ &= \frac{\beta\alpha + \delta x}{\beta\theta + \delta} \frac{\theta^{\alpha+1} e^{-\theta x} x^{\alpha-1}}{\Gamma(\alpha + 1)}, \quad x > 0; \theta > 0, \beta > 0, \delta > 0, \alpha = 1, 2, 3, \dots \end{aligned} \quad (3.1)$$

which is a 4-parameter generalized Lindley distribution with the following properties and special cases.

Properties

1. The CDF of the mixture is given by

$$\begin{aligned} G(x) &= \frac{\theta}{\theta + s} \frac{\gamma(\alpha, \theta x)}{\Gamma(\alpha)} + \frac{s}{\theta + s} \frac{\gamma(\alpha + 1, \theta x)}{\Gamma(\alpha + 1)} = \frac{[\theta\alpha\gamma(\alpha, \theta x) + s\gamma(\alpha + 1, \theta x)]}{(\theta + s)\Gamma(\alpha + 1)} \\ &= \frac{[\theta\alpha\beta\gamma(\alpha, \theta x) + \delta\gamma(\alpha + 1, \theta x)]}{(\beta\theta + \delta)\Gamma(\alpha + 1)} \end{aligned} \quad (3.2)$$

2. The survival function is

$$\begin{aligned} S(x) &= \frac{\theta}{\theta + s} \frac{\Gamma(\alpha, \theta x)}{\Gamma(\alpha)} + \frac{s}{\theta + s} \frac{\Gamma(\alpha + 1, \theta x)}{\Gamma(\alpha + 1)} = \frac{[\theta\alpha\Gamma(\alpha, \theta x) + s\Gamma(\alpha + 1, \theta x)]}{(\theta + s)\Gamma(\alpha + 1)} \\ &= \frac{[\theta\alpha\beta\Gamma(\alpha, \theta x) + \delta\Gamma(\alpha + 1, \theta x)]}{(\beta\theta + \delta)\Gamma(\alpha + 1)} \end{aligned} \quad (3.3)$$

3 and the hazard function is thus

$$h(x) = \frac{\frac{\beta\alpha + \delta x}{\beta\theta + \delta} \frac{\theta^{\alpha+1}}{\Gamma(\alpha + 1)} e^{-\theta x} x^{\alpha-1}}{\frac{[\theta\alpha\beta\Gamma(\alpha, \theta x) + \delta\Gamma(\alpha + 1, \theta x)]}{(\beta\theta + \delta)\Gamma(\alpha + 1)}} = \frac{(\beta\alpha + \delta x)\theta^{\alpha+1} e^{-\theta x} x^{\alpha-1}}{[\theta\alpha\beta\Gamma(\alpha, \theta x) + \delta\Gamma(\alpha + 1, \theta x)]} \quad (3.4)$$

4. The MGF of the mixed distribution is

$$M_x(t) = \frac{\theta}{\theta + s} \left(\frac{\theta}{\theta - t} \right)^\alpha + \frac{s}{\theta + s} \left(\frac{\theta}{\theta - t} \right)^{\alpha+1} = \frac{\theta^{\alpha+1}[\theta - t + s]}{(\theta + s)(\theta - t)^{\alpha+1}} = \frac{\theta^{\alpha+1}[\beta(\theta - t) + \delta]}{(\beta\theta + \delta)(\theta - t)^{\alpha+1}} \quad (3.5)$$

5. The r^{th} moment about the origin of the 4-parameter generalized generalized Lindley distribution is given by

$$E(X^r) = \frac{\theta}{\theta + s} \frac{\Gamma(s + \alpha)}{\theta^r \Gamma(\alpha)} + \frac{s}{\theta + s} \frac{\Gamma(r + \alpha + 1)}{\theta^r \Gamma(\alpha + 1)} = \frac{[\alpha\theta + s(r + \alpha)] \Gamma(r + \alpha)}{(\theta + s)\theta^r \Gamma(\alpha + 1)} = \frac{[\beta\alpha\theta + \delta(r + \alpha)] \Gamma(r + \alpha)}{(\beta\theta + \delta)\theta^r \Gamma(\alpha + 1)} \quad (3.6)$$

and the first four moments are therefore

$$E(X) = \frac{[\beta\alpha\theta + \delta(1 + \alpha)]}{(\beta\theta + \delta)\theta} \quad (3.7)$$

$$E(X^2) = \frac{[\beta\alpha\theta + \delta(2 + \alpha)](1 + \alpha)}{(\beta\theta + \delta)\theta^2} \quad (3.8)$$

$$E(X^3) = \frac{[\beta\alpha\theta + \delta(3 + \alpha)](2 + \alpha)(1 + \alpha)}{(\beta\theta + \delta)\theta^3} \quad (3.9)$$

$$E(X^4) = \frac{[\beta\alpha\theta + \delta(4 + \alpha)](3 + \alpha)(2 + \alpha)(1 + \alpha)}{(\beta\theta + \delta)\theta^4} \quad (3.10)$$

6. The central moments are

i. Variance

$$\begin{aligned}\mu_2 &= \frac{[\beta\alpha\theta + \delta(2 + \alpha)](1 + \alpha)}{(\beta\theta + \delta)\theta^2} - \left\{ \frac{[\beta\alpha\theta + \delta(1 + \alpha)]}{(\beta\theta + \delta)\theta} \right\}^2 \\ &= \frac{\beta\alpha(\alpha + 1)\theta(\beta\theta + \delta) + \delta(\alpha + 1)(\alpha + 2)(\beta\theta + \delta) - (\beta\alpha\theta)^2 - \delta^2(\alpha + 1)^2 + 2\beta\alpha\delta\theta(\alpha + 1)}{\theta^2(\beta\theta + \delta)^2}\end{aligned}\quad (3.11)$$

ii. Coefficient of Skewness

$$\begin{aligned}\frac{\mu_3}{\sigma^3} &= \frac{1}{\sigma^3} \left\{ \frac{[\beta\alpha\theta + \delta(3 + \alpha)](2 + \alpha)(1 + \alpha)}{(\beta\theta + \delta)\theta^3} - 3 \left[\frac{[\beta\alpha\theta + \delta(1 + \alpha)]}{(\beta\theta + \delta)\theta} \right] \left[\frac{[\beta\alpha\theta + \delta(2 + \alpha)](1 + \alpha)}{(\beta\theta + \delta)\theta^2} \right] + \right. \\ &\quad \left. 2 \left[\frac{[\beta\alpha\theta + \delta(1 + \alpha)]}{(\beta\theta + \delta)\theta} \right]^3 \right\} \\ &= \frac{(\alpha + 1)(\alpha + 2)(\beta\theta + \delta)^2[\beta\alpha\theta + \delta(\alpha + 3)] - 3(\alpha + 1)(\beta\theta + \delta)[(\beta\alpha\theta)^2 + \beta\alpha\theta\delta(\alpha + 1) + \beta\alpha\theta\delta(\alpha + 2) + \delta^2(\alpha + 1)(\alpha + 2)] + 2[(\beta\alpha\theta)^3 + 3(\beta\alpha\theta)^2\delta(\alpha + 1) + 3\beta\alpha\theta\delta^2(\alpha + 1)^2 + \delta^3(\alpha + 1)^3]}{\sigma^3\theta^3(\beta\theta + \delta)^3}\end{aligned}\quad (3.12)$$

iii. Coefficient of Kurtosis

$$\begin{aligned}\frac{\mu_4}{\sigma^4} &= \frac{1}{\sigma^4} \left\{ \frac{[\beta\alpha\theta + \delta(4 + \alpha)](3 + \alpha)(2 + \alpha)(1 + \alpha)}{(\beta\theta + \delta)\theta^4} - 4 \left[\frac{[\beta\alpha\theta + \delta(3 + \alpha)](2 + \alpha)(1 + \alpha)}{(\beta\theta + \delta)\theta^3} \right] \right. \\ &\quad \left[\frac{[\beta\alpha\theta + \delta(1 + \alpha)]}{(\beta\theta + \delta)\theta} \right] + 6 \left[\frac{[\beta\alpha\theta + \delta(2 + \alpha)](1 + \alpha)}{(\beta\theta + \delta)\theta^2} \right] \left[\frac{[\beta\alpha\theta + \delta(1 + \alpha)]}{(\beta\theta + \delta)\theta} \right]^2 - \\ &\quad \left. 3 \left[\frac{[\beta\alpha\theta + \delta(1 + \alpha)]}{(\beta\theta + \delta)\theta} \right]^4 \right\} \\ &= \frac{(\alpha + 1)(\alpha + 2)(\alpha + 3)(\beta\theta + \delta)^3[\beta\alpha\theta + \delta(\alpha + 4)] - 4(\alpha + 1)(\alpha + 2)(\beta\theta + \delta)^2[(\beta\alpha\theta)^2 + \beta\alpha\theta\delta(\alpha + 1) + \beta\alpha\theta\delta(\alpha + 3) + \delta^2(\alpha + 1)(\alpha + 3)] + 6(\alpha + 1)(\beta\theta + \delta)[(\beta\alpha\theta)^3 + \beta\alpha\theta\delta^2(\alpha + 1)^2 + 2\beta\alpha\theta\delta(\alpha + 1) + (\beta\alpha\theta)^2\delta(\alpha + 2) + \delta^3(\alpha + 1)^2(\alpha + 2) + 2\beta\alpha\theta\delta^2(\alpha + 1)(\alpha + 2)] - 3[(\beta\alpha\theta)^4 + 4(\beta\alpha\theta)^3\delta(\alpha + 1) + 6(\beta\alpha\theta\delta)^2(\alpha + 1)^2 + 4\beta\alpha\theta\delta^3(\alpha + 1)^3 + \delta^4(\alpha + 1)^4]}{\sigma^4\theta^4(\beta\theta + \delta)^4}\end{aligned}\quad (3.13)$$

