The Topp Leone-G 
Power Series Class of 
Distributions with Applications

Boikanyo Makubate¹, Kethamile Rannona², 
Broderick Oluyede³ and Fastel Chipepa⁴∗

*Corresponding author

1. Department of Mathematics and Statistical Sciences, Botswana International University of Science and Technology, Botswana, makubateb@biust.ac.bw
2. Department of Mathematics and Statistical Sciences, Botswana International University of Science and Technology, Botswana, kethamile.rannona@studentmail.biust.ac.bw
3. Department of Mathematics and Statistical Sciences, Botswana International University of Science and Technology, Botswana, oluyedeo@biust.ac.bw
4. Department of Mathematics and Statistical Sciences, Botswana International University of Science and Technology, Botswana, chipepaf@biust.ac.bw

Abstract

We present a new class of distributions called the Topp-Leone-G Power Series (TL-GPS) class of distributions. This model is obtained by compounding the Topp-Leone-G distribution with the power series distribution. Statistical properties of the TL-GPS class of distributions are obtained. Maximum likelihood estimates for the proposed model were obtained. A simulation study is carried out for the special case of Topp-Leone Log-Logistic Poisson distribution to assess the performance of the maximum likelihood estimates. Finally, we apply Topp-Leone-log-logistic Poisson distribution to real data sets to illustrate the usefulness and applicability of the proposed class of distributions.

Key Words: Topp-Leone-G Distribution; Power Series Distribution; Maximum Likelihood Estimation.

Mathematical Subject Classification: 60E05, 62E15.

1. Introduction

Statistical distributions are widely used to explain different types of real life events. Because of their usefulness, statistical distribution theory is extensively researched and new distributions are being developed. The Topp Leone (TL) distribution is among the distributions used within the theory and practice of statistics. It was proposed by Topp and Leone (1955) as a lifetime model. Nadarajah and Kotz (2003) studied its properties and provided its moments and the characteristic function. Numerous authors also studied the TL distribution. Ghitany et al. (2005) provided some reliability measures of the TL distribution, while Vicaria et al. (2008) introduced a two-sided generalized version of the TL distribution and Al-Zahrani (2012) derived the goodness-of-fit test for the TL distribution.

Al-Shomrani et al. (2016) proposed the Topp-Leone generated family of distributions with cumulative distribution function (cdf), probability density function (pdf), and survival function given by

$$F_{TL-G}(x;b, \psi) = [1 - \bar{G}(x; \psi)]^2b,$$  

(1)
The Topp-Leone-G Power Series Class of Distributions with Applications

In this paper, we develop a new class of distributions called the Topp-Leone-G Power Series (TL-GPS) class of distributions. We motivate the development of the TL-GPS class of distributions by the flexibility in data fitting obtained from the TL-GPS class of distributions and the applicability of the power series distributions to data sets that exhibit monotonic or non-monotonic hazard rate shapes. Another motivation for developing the TL-GPS class of distributions is the applicability of the power series distributions in different fields such as finance, economics, and actuarial sciences.

This paper is organized as follows. In Section 2 we introduce the new class of distributions and present its cdf and pdf. We also discuss some sub-classes of the TL-GPS distribution and present some special cases when the baseline cdf is specified. Some statistical properties of the TL-GPS distribution including moments, conditional moments, order statistics, and Rényi entropy are presented in Section 3. Maximum likelihood estimates of the unknown parameters are given in Section 4. Monte Carlo simulations for special cases are conducted in Section 5. Applications are given in Section 6, followed by some concluding remarks.

2. The Model

In this section, we develop the TL-GPS class of distributions and derive some statistical properties which include series expansion of the pdf, quantile and hazard functions, sub-classes and some special cases.

Suppose that the random variable \( X \) has the Topp-Leone-G distribution with cdf defined by equation (1). Given \( N \), let \( X_1, \ldots, X_N \) be independent and identically distributed random variables from the Topp-Leone-G distribution. Let \( N \) be a discrete random variable with a power series distribution (truncated at zero) and probability mass function (pmf)

\[
P(N = n) = \frac{a_n \theta^n}{C(\theta)}, \quad n = 1, 2, \ldots,
\]

where \( a_n \geq 0 \) depends only on \( n \), \( C(\theta) = \sum_{n=1}^{\infty} a_n \theta^n \) and \( \theta \in (0, s) \) (\( s \) can be \( \infty \)) is chosen such that \( C(\theta) \) is finite and its three derivatives with respect to \( \theta \) are defined and given by \( C'(\cdot), C''(\cdot) \) and \( C'''(\cdot) \), respectively. The power series family of distributions includes Binomial, Poisson, Geometric and Logarithmic distributions. See Johnson et al. (1994) for additional details. Let \( X = \min(X_1, \ldots, X_N) \), then the conditional cdf of \( X \mid N = n \) is given by

\[
F_{X\mid N = n}(x) = 1 - [S_{TL-G}(x; b, \psi)]^n, \quad x > 0.
\]

The Topp-Leone-G Power Series class of distributions is defined by the marginal cdf of \( X \). The general form of the cdf and pdf of the Topp-Leone-G Power Series class of distributions are given by

\[
f_{TL-GPS}(x; \theta, b, \psi) = \frac{\theta f_{TL-G}(x; b, \psi) C'(\theta S_{TL-G}(x; b, \psi))}{C(\theta)},
\]

and

\[
S_{TL-G}(x; b, \psi) = 1 - F_{TL-G}(x; b, \psi) = 1 - [1 - \hat{G}(x; \psi)]^b,
\]

respectively, for \( b > 0 \), where \( \hat{G}(x; \psi) \) is the baseline cdf depending on a parameter vector \( \psi \), \( g(x; \psi) = dG(x; \psi)/dx \), and \( \hat{G}(x; \psi) = 1 - G(x; \psi) \) is the survival function.
The quantile function of the TL-GPS class of distributions is easily obtained by inverting equation \((5)\),

\[ X = \frac{C(\theta S_{TL-G}(x; b, \psi))}{C(\theta)} - 1 \]

so that

\[ C(\theta S_{TL-G}(x; b, \psi)) = C(\theta)(1 - u). \]

This is equivalent to

\[ C^{-1}(C(\theta)(1 - u)) = \theta S_{TL-G}(x; b, \psi), \]

Therefore, we obtain the quantile values from the TL-GPS class of distributions by solving the non-linear equation

\[ C^{-1}(C(\theta)(1 - u)) - \theta S_{TL-G}(x; b, \psi) = 0, \]

using iterative methods in R, SAS or MATLAB software.

2.2. Expansion of the Density Function

Expansion of the density function of the TL-GPS class of distributions is presented in this sub-section. Equation \((6)\) can be rewritten as

\[ f_{TL-GPS}(x; \theta, b, \psi) = \sum_{n=1}^{\infty} \frac{n \alpha}{C(\theta)} n \alpha^n 2b g(x; \psi) \bar{G}(x; \psi) [1 - \bar{G}(x; \psi)^2]^{b-1} [1 - (1 - \bar{G}(x; \psi)^2)^{b}]^{n-1}. \]

Using the generalized binomial expansion

\[ [1 - (1 - \bar{G}(x; \psi)^2)^{b}]^{n-1} = \sum_{i=0}^{\infty}(-1)^i \binom{n-1}{i} [1 - \bar{G}(x; \psi)^2]^b, \]

the pdf of the TL-GPS class of distribution is given by

\[ f_{TL-GPS}(x; \theta, b, \psi) = \sum_{i=0}^{\infty} \sum_{n=1}^{\infty} (-1)^i \binom{n-1}{i} \frac{n \alpha^n}{C(\theta)} 2b g(x; \psi) \bar{G}(x; \psi) [1 - \bar{G}(x; \psi)^2]^{b(i+1)-1}. \]
Also, applying the generalized binomial expansion

\[ [1 - \tilde{G}(x; \psi)^2]^b(b+1)^{-1} = \sum_{j=0}^{\infty} (-1)^j \binom{b(i+1) - 1}{j} \tilde{G}(x; \psi)^{2j} \]

we get

\[
\begin{align*}
  f_{TL-GPS}(x; \theta, b, \psi) &= \sum_{i,j,k=0}^{\infty} (-1)^{i+j+k} \binom{n-1}{i} \binom{b(i+1) - 1}{j} \binom{2j+1}{k} \frac{n a_n \theta^n}{C(\theta)} 2b \\
  &\times g(x; \psi) \tilde{G}(x; \psi)^{2j+1}.
\end{align*}
\]