7. The probability function of the k^{th} order statistic for the finite mixture is given by

$$f_k(x) = \frac{n!(\beta\alpha + \delta x)\theta^{\alpha+1}e^{-\theta x}x^{\alpha-1}}{(k-1)!(n-k)!(\beta\theta + \delta)\Gamma(\alpha + 1)} \sum_{i=0}^{n-k} \binom{n-k}{i} (-1)^i \left[\frac{[\theta\alpha\beta\gamma(\alpha, \theta x) + \delta\gamma(\alpha + 1, \theta x)]}{(\beta\theta + \delta)\Gamma(\alpha + 1)} \right]^{i+k-1}\quad (3.14)$$

8. Parameter estimation

Method of moments estimation

The parameter estimates of the finite mixture are obtained by solving the below equations simultaneously using the Newton-Raphson method.

$$\begin{aligned}\frac{[\beta\alpha\theta + \delta(1 + \alpha)]}{(\beta\theta + \delta)\theta} &= \bar{x} \\ \frac{[\beta\alpha\theta + \delta(2 + \alpha)](1 + \alpha)}{(\beta\theta + \delta)\theta^2} &= \frac{\sum_{i=1}^n x_i^2}{n} \\ \frac{[\beta\alpha\theta + \delta(3 + \alpha)](2 + \alpha)(1 + \alpha)}{(\beta\theta + \delta)\theta^3} &= \frac{\sum_{i=1}^n x_i^3}{n} \\ \frac{[\beta\alpha\theta + \delta(4 + \alpha)](3 + \alpha)(2 + \alpha)(1 + \alpha)}{(\beta\theta + \delta)\theta^4} &= \frac{\sum_{i=1}^n x_i^4}{n}\end{aligned}$$

Maximum likelihood estimation

The likelihood function of the 4-parameter finite Erlang mixture is given by

$$\begin{aligned} L(\theta, \beta, \delta, \alpha) &= \prod_{i=1}^n \frac{\beta\alpha + \delta x_i}{\beta\theta + \delta} \frac{\theta^{\alpha+1} e^{-\theta x_i} x_i^{\alpha-1}}{\Gamma(\alpha + 1)} \\ &= [(\beta\theta + \delta)\Gamma(\alpha + 1)]^{-n} \theta^{n(\alpha+1)} e^{-\theta \sum_{i=1}^n x_i} \prod_{i=1}^n x_i^{\alpha-1} \prod_{i=1}^n [\beta\alpha + \delta x_i] \end{aligned} \quad (3.15)$$

and the log-likelihood function is

$$\begin{aligned} \mathbf{L} = \log L(\theta, \beta, \delta, \alpha) &= -n \log [(\beta\theta + \delta)\Gamma(\alpha + 1)] + n(\alpha + 1) \log \theta - \theta \sum_{i=1}^n x_i + (\alpha - 1) \sum_{i=1}^n \log x_i + \\ &\quad \sum_{i=1}^n \log [\beta\alpha + \delta x_i] \end{aligned} \quad (3.16)$$

The partial derivatives with respect to the parameters are as outlined below.

$$\frac{\delta \mathbf{L}}{\delta \theta} = -\frac{n\beta}{(\beta\theta + \delta)} + \frac{n(\alpha + 1)}{\theta} - \sum_{i=1}^n x_i \quad (3.17)$$

$$\frac{\delta \mathbf{L}}{\delta \beta} = -\frac{n\theta}{(\beta\theta + \delta)} + \sum_{i=1}^n \frac{\alpha}{\beta\alpha + \delta x_i} \quad (3.18)$$

$$\frac{\delta \mathbf{L}}{\delta \delta} = -\frac{n}{(\beta\theta + \delta)} + \sum_{i=1}^n \frac{x_i}{\beta\alpha + \delta x_i} \quad (3.19)$$

$$\frac{\delta \mathbf{L}}{\delta \alpha} = -\frac{n\Gamma'(\alpha + 1)}{\Gamma(\alpha + 1)} + n \log \theta + \sum_{i=1}^n \log x_i + \sum_{i=1}^n \frac{\beta}{\beta\alpha + \delta x_i} \quad (3.20)$$

The above equations (3.17)-(3.20) are equated to zero and solved simultaneously, using the Newton-Raphson method, to obtain numerical estimates of the parameters.

Special cases

i. when $\delta=1$, we have Type I 3-parameter Lindley distribution.

$$g(x) = \frac{\theta^{\alpha+1}(\beta\alpha + x) e^{-\theta x} x^{\alpha-1}}{\beta\theta \Gamma(\alpha + 1)}, \quad x > 0; \theta > 0, \beta > 0, \alpha = 1, 2, 3, \dots \quad (3.21)$$

ii. when $\beta=1$, we have Type II 3-parameter Lindley distribution.

$$g(x) = \frac{\theta^{\alpha+1}(\alpha + \delta x) e^{-\theta x} x^{\alpha-1}}{\theta + \delta \Gamma(\alpha + 1)}, \quad x > 0; \theta > 0, \delta > 0, \alpha = 1, 2, 3, \dots \quad (3.22)$$

(Zakerzadeh and Dolati[16])

iii. when $\alpha=1$, we have Type III 3-parameter Lindley distribution.

$$g(x) = \frac{\theta^2(\beta + \delta x)}{\beta\theta + \delta} e^{-\theta x}, \quad x > 0; \theta > 0, \beta > 0, \delta > 0 \quad (3.23)$$

iv. when $\beta=\delta=1$, we have Type I 2-parameter Lindley distribution.

$$g(x) = \frac{\theta^{\alpha+1}(\alpha + x) e^{-\theta x} x^{\alpha-1}}{\theta + 1 \Gamma(\alpha + 1)}, \quad x > 0; \theta > 0, \alpha = 1, 2, 3, \dots \quad (3.24)$$

v. when $\alpha=\delta=1$, we have Type II 2-parameter Lindley distribution.

$$g(x) = \frac{\theta^2(\beta + x)}{\beta\theta + 1} e^{-\theta x}, \quad x > 0; \theta > 0, \beta > 0 \quad (3.25)$$

(Shanker et al.[14])

vi. when $\alpha=\beta=1$, we have Type III 2-parameter Lindley distribution.

$$g(x) = \frac{\theta^2(1 + \delta x)}{\theta + \delta} e^{-\theta x}, \quad x > 0; \theta > 0, \delta > 0 \quad (3.26)$$

vii. when $\alpha=\beta=\delta=1$, we have 1-parameter Lindley distribution.

$$g(x) = \frac{\theta^2(1 + x)}{\theta + 1} e^{-\theta x}, \quad x > 0; \theta > 0 \quad (3.27)$$

4. The two component four parameter finite Erlang mixture: Case 2

Let $g_1(x) = \text{Gamma}(\alpha, \theta)$, $g_2(x) = \text{Gamma}(\alpha + 2, \theta)$, $\omega = \frac{\theta^2}{\theta^2 + s}$, and $(1 - \omega) = \frac{s}{\theta^2 + s}$

Then
$$g(x) = \frac{\theta^2}{\theta^2 + s} \frac{\theta^\alpha}{\Gamma(\alpha)} e^{-\theta x} x^{\alpha-1} + \frac{s}{\theta^2 + s} \frac{\theta^{\alpha+2}}{\Gamma(\alpha + 2)} e^{-\theta x} x^{\alpha+1} = \frac{\theta^{\alpha+2}}{\theta^2 + s} e^{-\theta x} \left(\frac{x^{\alpha-1}}{\Gamma(\alpha)} + \frac{s x^{\alpha+1}}{\Gamma(\alpha + 2)} \right)$$

$$= \frac{\theta^{\alpha+2}}{\theta^2 + s} e^{-\theta x} \frac{x^{\alpha-1}}{\Gamma(\alpha + 2)} [\alpha(\alpha + 1) + s x^2]$$

let $s = \frac{\delta}{\beta}$

$$g(x) = \frac{\theta^{\alpha+2}}{\theta^2 + \frac{\delta}{\beta}} e^{-\theta x} \frac{x^{\alpha-1}}{\Gamma(\alpha + 2)} \left(\alpha(\alpha + 1) + \frac{\delta}{\beta} x^2 \right)$$

$$= \frac{\beta\alpha(\alpha + 1) + \delta x^2}{\beta\theta^2 + \delta} \frac{\theta^{\alpha+2}}{\Gamma(\alpha + 2)} e^{-\theta x} x^{\alpha-1}, \quad x > 0; \theta > 0, \beta > 0, \delta > 0, \alpha = 1, 2, 3, \dots \quad (4.1)$$

which is a 4-parameter generalized finite Erlang mixture with the following properties and special cases.

Properties

1. The CDF of the 4-parameter generalized finite Erlang mixture is given by

$$G(x) = \frac{\theta^2}{\theta^2 + s} \frac{\gamma(\alpha, \theta x)}{\Gamma(\alpha)} + \frac{s}{\theta^2 + s} \frac{\gamma(\alpha + 2, \theta x)}{\Gamma(\alpha + 2)} = \frac{[\theta^2\alpha(\alpha + 1)\gamma(\alpha, \theta x) + s\gamma(\alpha + 2, \theta x)]}{(\theta^2 + s)\Gamma(\alpha + 2)}$$

$$= \frac{[\beta\theta^2\alpha(\alpha + 1)\gamma(\alpha, \theta x) + \delta\gamma(\alpha + 2, \theta x)]}{(\beta\theta^2 + \delta)\Gamma(\alpha + 2)} \quad (4.2)$$

2. The survival function of the mixed distribution is

$$S(x) = \frac{\theta^2}{\theta^2 + s} \frac{\Gamma(\alpha, \theta x)}{\Gamma(\alpha)} + \frac{s}{\theta^2 + s} \frac{\Gamma(\alpha + 2, \theta x)}{\Gamma(\alpha + 2)} = \frac{[\theta^2\alpha(\alpha + 1)\Gamma(\alpha, \theta x) + s\Gamma(\alpha + 2, \theta x)]}{(\theta^2 + s)\Gamma(\alpha + 2)}$$

$$= \frac{[\beta\theta^2\alpha(\alpha + 1)\Gamma(\alpha, \theta x) + \delta\Gamma(\alpha + 2, \theta x)]}{(\beta\theta^2 + \delta)\Gamma(\alpha + 2)} \quad (4.3)$$

3. and the hazard function is

$$h(x) = \frac{\frac{\beta\alpha(\alpha+1)+\delta x^2}{\beta\theta^2+\delta} \frac{\theta^{\alpha+2}}{\Gamma(\alpha+2)} e^{-\theta x} x^{\alpha-1}}{\frac{[\beta\theta^2\alpha(\alpha+1)\Gamma(\alpha,\theta x)+\delta\Gamma(\alpha+2,\theta x)]}{(\beta\theta^2+\delta)\Gamma(\alpha+2)}} = \frac{[\beta\alpha(\alpha + 1) + \delta x^2]\theta^{\alpha+2} e^{-\theta x} x^{\alpha-1}}{\beta\theta^2\alpha(\alpha + 1)\Gamma(\alpha, \theta x) + \delta\Gamma(\alpha + 2, \theta x)} \quad (4.4)$$

4. The MGF is given by

$$M_x(t) = \frac{\theta^2}{\theta^2 + s} \left(\frac{\theta}{\theta - t} \right)^\alpha + \frac{s}{\theta^2 + s} \left(\frac{\theta}{\theta - t} \right)^{\alpha+2} = \frac{\theta^{\alpha+2} [(\theta - t)^{\alpha+2} + s]}{(\theta^2 + s)(\theta - t)^{\alpha+2}} = \frac{\theta^{\alpha+2} [\beta(\theta - t)^{\alpha+2} + \delta]}{(\beta\theta^2 + \delta)(\theta - t)^{\alpha+2}} \quad (4.5)$$

5. The r^{th} raw moment of the finite mixture is

$$\begin{aligned} E(X^r) &= \frac{\theta^2}{\theta^2 + s} \frac{\Gamma(r + \alpha)}{\theta^r \Gamma(\alpha)} + \frac{s}{\theta^2 + s} \frac{\Gamma(r + \alpha + 2)}{\theta^r \Gamma(\alpha + 2)} = \frac{\Gamma(r + \alpha) [\theta^2 \alpha(\alpha + 1) + s(r + \alpha)(r + \alpha + 1)]}{(\theta^2 + s)\theta^r \Gamma(\alpha + 2)} \\ &= \frac{\Gamma(r + \alpha) [\beta\theta^2 \alpha(\alpha + 1) + \delta(r + \alpha)(r + \alpha + 1)]}{(\beta\theta^2 + \delta)\theta^r \Gamma(\alpha + 2)} \end{aligned} \quad (4.6)$$

and the first four raw moments are thus

$$E(X) = \frac{[\beta\theta^2 \alpha(\alpha + 1) + \delta(1 + \alpha)(\alpha + 2)]}{(\beta\theta^2 + \delta)\theta(1 + \alpha)} \quad (4.7)$$

$$E(X^2) = \frac{[\beta\theta^2 \alpha(\alpha + 1) + \delta(2 + \alpha)(\alpha + 3)]}{(\beta\theta^2 + \delta)\theta^2} \quad (4.8)$$

$$E(X^3) = \frac{(\alpha + 2) [\beta\theta^2 \alpha(\alpha + 1) + \delta(3 + \alpha)(\alpha + 4)]}{(\beta\theta^2 + \delta)\theta^3} \quad (4.9)$$

$$E(X^4) = \frac{(\alpha + 2)(\alpha + 3) [\beta\theta^2 \alpha(\alpha + 1) + \delta(4 + \alpha)(\alpha + 5)]}{(\beta\theta^2 + \delta)\theta^4} \quad (4.10)$$

6. The central moments are given by

i. Variance

$$\begin{aligned} \mu_2 &= \frac{\Gamma(2 + \alpha) [\beta\theta^2 \alpha(\alpha + 1) + \delta(2 + \alpha)(\alpha + 3)]}{(\beta\theta^2 + \delta)\theta^2 \Gamma(\alpha + 2)} - \left[\frac{\Gamma(1 + \alpha) [\beta\theta^2 \alpha(\alpha + 1) + \delta(1 + \alpha)(\alpha + 2)]}{(\beta\theta^2 + \delta)\theta \Gamma(\alpha + 2)} \right]^2 \\ &= \frac{\beta\alpha(\alpha + 1)^3 \theta^2 (\beta\theta^2 + \delta) + \delta(\alpha + 1)^2 (\alpha + 2)(\alpha + 3)(\beta\theta^2 + \delta) - \beta^2 \alpha^2 (\alpha + 1)^2 \theta^4 -}{\theta^2 (\alpha + 1)^2 (\beta\theta^2 + \delta)^2} \\ &\quad \frac{\delta^2 (\alpha + 1)^2 (\alpha + 2)^2 - 2\beta\alpha(\alpha + 1)\theta^2 \delta(\alpha + 1)(\alpha + 2)}{\theta^2 (\alpha + 1)^2 (\beta\theta^2 + \delta)^2} \end{aligned} \quad (4.11)$$

ii. Coefficient of Skewness

$$\begin{aligned} \frac{\mu_3}{\sigma^3} &= \frac{1}{\sigma^3} \left\{ \frac{\Gamma(3 + \alpha) [\beta\theta^2 \alpha(\alpha + 1) + \delta(3 + \alpha)(\alpha + 4)]}{(\beta\theta^2 + \delta)\theta^3 \Gamma(\alpha + 2)} - 3 \left[\frac{\Gamma(2 + \alpha) [\beta\theta^2 \alpha(\alpha + 1) + \delta(2 + \alpha)(\alpha + 3)]}{(\beta\theta^2 + \delta)\theta^2 \Gamma(\alpha + 2)} \right] \right. \\ &\quad \left. \left[\frac{\Gamma(1 + \alpha) [\beta\theta^2 \alpha(\alpha + 1) + \delta(1 + \alpha)(\alpha + 2)]}{(\beta\theta^2 + \delta)\theta \Gamma(\alpha + 2)} \right] + 2 \left[\frac{\Gamma(1 + \alpha) [\beta\theta^2 \alpha(\alpha + 1) + \delta(1 + \alpha)(\alpha + 2)]}{(\beta\theta^2 + \delta)\theta \Gamma(\alpha + 2)} \right]^3 \right\} \\ &= \frac{\beta\alpha(\alpha + 1)^4 (\alpha + 2)\theta^2 (\beta\theta^2 + \delta)^2 + \delta(\alpha + 1)^3 (\alpha + 2)(\alpha + 3)(\alpha + 4)(\beta\theta^2 + \delta)^2 - 3\beta^2 \alpha^2 (\alpha + 1)^4 \theta^4}{(\beta\theta^2 + \delta) - 3\beta\alpha(\alpha + 1)^4 (\alpha + 2)\delta\theta^2 (\beta\theta^2 + \delta) - 3\beta\alpha(\alpha + 1)^3 (\alpha + 2)(\alpha + 3)\delta\theta^2 (\beta\theta^2 + \delta) - 3(\alpha + 1)^3} \\ &\quad \frac{\sigma^3 \theta^3 (\alpha + 1)^3 (\beta\theta^2 + \delta)^3}{(\alpha + 2)^2 (\alpha + 3)\delta\theta^2 (\beta\theta^2 + \delta) + 2\beta^3 \alpha^3 (\alpha + 1)^3 \theta^6 + 3\beta^2 \alpha^2 (\alpha + 1)^3 (\alpha + 2)\theta^4 \delta + 3\beta\alpha(\alpha + 1)^3 (\alpha + 2)^2} \\ &\quad \frac{\theta^2 \delta^2 + \delta^3 (\alpha + 1)^3 (\alpha + 2)^3}{\theta^2 \delta^2 + \delta^3 (\alpha + 1)^3 (\alpha + 2)^3} \end{aligned} \quad (4.12)$$