Furthermore, using the binomial expansion

\[ \tilde{G}(x; \psi)^{2j+1} = [1 - G(x; \psi)]^{2j+1} = \sum_{k=0}^{\infty} (-1)^k \binom{2j+1}{k} G(x; \psi)^k \]

yields

\[
\begin{align*}
  f_{TL-GPS}(x; \theta, b, \psi) &= \sum_{i,j,k=0}^{\infty} (-1)^{i+j+k} \binom{n-1}{i} \binom{b(i+1) - 1}{j} \binom{2j+1}{k} \frac{n a_n \theta^n}{C(\theta)} 2b \\
  &\times g(x; \psi) G(x; \psi)^k \\
  &= \sum_{i,j,k=0}^{\infty} (-1)^{i+j+k} \binom{n-1}{i} \binom{b(i+1) - 1}{j} \binom{2j+1}{k} \frac{n a_n \theta^n}{C(\theta)} 2b \\
  &\times \left( \frac{k+1}{k+1} \right) g(x; \psi) G(x; \psi)^k \\
  &= \sum_{k=0}^{\infty} \eta_{k+1} g_{k+1}(x; \psi),
\end{align*}
\]

where

\[ g_{k+1}(x; \psi) = (k+1) g(x; \psi) G(x; \psi)^k \]

is the exponentiated-G (Exp-G) distribution with power parameter \( k+1 \), and

\[
\eta_{k+1} = \sum_{i,j=0}^{\infty} (-1)^{i+j+k} \binom{n-1}{i} \binom{b(i+1) - 1}{j} \binom{2j+1}{k} \frac{n a_n \theta^n}{C(\theta)} 2b k+1. \tag{11}
\]

It follows that the TL-GPS distribution can be expressed as an infinite linear combination of Exp-G densities.

### 2.3. Sub-classes of the TL-GPS Distribution

We derive expressions for cdfs of sub-classes of the TL-GPS class of distributions and these are presented in Table 1.

### 2.4. Some Special Cases of the TL-GPS Class of Distributions

In this section, we present some special cases of the TL-GPS class of distributions. We consider cases when the baseline distribution are Weibull and log-logistic distributions.

#### 2.4.1. Topp-Leone-Weibull-Poisson Distribution

The cdf and pdf of the Topp-Leone-Weibull Poisson (TL-WP) distribution are given by

\[
F_{TL-WP}(x; \theta, b, \alpha, \beta) = 1 - \frac{e^{\theta(1-(1-e^{-2\alpha^\beta x})^b)} - 1}{e^\beta - 1}
\]
Table 1: Sub-Classes of the TL-GPS Distribution

<table>
<thead>
<tr>
<th>Distribution</th>
<th>$a_n$</th>
<th>$C(\theta)$</th>
<th>$\text{cdf}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Topp-Leone G Poisson</td>
<td>$(n!)^{-1}$</td>
<td>$e^\theta - 1$</td>
<td>$1 - \frac{e^{\theta \left(1 - \frac{1 - \tilde{G}(x;\psi)^{2b}}{1 - \tilde{G}(x;\psi)^{2b}}\right)}}{e^\theta - 1}$</td>
</tr>
<tr>
<td>Topp-Leone G Geometric</td>
<td>$1$</td>
<td>$\theta (1 - \theta)^{-1}$</td>
<td>$1 - \frac{(1 - \frac{1 - \tilde{G}(x;\psi)^{2b}}{1 - \tilde{G}(x;\psi)^{2b}})(1 - \theta)}{\log(1 - \theta)}$</td>
</tr>
<tr>
<td>Topp-Leone G Logarithmic</td>
<td>$n^{-1}$</td>
<td>$-\log(1 - \theta)$</td>
<td>$1 - \frac{\log(1 - \frac{1 - \tilde{G}(x;\psi)^{2b}}{1 - \tilde{G}(x;\psi)^{2b}})}{\log(1 - \theta)}$</td>
</tr>
<tr>
<td>Topp-Leone G Binomial</td>
<td>$\left(\frac{m}{n}\right)$</td>
<td>$(1 + \theta)^m - 1$</td>
<td>$1 - \frac{(1 + \theta \left(1 - \frac{1 - \tilde{G}(x;\psi)^{2b}}{1 - \tilde{G}(x;\psi)^{2b}}\right))^m}{(1 + \theta)^m - 1}$</td>
</tr>
</tbody>
</table>