iii. Coefficient of Kurtosis

$$\begin{aligned}
 \frac{\mu_4}{\sigma^4} &= \frac{1}{\sigma^4} \left\{ \frac{\Gamma(4+\alpha) [\beta\theta^2\alpha(\alpha+1) + \delta(4+\alpha)(\alpha+5)]}{(\beta\theta^2 + \delta)\theta^4\Gamma(\alpha+2)} - 4 \left[\frac{\Gamma(3+\alpha) [\beta\theta^2\alpha(\alpha+1) + \delta(3+\alpha)(\alpha+4)]}{(\beta\theta^2 + \delta)\theta^3\Gamma(\alpha+2)} \right] \right. \\
 &\quad \left[\frac{\Gamma(1+\alpha) [\beta\theta^2\alpha(\alpha+1) + \delta(1+\alpha)(\alpha+2)]}{(\beta\theta^2 + \delta)\theta\Gamma(\alpha+2)} \right] + 6 \left[\frac{\Gamma(2+\alpha) [\beta\theta^2\alpha(\alpha+1) + \delta(2+\alpha)(\alpha+3)]}{(\beta\theta^2 + \delta)\theta^2\Gamma(\alpha+2)} \right] \\
 &\quad \left. \left[\frac{\Gamma(1+\alpha) [\beta\theta^2\alpha(\alpha+1) + \delta(1+\alpha)(\alpha+2)]}{(\beta\theta^2 + \delta)\theta\Gamma(\alpha+2)} \right]^2 - 3 \left[\frac{\Gamma(1+\alpha) [\beta\theta^2\alpha(\alpha+1) + \delta(1+\alpha)(\alpha+2)]}{(\beta\theta^2 + \delta)\theta\Gamma(\alpha+2)} \right]^4 \right\} \\
 &= \frac{\beta\alpha(\alpha+1)^5(\alpha+2)(\alpha+3)\theta^2(\beta\theta^2 + \delta)^3 + \delta(\alpha+1)^4(\alpha+2)(\alpha+3)(\alpha+4)(\alpha+5)(\beta\theta^2 + \delta)^3 - 4\beta^2\alpha^2}{(\alpha+1)^5(\alpha+2)^2\theta^4(\beta\theta^2 + \delta)^2 - 4\beta\alpha(\alpha+1)^5(\alpha+2)^2\delta\theta^2(\beta\theta^2 + \delta)^2 - 4\beta\alpha(\alpha+1)^4(\alpha+2)(\alpha+3)} \\
 &\quad \frac{(\alpha+4)\delta\theta^2(\beta\theta^2 + \delta)^2 - 4(\alpha+1)^4(\alpha+2)^2(\alpha+3)(\alpha+4)\delta^2(\beta\theta^2 + \delta)^2 + 6\beta^3\alpha^3(\alpha+1)^5\theta^6(\beta\theta^2 + \delta) + \sigma^4\theta^4(\alpha+1)^4(\beta\theta^2 + \delta)^4}{6\beta\alpha(\alpha+1)^5(\alpha+2)^2\delta^2\theta^2(\beta\theta^2 + \delta) + 12\beta^2\alpha^2(\alpha+1)^5(\alpha+2)\delta\theta^4(\beta\theta^2 + \delta) + 6\beta^2\alpha^2(\alpha+1)^4(\alpha+2)} \\
 &\quad \frac{(\alpha+3)\delta\theta^4(\beta\theta^2 + \delta) + 6(\alpha+1)^4(\alpha+2)^3(\alpha+3)\delta^3(\beta\theta^2 + \delta) + 12\beta\alpha(\alpha+1)^4(\alpha+2)^2(\alpha+3)\delta^2\theta^2}{(\beta\theta^2 + \delta) - 3\beta^4\alpha^4(\alpha+1)^4\theta^8 - 12\beta^3\alpha^3(\alpha+1)^4(\alpha+2)\theta^6\delta - 18\beta^2\alpha^2(\alpha+1)^4(\alpha+2)^2\theta^4\delta^2 -} \\
 &\quad \frac{12\beta\alpha(\alpha+1)^4(\alpha+2)^3\theta^2\delta^3 - 3\delta^4(\alpha+1)^4(\alpha+2)^4}{\hspace{15em}} \tag{4.13}
 \end{aligned}$$

7. The probability function of the k^{th} order statistic for the finite mixture is given by

$$f_k(x) = \frac{n![\beta\alpha(\alpha+1) + \delta x^2]\theta^{\alpha+2}e^{-\theta x}x^{\alpha-1}}{(k-1)!(n-k)!(\beta\theta^2 + \delta)\Gamma(\alpha+2)} \sum_{i=0}^{n-k} \binom{n-k}{i} (-1)^i \left[\frac{[\beta\theta^2\alpha(\alpha+1)\gamma(\alpha, \theta x) + \delta\gamma(\alpha+2, \theta x)]}{(\beta\theta^2 + \delta)\Gamma(\alpha+2)} \right]^{i+k-1} \tag{4.14}$$

8. Parameter estimation

Method of moments estimation

The method of moments estimators for the parameters of the mixed distribution can be obtained by solving the following equations simultaneously with the aid of the Newton-Raphson method.

$$\begin{aligned}
 \frac{[\beta\theta^2\alpha(\alpha+1) + \delta(1+\alpha)(\alpha+2)]}{(\beta\theta^2 + \delta)\theta(1+\alpha)} &= \bar{x} \\
 \frac{[\beta\theta^2\alpha(\alpha+1) + \delta(2+\alpha)(\alpha+3)]}{(\beta\theta^2 + \delta)\theta^2} &= \frac{1}{n} \sum_{i=1}^n x_i^2 \\
 \frac{(\alpha+2) [\beta\theta^2\alpha(\alpha+1) + \delta(3+\alpha)(\alpha+4)]}{(\beta\theta^2 + \delta)\theta^3} &= \frac{1}{n} \sum_{i=1}^n x_i^3 \\
 \frac{(\alpha+2)(\alpha+3) [\beta\theta^2\alpha(\alpha+1) + \delta(4+\alpha)(\alpha+5)]}{(\beta\theta^2 + \delta)\theta^4} &= \frac{1}{n} \sum_{i=1}^n x_i^4
 \end{aligned}$$

Maximum likelihood estimation

The likelihood function of the 4-parameter finite Erlang mixture is given by

$$\begin{aligned}
 L(\theta, \beta, \delta, \alpha) &= \prod_{i=1}^n \frac{\beta\alpha(\alpha+1) + \delta x_i^2}{\beta\theta^2 + \delta} \frac{\theta^{\alpha+2}}{\Gamma(\alpha+2)} e^{-\theta x_i} x_i^{\alpha-1} \\
 &= [(\beta\theta^2 + \delta)\Gamma(\alpha+2)]^{-n} \theta^{n(\alpha+2)} e^{-\theta \sum_{i=1}^n x_i} \prod_{i=1}^n x_i^{\alpha-1} \prod_{i=1}^n [\beta\alpha(\alpha+1) + \delta x_i^2] \tag{4.15}
 \end{aligned}$$

and the log-likelihood function is

$$\begin{aligned} \mathbf{L} = \log L(\theta, \beta, \delta, \alpha) = & -n \log [(\beta\theta^2 + \delta)\Gamma(\alpha + 2)] + n(\alpha + 2)\log\theta - \theta \sum_{i=1}^n x_i + (\alpha - 1) \sum_{i=1}^n \log x_i + \\ & \sum_{i=1}^n \log [\beta\alpha(\alpha + 1) + \delta x_i^2] \end{aligned} \quad (4.16)$$

The partial derivatives with respect to the parameters are obtained and the resulting equations are as follows;

$$\frac{\delta \mathbf{L}}{\delta \theta} = -\frac{2n\beta\theta}{(\beta\theta^2 + \delta)} + \frac{n(\alpha + 2)}{\theta} - \sum_{i=1}^n x_i \quad (4.17)$$

$$\frac{\delta \mathbf{L}}{\delta \beta} = -\frac{n\theta^2}{(\beta\theta^2 + \delta)} + \sum_{i=1}^n \frac{\alpha(\alpha + 1)}{\beta\alpha(\alpha + 1) + \delta x_i^2} \quad (4.18)$$

$$\frac{\delta \mathbf{L}}{\delta \delta} = -\frac{n}{(\beta\theta^2 + \delta)} + \sum_{i=1}^n \frac{x_i^2}{\beta\alpha(\alpha + 1) + \delta x_i^2} \quad (4.19)$$

$$\frac{\delta \mathbf{L}}{\delta \alpha} = -\frac{n\Gamma'(\alpha + 2)}{\Gamma(\alpha + 2)} + n\log\theta + \sum_{i=1}^n \log x_i + \sum_{i=1}^n \frac{\beta(\alpha + 1) + \beta\alpha}{\beta\alpha(\alpha + 1) + \delta x_i^2} \quad (4.20)$$

The numerical maximum likelihood estimates of the parameters are obtained by equating equations (4.17)-(4.20) to zero and solving them simultaneously using the Newton-Raphson method.