and

$$f_{\text{TL-WP}}(x; \theta, b, \alpha, \beta) = \frac{2b\alpha \beta x^{\beta - 1} e^{-2\alpha x^\beta} (1 - e^{-2\alpha x^\beta} b^{-1} e^{\theta (1 - (1 - e^{-2\alpha x^\beta} b))})}{e^\theta - 1},$$

respectively, for $\alpha, \beta, b, \theta > 0$ and $x > 0$. The hrf and rhfr are given by

$$h_{\text{TL-WP}}(x; \theta, b, \alpha, \beta) = 2b\alpha \beta x^{\beta - 1} e^{-2\alpha x^\beta} (1 - e^{-2\alpha x^\beta} b^{-1} e^{\theta (1 - (1 - e^{-2\alpha x^\beta} b))})$$

and

$$\tau_{\text{TL-WP}}(x; \theta, b, \alpha, \beta) = 2b\alpha \beta x^{\beta - 1} e^{-2\alpha x^\beta} (1 - e^{-2\alpha x^\beta} b^{-1} e^{\theta (1 - (1 - e^{-2\alpha x^\beta}))}),$$

respectively. Figure 1 shows the plots of the pdfs and hrf for the TL-WP distribution for selected parameter values.

Plots of the TL-WP pdf exhibit different shapes including almost symmetric, left-skewed, right-skewed, and reverse-J shapes. Plots of the hrf of the TL-WP distribution shows different shapes including increasing, decreasing, upside-down bathtub followed by bathtub and uni-modal shapes.
The quantile function of the TL-WP distribution is obtained by solving the non-linear equation

$$\log[((e^{\theta} - 1)(1 - u) + 1] - \theta(1 - [1 - e^{-2\alpha x^\beta}]^b)] = 0.$$  \hspace{1cm} (12)

As such, random numbers can be generated from the TL-WP distribution by numerically solving the non-linear equation (12). Quantile values of the TL-WP distribution are given in Table 2.

<table>
<thead>
<tr>
<th>$u$</th>
<th>$(0.8,2,1.0,9,1.0)$</th>
<th>$(1.5,1.2,1.8,2.1)$</th>
<th>$(3.5,1.2,5.5,0.6)$</th>
<th>$(0.5,1.0,0.3,0.1)$</th>
<th>$(2.0,3.0,0.4,1.5)$</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.1</td>
<td>0.0112</td>
<td>0.3069</td>
<td>0.7432</td>
<td>0.2066</td>
<td>0.0011</td>
</tr>
<tr>
<td>0.2</td>
<td>0.0261</td>
<td>0.3877</td>
<td>0.7814</td>
<td>0.2806</td>
<td>0.0041</td>
</tr>
<tr>
<td>0.3</td>
<td>0.0446</td>
<td>0.4529</td>
<td>0.8082</td>
<td>0.3412</td>
<td>0.0100</td>
</tr>
<tr>
<td>0.4</td>
<td>0.0971</td>
<td>0.5751</td>
<td>0.8520</td>
<td>0.4552</td>
<td>0.0379</td>
</tr>
<tr>
<td>0.6</td>
<td>0.1357</td>
<td>0.6417</td>
<td>0.8732</td>
<td>0.5170</td>
<td>0.0688</td>
</tr>
<tr>
<td>0.7</td>
<td>0.1891</td>
<td>0.7193</td>
<td>0.8964</td>
<td>0.5885</td>
<td>0.1264</td>
</tr>
<tr>
<td>0.8</td>
<td>0.2704</td>
<td>0.8196</td>
<td>0.9245</td>
<td>0.6804</td>
<td>0.2494</td>
</tr>
<tr>
<td>0.9</td>
<td>0.4226</td>
<td>0.9764</td>
<td>0.9666</td>
<td>0.8245</td>
<td>0.6031</td>
</tr>
</tbody>
</table>

2.4.2. Topp-Leone-Weibull-Binomial Distribution

The cdf and pdf of the Topp-Leone-Weibull Binomial (TL-WB) distribution are given by

$$F_{TL-WB}(x; \theta, b, \alpha, \beta, m) = 1 - \frac{(1 + \theta(1 - [1 - e^{-2\alpha x^\beta}]^b))^{m-1}}{(1 + \theta)^m - 1}$$

and

$$f_{TL-WB}(x; \theta, b, \alpha, \beta, m) = 2b\theta\alpha\beta x^{\beta-1}e^{-2\alpha x^\beta}(1 - e^{-2\alpha x^\beta})^{b-1}$$

$$\times \frac{m(1 + \theta(1 - [1 - e^{-2\alpha x^\beta}]^b))^{m-1}}{(1 + \theta)^m - 1},$$

respectively for $\alpha, \beta, b, \theta > 0$ and $x > 0$. The hrf and rhrf are given by

$$h_{TL-WB}(x; \theta, b, \alpha, \beta, m) = 2b\theta\alpha\beta x^{\beta-1}e^{-2\alpha x^\beta}(1 - e^{-2\alpha x^\beta})^{b-1}$$

$$\times \frac{m(1 + \theta(1 - [1 - e^{-2\alpha x^\beta}]^b))^{m-1}}{(1 + \theta)^m - 1}$$

and

$$\tau_{TL-WB}(x; \theta, b, \alpha, \beta, m) = 2b\theta\alpha\beta x^{\beta-1}e^{-2\alpha x^\beta}(1 - e^{-2\alpha x^\beta})^{b-1}$$

$$\times \frac{m(1 + \theta(1 - [1 - e^{-2\alpha x^\beta}]^b))^{m-1}}{(1 + \theta)^m - (1 + \theta(1 - [1 - e^{-2\alpha x^\beta}]^b))^m},$$

respectively. Figure 2 shows the plots of the pdfs and hrfs for the TL-WB distribution for selected parameters values. Plots of the TL-WB pdf exhibit different shapes including symmetric, skewed to the right, skewed to the left and reverse-J shapes. Plots of the hrf of the TL-WB distribution shows different shapes including increasing, decreasing, bathtub and uni-modal shapes.

The quantile function of the TL-WB distribution can be obtained by solving the non-linear equation

$$[((1 + \theta)^m - 1)(1 - u) + 1]^\frac{1}{m} - \theta(1 - [1 - e^{-2\alpha x^\beta}]^b) = 0.$$  \hspace{1cm} (13)
As such, random numbers can be generated from the TL-WB power series distribution by numerically solving the non-linear equation (13). Quantile values of the TL-WB distribution are given in Table 3.

Table 3: Table of Quantiles for TL-WB Distribution

<table>
<thead>
<tr>
<th>$(\theta, \alpha, \beta, b, m)$</th>
<th>$(0.8, 2.1, 0.9, 1.0, 1.5)$</th>
<th>$(1.2, 1.8, 2.1, 3.5, 1.2)$</th>
<th>$(5.5, 0.6, 0.5, 1.0, 0.3)$</th>
<th>$(0.1, 1.2, 1.8, 0.4, 0.7)$</th>
<th>$(1.5, 0.9, 0.5, 0.3, 1.1)$</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.1</td>
<td>0.0167</td>
<td>0.5307</td>
<td>0.0219</td>
<td>0.0069</td>
<td>0.0000</td>
</tr>
<tr>
<td>0.2</td>
<td>0.0382</td>
<td>0.5999</td>
<td>0.0819</td>
<td>0.0230</td>
<td>0.0001</td>
</tr>
<tr>
<td>0.3</td>
<td>0.0639</td>
<td>0.6504</td>
<td>0.1755</td>
<td>0.0500</td>
<td>0.0001</td>
</tr>
<tr>
<td>0.4</td>
<td>0.0947</td>
<td>0.6938</td>
<td>0.3022</td>
<td>0.0925</td>
<td>0.0004</td>
</tr>
<tr>
<td>0.5</td>
<td>0.1323</td>
<td>0.7346</td>
<td>0.4653</td>
<td>0.1586</td>
<td>0.0019</td>
</tr>
<tr>
<td>0.6</td>
<td>0.1795</td>
<td>0.7756</td>
<td>0.6730</td>
<td>0.2635</td>
<td>0.0082</td>
</tr>
<tr>
<td>0.7</td>
<td>0.2420</td>
<td>0.8197</td>
<td>0.9435</td>
<td>0.4393</td>
<td>0.0329</td>
</tr>
<tr>
<td>0.8</td>
<td>0.3323</td>
<td>0.8714</td>
<td>1.3200</td>
<td>0.7695</td>
<td>0.1350</td>
</tr>
<tr>
<td>0.9</td>
<td>0.4908</td>
<td>0.9435</td>
<td>1.9431</td>
<td>1.5783</td>
<td>0.7004</td>
</tr>
</tbody>
</table>