Special cases

i. when $\delta = 1$, we have type I 3-parameter finite Erlang mixture.

$$g(x) = \frac{\beta\alpha(\alpha + 1) + x^2}{\beta\theta^2 + 1} \frac{\theta^{\alpha+2}}{\Gamma(\alpha + 2)} e^{-\theta x} x^{\alpha-1}, \quad x > 0; \theta > 0, \beta > 0, \alpha = 1, 2, 3, \dots \quad (4.21)$$

ii. when $\beta = 1$, we have type II 3-parameter finite Erlang mixture.

$$g(x) = \frac{\alpha(\alpha + 1) + \delta x^2}{\theta^2 + \delta} \frac{\theta^{\alpha+2}}{\Gamma(\alpha + 2)} e^{-\theta x} x^{\alpha-1}, \quad x > 0; \theta > 0, \delta > 0, \alpha = 1, 2, 3, \dots \quad (4.22)$$

iii. when $\alpha = 1$, we have type III 3-parameter finite Erlang mixture.

$$g(x) = \frac{2\beta + \delta x^2}{\beta\theta^2 + \delta} \frac{\theta^3}{2} e^{-\theta x}, \quad x > 0; \theta > 0, \beta > 0, \delta > 0 \quad (4.23)$$

iv. when $\beta = \delta = 1$, we have type I 2-parameter finite Erlang mixture.

$$g(x) = \frac{\alpha(\alpha + 1) + x^2}{\theta^2 + 1} \frac{\theta^{\alpha+2}}{\Gamma(\alpha + 2)} e^{-\theta x} x^{\alpha-1}, \quad x > 0; \theta > 0, \alpha = 1, 2, 3, \dots \quad (4.24)$$

v. when $\alpha = \delta = 1$, we have type II 2-parameter finite Erlang mixture.

$$g(x) = \frac{2\beta + x^2}{\beta\theta^2 + 1} \frac{\theta^3}{2} e^{-\theta x}, \quad x > 0; \theta > 0, \beta > 0 \quad (4.25)$$

vi. when $\alpha = \beta = 1$, we have type III 2-parameter finite Erlang mixture.

$$g(x) = \frac{2 + \delta x^2}{\theta^2 + \delta} \frac{\theta^3}{2} e^{-\theta x}, \quad x > 0; \theta > 0, \delta > 0 \quad (4.26)$$

When $\delta = 2$, the type III 2-parameter finite Erlang mixture becomes the Akash distribution. (Shanker[9]).

vii. when $\alpha = \beta = \delta = 1$, we have 1-parameter finite Erlang mixture.

$$g(x) = \frac{2 + x^2}{\theta^2 + 1} \frac{\theta^3}{2} e^{-\theta x}, \quad x > 0; \theta > 0 \quad (4.27)$$

5. The two component four parameter finite Erlang mixture: Case 3

Let $g_1(x) = \text{Gamma}(\alpha, \theta)$, $g_2(x) = \text{Gamma}(\alpha + 3, \theta)$, $\omega = \frac{\theta^3}{\theta^3 + s}$, and $(1 - \omega) = \frac{s}{\theta^3 + s}$

Then $g(x) = \frac{\theta^3}{\theta^3 + s} \frac{\theta^\alpha}{\Gamma(\alpha)} e^{-\theta x} x^{\alpha-1} + \frac{s}{\theta^3 + s} \frac{\theta^{\alpha+3}}{\Gamma(\alpha + 3)} e^{-\theta x} x^{\alpha+2} = \frac{\theta^{\alpha+3}}{\theta^3 + s} e^{-\theta x} \left(\frac{x^{\alpha-1}}{\Gamma(\alpha)} + \frac{s x^{\alpha+2}}{\Gamma(\alpha + 3)} \right)$

$$= \frac{\theta^{\alpha+3}}{\theta^3 + s} e^{-\theta x} \frac{x^{\alpha-1}}{\Gamma(\alpha + 3)} [\alpha(\alpha + 1)(\alpha + 2) + s x^3]$$

Let $s = \frac{\delta}{\beta}$

$$g(\lambda) = \frac{\theta^{\alpha+3}}{\theta^3 + \frac{\delta}{\beta}} e^{-\theta x} \frac{x^{\alpha-1}}{\Gamma(\alpha + 3)} \left(\alpha(\alpha + 1)(\alpha + 2) + \frac{\delta}{\beta} x^3 \right)$$

$$= \frac{\beta \alpha(\alpha + 1)(\alpha + 2) + \delta x^3}{\beta \theta^3 + \delta} \frac{\theta^{\alpha+3}}{\Gamma(\alpha + 3)} e^{-\theta x} x^{\alpha-1}, \quad x > 0; \theta > 0, \beta > 0, \delta > 0, \alpha = 1, 2, 3, \dots \quad (5.1)$$

which is a 4-parameter generalized finite Erlang mixture with the following properties and special cases.

Properties

1. The CDF of the 4-parameter generalized finite Erlang mixture is

$$G(x) = \frac{\theta^3}{\theta^3 + s} \frac{\gamma(\alpha, \theta x)}{\Gamma(\alpha)} + \frac{s}{\theta^3 + s} \frac{\gamma(\alpha + 3, \theta x)}{\Gamma(\alpha + 3)} = \frac{\theta^3 \alpha(\alpha + 1)(\alpha + 2) \gamma(\alpha, \theta x) + s \gamma(\alpha + 3, \theta x)}{(\theta^3 + s) \Gamma(\alpha + 3)}$$

$$= \frac{\beta \theta^3 \alpha(\alpha + 1)(\alpha + 2) \gamma(\alpha, \theta x) + \delta \gamma(\alpha + 3, \theta x)}{(\beta \theta^3 + \delta) \Gamma(\alpha + 3)} \quad (5.2)$$

2. and the survival function is

$$S(x) = \frac{\theta^3}{\theta^3 + s} \frac{\Gamma(\alpha, \theta x)}{\Gamma(\alpha)} + \frac{s}{\theta^3 + s} \frac{\Gamma(\alpha + 3, \theta x)}{\Gamma(\alpha + 3)} = \frac{\theta^3 \alpha(\alpha + 1)(\alpha + 2) \Gamma(\alpha, \theta x) + s \Gamma(\alpha + 3, \theta x)}{(\theta^3 + s) \Gamma(\alpha + 3)}$$

$$= \frac{\beta \theta^3 \alpha(\alpha + 1)(\alpha + 2) \Gamma(\alpha, \theta x) + \delta \Gamma(\alpha + 3, \theta x)}{(\beta \theta^3 + \delta) \Gamma(\alpha + 3)} \quad (5.3)$$

3. The hazard function is given by

$$h(x) = \frac{\frac{\beta \alpha(\alpha+1)(\alpha+2)+\delta x^3}{\beta \theta^3 + \delta} \frac{\theta^{\alpha+3}}{\Gamma(\alpha+3)} e^{-\theta x} x^{\alpha-1}}{\frac{\beta \theta^3 \alpha(\alpha+1)(\alpha+2) \Gamma(\alpha, \theta x) + \delta \Gamma(\alpha+3, \theta x)}{(\beta \theta^3 + \delta) \Gamma(\alpha+3)}} = \frac{[\beta \alpha(\alpha + 1)(\alpha + 2) + \delta x^3] \theta^{\alpha+3} e^{-\theta x} x^{\alpha-1}}{\beta \theta^3 \alpha(\alpha + 1)(\alpha + 2) \Gamma(\alpha, \theta x) + \delta \Gamma(\alpha + 3, \theta x)} \quad (5.4)$$

4. and the MGF is

$$M_x(t) = \frac{\theta^3}{\theta^3 + s} \left(\frac{\theta}{\theta - t} \right)^\alpha + \frac{s}{\theta^3 + s} \left(\frac{\theta}{\theta - t} \right)^{\alpha+3} = \frac{\theta^{\alpha+3} [(\theta - t)^3 + s]}{(\theta^3 + s)(\theta - t)^{\alpha+3}} = \frac{\theta^{\alpha+3} [\beta(\theta - t)^3 + \delta]}{(\beta \theta^3 + \delta)(\theta - t)^{\alpha+3}} \quad (5.5)$$