2.4.3. Topp-Leone-Log-Logistic-Poisson Distribution

The cdf and pdf of the Topp-Leone-Log-Logistic-Poisson (TL-LLP) distribution are given by

$$F_{\text{TL-LLP}}(x; \theta, b, c) = 1 - \frac{e^{\theta(1-[1-(1+x^c)^{-2}]^b)} - 1}{e^\theta - 1}$$

and

$$f_{\text{TL-LLP}}(x; \theta, b, c) = \frac{2\theta bcx^{c-1}(1+x^c)^{-3}(1-(1+x^c)^{-2})b-1e^{\theta(1-[1-(1+x^c)^{-2}]^b)}}{e^\theta - 1},$$

respectively for $\theta, b, c > 0$ and $x > 0$. The hrf and rhrf are given by

$$h_{\text{TL-LLP}}(x; \theta, b, c) = 2\theta bcx^{c-1}(1+x^c)^{-3}(1-(1+x^c)^{-2})b-1e^{\theta(1-[1-(1+x^c)^{-2}]^b)}e^{\theta(1-(1+x^c)^{-2})^b} - 1$$

and

$$r_{\text{TL-LLP}}(x; \theta, b, c) = \frac{20bcx^{c-1}(1+x^c)^{-3}(1-(1+x^c)^{-2})b-1e^{\theta(1-[1-(1+x^c)^{-2}]^b)}}{e^\theta - e^{\theta(1-(1+x^c)^{-2})^b}} ,$$

respectively. Figure 3 shows the plots of the hrf for the TL-LLP distribution for selected parameters values. The plots shows different shapes including reverse-J, decreasing, bathtub followed by an upside-down bathtub and upside-down bathtub shapes.
The quantile function of the TL-LLP distribution obtained by solving the non-linear equation
\[
\ln[(e^\theta - 1)(1-u) + 1] - \theta (1 - [1 - (1+x^c)^{-2}]^b) = 0. \tag{14}
\]
Therefore, random numbers can be generated from the TL-LLP distribution by numerically solving the non-linear equation (14). Quantile values of the TL-LLP distribution are given in Table 4.

<table>
<thead>
<tr>
<th>(u)</th>
<th>(0.8,1.0,0.9)</th>
<th>(1.0,1.5,1.2)</th>
<th>(1.8,2.1,3.5)</th>
<th>(1.2,5.5,0.6)</th>
<th>(0.5,1.0,0.3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.1</td>
<td>0.1500</td>
<td>0.1375</td>
<td>0.5753</td>
<td>0.4053</td>
<td>0.0000</td>
</tr>
<tr>
<td>0.2</td>
<td>0.2535</td>
<td>0.2229</td>
<td>0.6551</td>
<td>0.6659</td>
<td>0.0004</td>
</tr>
<tr>
<td>0.3</td>
<td>0.3646</td>
<td>0.3085</td>
<td>0.7161</td>
<td>0.9585</td>
<td>0.0021</td>
</tr>
<tr>
<td>0.4</td>
<td>0.4950</td>
<td>0.4029</td>
<td>0.7715</td>
<td>1.3202</td>
<td>0.0078</td>
</tr>
<tr>
<td>0.5</td>
<td>0.6583</td>
<td>0.5143</td>
<td>0.8268</td>
<td>1.8012</td>
<td>0.0259</td>
</tr>
<tr>
<td>0.6</td>
<td>0.8776</td>
<td>0.6552</td>
<td>0.8867</td>
<td>2.4944</td>
<td>0.0820</td>
</tr>
<tr>
<td>0.7</td>
<td>1.2010</td>
<td>0.8496</td>
<td>0.9572</td>
<td>3.6101</td>
<td>0.2722</td>
</tr>
<tr>
<td>0.8</td>
<td>1.7550</td>
<td>1.1574</td>
<td>1.0511</td>
<td>5.7606</td>
<td>1.0841</td>
</tr>
<tr>
<td>0.9</td>
<td>3.0603</td>
<td>1.8061</td>
<td>1.2090</td>
<td>11.8717</td>
<td>7.3663</td>
</tr>
</tbody>
</table>

### 2.4.4. Topp-Leone-Log-Logistic Binomial Distribution

The cdf and the pdf of the Topp-Leone-Log-Logistic Binomial (TL-LLB) distribution are given by
\[
F_{TL-LLB}(x; \theta,b,c,m) = 1 - \frac{(1 + \theta(1 - [1 - (1+x^c)^{-2}]^b))^m - 1}{(1 + \theta)^m - 1}
\]
and
\[
f_{TL-LLB}(x; \theta,b,c,m) = 2 \theta bc x^{c-1} (1+x^c)^{-3} (1 - (1+x^c)^{-2})^{b-1} \times \frac{m(1 + \theta(1 - [1 - (1+x^c)^{-2}]^b))^m - 1}{(1 + \theta)^m - 1},
\]
respectively for θ, b, c > 0 and x > 0. The hrf and rhrf are given by

\[ h_{TL-LLB}(x; \theta, b, c, m) = 2\theta b cx^{c-1}(1+x^c)^{-3}(1-(1+x^c)^{-2})^{b-1} \times \frac{m(1+\theta(1-[1-(1+x^c)^{-2}]b))^{m-1}}{(1+\theta(1-[1-(1+x^c)^{-2}]b))^{m}} \]

and

\[ \tau_{TL-LLB}(x; \theta, b, c, m) = 2\theta b cx^{c-1}(1+x^c)^{-3}(1-(1+x^c)^{-2})^{b-1} \times \frac{m(1+\theta(1-[1-(1+x^c)^{-2}]b))^{m-1}}{(1+\theta)^m-(1+\theta(1-[1-(1+x^c)^{-2}]b))^{m}} \]

respectively. Figure 4 shows the plots of the pdfs and hrfs for the TL-WP distribution for selected parameters values.

Plots of the TL-LLB pdf exhibit different shapes skewed to the right, skewed to the left, reverse-J and almost symmetric shapes. Plots of the hrf of the TL-LLB distribution shows different shapes including reverse-J, decreasing, bathtub followed by an upside-down bathtub and uni-modal shapes.

The quantile function obtained by solving the non-linear equation

\[ [(1+\theta)^m - 1)(1-u) + 1]^\frac{1}{m} - 1 + \theta(1-[1-(1+x^c)^{-2}]b) = 0. \quad (15) \]

Therefore, random numbers can be generated from the TL-LLB distribution by numerically solving the non-linear equation (15). Quantile values of the TL-LLB distribution are given in Table 5.