5. The r^{th} raw moment of the 4-parameter generalized finite Erlang mixture is

$$E(X^r) = \frac{\theta^3}{\theta^3 + s} \frac{\Gamma(r + \alpha)}{\theta^r \Gamma(\alpha)} + \frac{s}{\theta^3 + s} \frac{\Gamma(r + \alpha + 3)}{\theta^r \Gamma(\alpha + 3)}$$

$$= \frac{\Gamma(r + \alpha) [\theta^3 \alpha(\alpha + 1)(\alpha + 2) + s(r + \alpha)(r + \alpha + 1)(r + \alpha + 2)]}{(\theta^3 + s) \theta^r \Gamma(\alpha + 3)}$$

$$= \frac{\Gamma(r + \alpha) [\beta \theta^3 \alpha(\alpha + 1)(\alpha + 2) + \delta(r + \alpha)(r + \alpha + 1)(r + \alpha + 2)]}{(\beta \theta^3 + \delta) \theta^r \Gamma(\alpha + 3)} \quad (5.6)$$

and in particular the first four raw moments are

$$E(X) = \frac{\beta\theta^3\alpha(\alpha+1)(\alpha+2) + \delta(1+\alpha)(\alpha+2)(\alpha+3)}{(\beta\theta^3 + \delta)\theta(\alpha+2)(\alpha+1)} \quad (5.7)$$

$$E(X^2) = \frac{\beta\theta^3\alpha(\alpha+1)(\alpha+2) + \delta(2+\alpha)(\alpha+3)(\alpha+4)}{(\beta\theta^3 + \delta)\theta^2(\alpha+2)} \quad (5.8)$$

$$E(X^3) = \frac{\beta\theta^3\alpha(\alpha+1)(\alpha+2) + \delta(3+\alpha)(\alpha+4)(\alpha+5)}{(\beta\theta^3 + \delta)\theta^3} \quad (5.9)$$

$$E(X^4) = \frac{(3+\alpha)[\beta\theta^3\alpha(\alpha+1)(\alpha+2) + \delta(4+\alpha)(\alpha+5)(\alpha+6)]}{(\beta\theta^3 + \delta)\theta^4} \quad (5.10)$$

6. The central moments are given by

i. Variance

$$\begin{aligned} \mu_2 &= \frac{\Gamma(2+\alpha)[\beta\theta^3\alpha(\alpha+1)(\alpha+2) + \delta(2+\alpha)(\alpha+3)(\alpha+4)]}{(\beta\theta^3 + \delta)\theta^2\Gamma(\alpha+3)} - \\ &\quad \left[\frac{\Gamma(1+\alpha)[\beta\theta^3\alpha(\alpha+1)(\alpha+2) + \delta(1+\alpha)(\alpha+2)(\alpha+3)]}{(\beta\theta^3 + \delta)\theta\Gamma(\alpha+3)} \right]^2 \\ &= \frac{\beta\alpha(\alpha+1)^3(\alpha+2)^2\theta^3(\beta\theta^3 + \delta) + \delta(\alpha+1)^2(\alpha+2)^2(\alpha+3)(\alpha+4)(\beta\theta^3 + \delta) -}{\theta^2(\alpha+1)^2(\alpha+2)^2(\beta\theta^3 + \delta)^2} \\ &\quad \frac{\beta^2\alpha^2(\alpha+1)^2(\alpha+2)^2\theta^6 - \delta^2(\alpha+1)^2(\alpha+2)^2(\alpha+3)^2 - 2\beta\delta\alpha(\alpha+1)^2(\alpha+2)^2(\alpha+3)\theta^3}{\theta^2(\alpha+1)^2(\alpha+2)^2(\beta\theta^3 + \delta)^2} \end{aligned} \quad (5.11)$$

ii. Coefficient of Skewness

$$\begin{aligned} \frac{\mu_3}{\sigma^3} &= \frac{1}{\sigma^3} \left\{ \frac{\Gamma(3+\alpha)[\beta\theta^3\alpha(\alpha+1)(\alpha+2) + \delta(3+\alpha)(\alpha+4)(\alpha+5)]}{(\beta\theta^3 + \delta)\theta^3\Gamma(\alpha+3)} - \right. \\ &\quad 3 \left[\frac{\Gamma(2+\alpha)[\beta\theta^3\alpha(\alpha+1)(\alpha+2) + \delta(2+\alpha)(\alpha+3)(\alpha+4)]}{(\beta\theta^3 + \delta)\theta^2\Gamma(\alpha+3)} \right] \\ &\quad \left[\frac{\Gamma(1+\alpha)[\beta\theta^3\alpha(\alpha+1)(\alpha+2) + \delta(1+\alpha)(\alpha+2)(\alpha+3)]}{(\beta\theta^3 + \delta)\theta\Gamma(\alpha+3)} \right] + \\ &\quad \left. 2 \left[\frac{\Gamma(1+\alpha)[\beta\theta^3\alpha(\alpha+1)(\alpha+2) + \delta(1+\alpha)(\alpha+2)(\alpha+3)]}{(\beta\theta^3 + \delta)\theta\Gamma(\alpha+3)} \right]^3 \right\} \\ &= \frac{\beta\alpha(\alpha+1)^4(\alpha+2)^4\theta^3(\beta\theta^3 + \delta)^2 + \delta(\alpha+1)^3(\alpha+2)^3(\alpha+3)(\alpha+4)(\alpha+5)(\beta\theta^3 + \delta)^2 -}{\sigma^3\theta^3(\alpha+1)^3(\alpha+2)^3(\beta\theta^3 + \delta)^3} \\ &\quad \frac{3\beta^2\alpha^2(\alpha+1)^4(\alpha+2)^3\theta^6(\beta\theta^3 + \delta) - 3\beta\delta\alpha(\alpha+1)^2(\alpha+2)^2(\alpha+3)\theta^3(\beta\theta^3 + \delta) - 3\beta\delta\alpha(\alpha+1)^3}{\sigma^3\theta^3(\alpha+1)^3(\alpha+2)^3(\beta\theta^3 + \delta)^3} \\ &\quad \frac{(\alpha+2)^3(\alpha+3)(\alpha+4)\theta^3(\beta\theta^3 + \delta) - 3\delta^2(\alpha+1)^3(\alpha+2)^3(\alpha+3)^2(\alpha+4)(\beta\theta^3 + \delta) + 2\beta^3\alpha^3}{\sigma^3\theta^3(\alpha+1)^3(\alpha+2)^3(\beta\theta^3 + \delta)^3} \\ &\quad \frac{(\alpha+1)^3(\alpha+2)^3\theta^6 + 6\beta^2\delta\alpha^2(\alpha+1)^3(\alpha+2)^3(\alpha+3)\theta^6 + 6\beta\delta^2\alpha(\alpha+1)^3(\alpha+2)^2(\alpha+3)^2\theta^3\delta^3}{\sigma^3\theta^3(\alpha+1)^3(\alpha+2)^3(\beta\theta^3 + \delta)^3} \\ &\quad \frac{(\alpha+1)^3(\alpha+2)^3(\alpha+3)^3}{\sigma^3\theta^3(\alpha+1)^3(\alpha+2)^3(\beta\theta^3 + \delta)^3} \end{aligned} \quad (5.12)$$

iii. Coefficient of Kurtosis

$$\begin{aligned}
\frac{\mu_4}{\sigma^4} &= \frac{1}{\sigma^4} \left\{ \frac{\Gamma(4+\alpha)[\beta\theta^3\alpha(\alpha+1)(\alpha+2) + \delta(4+\alpha)(\alpha+5)(\alpha+6)]}{(\beta\theta^3 + \delta)\theta^4\Gamma(\alpha+3)} \right. \\
&\quad 4 \left[\frac{\Gamma(3+\alpha)[\beta\theta^3\alpha(\alpha+1)(\alpha+2) + \delta(3+\alpha)(\alpha+4)(\alpha+5)]}{(\beta\theta^3 + \delta)\theta^3\Gamma(\alpha+3)} \right] \\
&\quad \left[\frac{\Gamma(1+\alpha)[\beta\theta^3\alpha(\alpha+1)(\alpha+2) + \delta(1+\alpha)(\alpha+2)(\alpha+3)]}{(\beta\theta^3 + \delta)\theta\Gamma(\alpha+3)} \right] + \\
&\quad 6 \left[\frac{\Gamma(2+\alpha)[\beta\theta^3\alpha(\alpha+1)(\alpha+2) + \delta(2+\alpha)(\alpha+3)(\alpha+4)]}{(\beta\theta^3 + \delta)\theta^2\Gamma(\alpha+3)} \right] \\
&\quad \left[\frac{\Gamma(1+\alpha)[\beta\theta^3\alpha(\alpha+1)(\alpha+2) + \delta(1+\alpha)(\alpha+2)(\alpha+3)]}{(\beta\theta^3 + \delta)\theta\Gamma(\alpha+3)} \right]^2 \\
&\quad \left. - 3 \left[\frac{\Gamma(1+\alpha)[\beta\theta^3\alpha(\alpha+1)(\alpha+2) + \delta(1+\alpha)(\alpha+2)(\alpha+3)]}{(\beta\theta^3 + \delta)\theta\Gamma(\alpha+3)} \right]^4 \right\} \\
&= \frac{\beta\alpha(\alpha+1)^5(\alpha+2)^5(\alpha+3)\theta^3(\beta\theta^3 + \delta)^3 + \delta(\alpha+1)^4(\alpha+2)^4(\alpha+3)(\alpha+4)(\alpha+5)(\alpha+6)}{(\beta\theta^3 + \delta)^3 - 4\beta^2\alpha^2(\alpha+1)^5(\alpha+2)^5\theta^6(\beta\theta^3 + \delta)^2 + 4\beta\delta\alpha(\alpha+1)^5(\alpha+2)^5(\alpha+3)\theta^3(\beta\theta^3 + \delta)^2 +} \\
&\quad \frac{4\beta\delta\alpha(\alpha+1)^4(\alpha+2)^4(\alpha+3)(\alpha+4)(\alpha+5)\theta^3(\beta\theta^3 + \delta)^2 + 4\delta^2(\alpha+1)^4(\alpha+2)^4(\alpha+3)^2(\alpha+4)}{(\alpha+5)(\beta\theta^3 + \delta)^2 + 6\beta^3\alpha^3(\alpha+1)^5(\alpha+2)^4\theta^9(\beta\theta^3 + \delta) + 6\beta\delta^2\alpha(\alpha+1)^5(\alpha+2)^4(\alpha+3)^2\theta^3} \\
&\quad \frac{\theta^4(\alpha+1)^4(\alpha+2)^4(\beta\theta^3 + \delta)^4}{(\beta\theta^3 + \delta) + 12\beta^2\delta\alpha^2(\alpha+1)^5(\alpha+2)^4(\alpha+3)\theta^6(\beta\theta^3 + \delta) + 6\beta^2\delta\alpha^2(\alpha+1)^4(\alpha+2)^4(\alpha+3)(\alpha+4)} \\
&\quad \frac{\theta^6(\beta\theta^3 + \delta) + 6\delta^3(\alpha+1)^4(\alpha+2)^4(\alpha+3)^3(\alpha+4)(\beta\theta^3 + \delta) + 12\beta\delta^2\alpha(\alpha+1)^4(\alpha+2)^4(\alpha+3)^2}{(\alpha+4)\theta^3(\beta\theta^3 + \delta) - 3\beta^4\alpha^4(\alpha+1)^4(\alpha+2)^4\theta^{12} + 12\beta^3\delta\alpha^3(\alpha+1)^4(\alpha+2)^4(\alpha+3)\theta^9 + 18\beta^2\delta^2\alpha^2} \\
&\quad \frac{(\alpha+1)^4(\alpha+2)^4(\alpha+3)^2\theta^6 + 12\beta\delta^3\alpha(\alpha+1)^4(\alpha+2)^4(\alpha+3)^3\theta^3 + 3\delta^4(\alpha+1)^4(\alpha+2)^4(\alpha+3)^4}{}
\end{aligned} \tag{5.13}$$

7. The probability function of the k^{th} order statistic for the finite mixture is given by

$$\begin{aligned}
f_k(x) &= \frac{n![\beta\alpha(\alpha+1)(\alpha+2) + \delta x^3]\theta^{\alpha+3}e^{-\theta x}x^{\alpha-1}}{(k-1)!(n-k)![\beta\theta^3 + \delta]\Gamma(\alpha+3)} \sum_{i=0}^{n-k} \binom{n-k}{i} (-1)^i \\
&\quad \left[\frac{\beta\theta^3\alpha(\alpha+1)(\alpha+2)\gamma(\alpha, \theta x) + \delta\gamma(\alpha+3, \theta x)}{(\beta\theta^3 + \delta)\Gamma(\alpha+3)} \right]^{i+k-1}
\end{aligned} \tag{5.14}$$

8. Parameter estimation

Method of moments estimation

By solving the equations below simultaneously using the Newton-Raphson method, the estimators of the mixture distribution are obtained.

$$\begin{aligned}
\frac{\beta\theta^3\alpha(\alpha+1)(\alpha+2) + \delta(1+\alpha)(\alpha+2)(\alpha+3)}{(\beta\theta^3 + \delta)\theta(\alpha+1)(\alpha+2)} &= \bar{x} \\
\frac{\beta\theta^3\alpha(\alpha+1)(\alpha+2) + \delta(2+\alpha)(\alpha+3)(\alpha+4)}{(\beta\theta^3 + \delta)\theta^2(\alpha+2)} &= \frac{1}{n} \sum_{i=1}^n x_i^2 \\
\frac{\beta\theta^3\alpha(\alpha+1)(\alpha+2) + \delta(3+\alpha)(\alpha+4)(\alpha+5)}{(\beta\theta^3 + \delta)\theta^3} &= \frac{1}{n} \sum_{i=1}^n x_i^3 \\
\frac{(3+\alpha)[\beta\theta^3\alpha(\alpha+1)(\alpha+2) + \delta(4+\alpha)(\alpha+5)(\alpha+6)]}{(\beta\theta^3 + \delta)\theta^4} &= \frac{1}{n} \sum_{i=1}^n x_i^4
\end{aligned}$$

Maximum likelihood estimation

The likelihood function of the 4-parameter finite Erlang mixture is

$$\begin{aligned} L(\theta, \beta, \delta, \alpha) &= \prod_{i=1}^n \frac{\beta\alpha(\alpha+1)(\alpha+2) + \delta x_i^3}{\beta\theta^3 + \delta} \frac{\theta^{\alpha+3}}{\Gamma(\alpha+3)} e^{-\theta x_i} x_i^{\alpha-1} \\ &= [(\beta\theta^3 + \delta)\Gamma(\alpha+3)]^{-n} \theta^{n(\alpha+3)} e^{-\theta \sum_{i=1}^n x_i} \prod_{i=1}^n x_i^{\alpha-1} \prod_{i=1}^n [\beta\alpha(\alpha+1)(\alpha+2) + \delta x_i^3] \end{aligned} \quad (5.15)$$

and the log-likelihood function is

$$\begin{aligned} \mathbb{L} = \log L(\theta, \beta, \delta, \alpha) &= -n \log [(\beta\theta^3 + \delta)\Gamma(\alpha+3)] + n(\alpha+3) \log \theta - \theta \sum_{i=1}^n x_i + (\alpha-1) \sum_{i=1}^n \log x_i + \\ &\quad \sum_{i=1}^n \log [\beta\alpha(\alpha+1)(\alpha+2) + \delta x_i^3] \end{aligned} \quad (5.16)$$

The derivatives with respect to respective parameters are

$$\frac{\delta \mathbb{L}}{\delta \theta} = -\frac{3n\beta\theta^2}{(\beta\theta^3 + \delta)} + \frac{n(\alpha+3)}{\theta} - \sum_{i=1}^n x_i \quad (5.17)$$

$$\frac{\delta \mathbb{L}}{\delta \beta} = -\frac{n\theta^3}{(\beta\theta^3 + \delta)} + \sum_{i=1}^n \frac{\alpha(\alpha+1)(\alpha+2)}{\beta\alpha(\alpha+1)(\alpha+2) + \delta x_i^3} \quad (5.18)$$

$$\frac{\delta \mathbb{L}}{\delta \delta} = -\frac{n}{(\beta\theta^3 + \delta)} + \sum_{i=1}^n \frac{x_i^3}{\beta\alpha(\alpha+1)(\alpha+2) + \delta x_i^3} \quad (5.19)$$

$$\frac{\delta \mathbb{L}}{\delta \alpha} = -\frac{n\Gamma'(\alpha+3)}{\Gamma(\alpha+3)} + n \log \theta + \sum_{i=1}^n \log x_i + \sum_{i=1}^n \frac{\beta(\alpha+1)(\alpha+2) + \beta\alpha(\alpha+2) + \beta\alpha(\alpha+1)}{\beta\alpha(\alpha+1)(\alpha+2) + \delta x_i^3} \quad (5.20)$$

By equating the above equations (5.17)-(5.20) to zero and solving them simultaneously using the Newton-Raphson method, the maximum likelihood estimates of the parameters are obtained numerically.

Special cases

i. when $\delta = 1$, we have type I 3-parameter finite Erlang mixture.

$$g(x) = \frac{\beta\alpha(\alpha+1)(\alpha+2) + x^3}{\beta\theta^3 + 1} \frac{\theta^{\alpha+3}}{\Gamma(\alpha+3)} e^{-\theta x} x^{\alpha-1}, \quad x > 0; \theta > 0, \beta > 0, \alpha = 1, 2, 3, \dots \quad (5.21)$$

ii. when $\beta = 1$, we have type II 3-parameter finite Erlang mixture.

$$g(x) = \frac{\alpha(\alpha+1)(\alpha+2) + \delta x^3}{\theta^3 + \delta} \frac{\theta^{\alpha+3}}{\Gamma(\alpha+3)} e^{-\theta x} x^{\alpha-1}, \quad x > 0; \theta > 0, \delta > 0, \alpha = 1, 2, 3, \dots \quad (5.22)$$

iii. when $\alpha = 1$, we have type III 3-parameter finite Erlang mixture.

$$g(x) = \frac{6\beta + \delta x^3}{\beta\theta^3 + \delta} \frac{\theta^4}{6} e^{-\theta x}, \quad x > 0; \theta > 0, \beta > 0, \delta > 0 \quad (5.23)$$

iv. when $\beta = \delta = 1$, we have type I 2-parameter finite Erlang mixture.

$$g(x) = \frac{\alpha(\alpha+1)(\alpha+2) + x^3}{\theta^3 + 1} \frac{\theta^{\alpha+3}}{\Gamma(\alpha+3)} e^{-\theta x} x^{\alpha-1}, \quad x > 0; \theta > 0, \alpha = 1, 2, 3, \dots \quad (5.24)$$

v. when $\alpha = \delta = 1$, we have type II 2-parameter finite Erlang mixture.

$$g(x) = \frac{6\beta + x^3}{\beta\theta^3 + 1} \frac{\theta^4}{6} e^{-\theta x}, \quad x > 0; \theta > 0, \beta > 0 \quad (5.25)$$

vi. when $\alpha = \beta = 1$, we have type III 2-parameter finite Erlang mixture.

$$g(x) = \frac{6 + \delta x^3 \theta^4}{\theta^3 + \delta} \frac{1}{6} e^{-\theta x}, \quad x > 0; \theta > 0, \delta > 0 \quad (5.26)$$

When $\delta = 6$, the distribution is a one parameter Rama. (Shanker[10])

vii. when $\alpha = \beta = \delta = 1$, we have 1-parameter finite Erlang mixture.

$$g(x) = \frac{6 + x^3 \theta^4}{\theta^3 + 1} \frac{1}{6} e^{-\theta x}, \quad x > 0; \theta > 0 \quad (5.27)$$

6. Application

An application of the three cases of the generalized finite Erlang mixture has been demonstrated in this section. To assess and compare their goodness of fit, the three distributions have been fitted to data on the relief times in minutes of patients receiving an analgesic. The data set was provided by Gross and Clark[31] in 1975 and has since been applied by various authors including Shanker[9] in studying the Shanker distribution, Shanker[26] in fitting the Amarendra distribution, Nwike and Iwok[18] in evaluating a three-parameter Sujatha distribution, and Oguntunde[30] in assessing the generalized inverse exponential distribution. The $-2 \log$ -likelihood ($-2\ln(L)$), Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC) and Akaike Information Criterion Corrected (AICC) statistics have been computed and used for comparison, and they are computed using the formulae below.

$AIC = -2\ln L + 2k$, $BIC = -2\ln L + k \ln n$, $AICC = AIC + \frac{2k(k+1)}{n-k-1}$, where k is the number of parameters and n is the sample size.

Data set: The relief times (in minutes) of 20 patients receiving an analgesic

1.1,1.4,1.3,1.7,1.9,1.8,1.6,2.2,1.7,2.7,4.1,1.8,1.5,1.2,1.4,3.0,1.7,2.3,1.6,2.0

Table 1. Parameters estimates, $-2\ln(L)$, AIC, BIC and AICC statistics for the 3 cases of the 2-component 4-parameter Erlang mixture, and other mixed finite distributions using the relief times' data set.

Distribution		Estimated parameters				$-2\ln(L)$	AIC	BIC	AICC
Akash distribution		-	$\hat{\theta}=1.1569$	-	-	59.52	61.52	62.52	61.74
Exponential distribution		-	$\hat{\theta}=0.5263$	-	-	65.67	67.67	68.67	67.9
Shanker distribution		-	$\hat{\theta}=0.8039$	-	-	59.78	61.78	62.78	62.01
Lindley distribution		-	$\hat{\theta}=0.8161$	-	-	60.5	62.5	63.5	62.72
Sujatha distribution		-	$\hat{\theta}=1.1367$	-	-	57.5	59.5	60.5	59.72
Amarendra distribution		-	$\hat{\theta}=1.4808$	-	-	55.64	57.64	58.63	57.86
2-component	Case 1	$\hat{\alpha}=8$	$\hat{\theta}=5.1$	$\hat{\beta}=0.001$	$\hat{\delta}=2.87$	36.7	44.7	48.68	47.37
4-parameter	Case 2	$\hat{\alpha}=7$	$\hat{\theta}=5.08$	$\hat{\beta}=0.0001$	$\hat{\delta}=3.69$	36.6	44.6	48.58	47.27
Erlang mixture	Case 3	$\hat{\alpha}=10$	$\hat{\theta}=5.52$	$\hat{\beta}=0.15$	$\hat{\delta}=3.42$	35.45	43.45	47.43	46.12

The finite Erlang mixtures give better fits compared to the rest of the finite mixtures, as seen in the statistics used in comparison, which are lower for the mixed finite Erlang distributions compared to the other mixed finite distributions. Case 2 gives a better fit than case 1, while case 3 gives the best fit among the 3 cases of the mixed Erlang distributions.

7. Conclusion

Three cases of the two component 4-parameter generalized Erlang mixture with varying mixing weights and component probability (Erlang) distributions have been derived, alongside their special cases, the two component 1, 2 and 3-parameter finite Erlang mixtures. The distribution function, survival function, hazard function, moment generating function, raw and central moments, mean, variance, coefficient of skewness, coefficient of

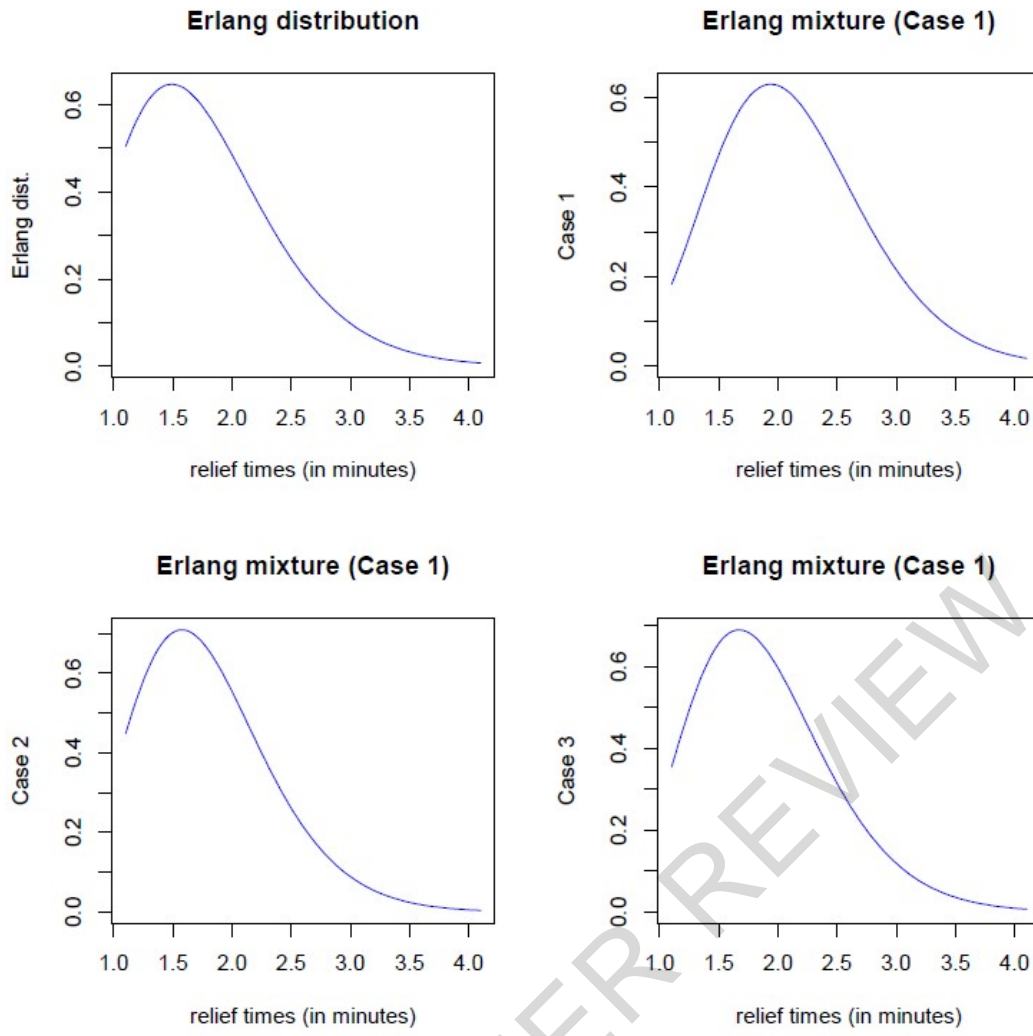


Figure 1: The pdfs for the Erlang distribution and the 3 cases of the mixed Erlang finite mixture using the relief times' data set.

kurtosis, and order statistics are among properties of the mixtures presented. Parameter estimation was carried out using the moments and maximum likelihood methods. Application of the finite Erlang mixtures to a real data set proved that they offered better fits compared to other mixed finite distributions. Construction of more finite Erlang mixtures using different mixing weights and probability distributions, and further applications of the finite mixed Erlang distributions is a recommendation for further research.

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