<table>
<thead>
<tr>
<th>(θ, b, c, m)</th>
<th>u</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.1</td>
<td>3.4643</td>
<td>1.6754</td>
<td>19.8517</td>
<td>1.3128</td>
<td>1.9504</td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.2</td>
<td>2.1130</td>
<td>1.3088</td>
<td>9.3969</td>
<td>1.0455</td>
<td>1.6754</td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.3</td>
<td>1.5031</td>
<td>1.0995</td>
<td>5.7043</td>
<td>0.8869</td>
<td>1.5145</td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.4</td>
<td>1.1310</td>
<td>0.9473</td>
<td>3.8018</td>
<td>0.7685</td>
<td>1.3955</td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.5</td>
<td>0.8695</td>
<td>0.8223</td>
<td>2.6371</td>
<td>0.6695</td>
<td>1.2965</td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.6</td>
<td>0.6689</td>
<td>0.7108</td>
<td>1.8467</td>
<td>0.5799</td>
<td>1.2070</td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.7</td>
<td>0.5041</td>
<td>0.6039</td>
<td>1.2700</td>
<td>0.4933</td>
<td>1.1196</td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.8</td>
<td>0.3599</td>
<td>0.4926</td>
<td>0.8222</td>
<td>0.4025</td>
<td>1.0262</td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.9</td>
<td>0.2213</td>
<td>0.3598</td>
<td>0.4466</td>
<td>0.2940</td>
<td>0.9084</td>
<td></td>
</tr>
</tbody>
</table>
3. Moments, Conditional Moments and Mean Deviations

In this section, the $r^{th}$ moment, conditional moments, mean deviations, Lorenz and Bonferroni curves of the TL-GPS class of distributions are presented.

3.1. Moments and Generating Function

If $X$ follows the TL-GPS distribution and $Y \sim \text{Exp-G}(k + 1)$, then using equation (10), the $r^{th}$ moment of the TL-GPS class of distributions is obtained as follows

$$
\mu'_r = E(X^r) = \int_0^\infty x^r \cdot f_{\text{TL-GPS}}(x; \theta, b, \psi)dx = \sum_{k=0}^\infty \eta_k + 1 E(Y^r),
$$

where $E[Y^r]$ is the $r^{th}$ moment of the Exp-G distribution with power parameter $(k + 1)$ and $\eta_k + 1$ is given by equation (11). The moment generating function (mgf) of the TL-GPS class of distributions is given by

$$
M_X(t) = E(e^{tX}) = \sum_{r=0}^\infty t^r E(X^r) = \sum_{k=0}^\infty \eta_k + 1 M_Y(t),
$$

where $M_Y(t)$ is the mgf of the Exp-G distribution and $\eta_k + 1$ is given by equation (11).

3.2. Conditional Moments

It is also of interest to obtain the $r^{th}$ conditional moments. The conditional $r^{th}$ moment of the TL-GPS distribution is given by

$$
E(X^r|X > t) = \frac{1}{F_{\text{TL-GPS}}(t; \theta, b, \psi)} \int_t^\infty x^r \cdot f_{\text{TL-GPS}}(x; \theta, b, \psi)dx = \sum_{k=0}^\infty \eta_k + 1 E(Y^r I_{Y^r > t}),
$$

where

$$
E(Y^r I_{Y^r > t}) = \int_t^\infty y^r g_{k+1}(y; \psi)dy.
$$

3.3. Mean Deviations, Lorenz and Bonferroni Curves

The mean deviation about the mean and mean deviation about the median as well as Lorenz and Bonferroni curves for the TL-GPS class of distributions are presented in this subsection.

3.3.1. Mean Deviations

If $X$ has the TL-GPS distribution, then we can derive the mean deviation about the mean $D(\mu)$ and the median deviation about the median $D(M)$ as follows

$$
D(\mu) = \int_0^\infty |x - \mu| f_{\text{TL-GPS}}(x; \theta, b, \psi)dx = 2\mu f_{\text{TL-GPS}}(x; \theta, b, \psi) - 2\mu + 2T(\mu)
$$

and

$$
D(M) = \int_0^\infty |x - M| f_{\text{TL-GPS}}(x; \theta, b, \psi)dx = -\mu + 2T(M),
$$

respectively, where $\mu = E(X)$ and $M = \text{Median}(X)$ is the median of $F_{\text{TL-GPS}}(x; \theta, b, \psi)$. Note that

$$
T(\mu) = \int_{\mu}^\infty x \cdot f_{\text{TL-GPS}}(x; \theta, b, \psi)dx = \sum_{k=0}^\infty \eta_k + 1 \int_{\mu}^\infty y g_{k+1}(y; \psi)dy.
$$
and
\[ T(M) = \int_M^\infty x \cdot f_{TLP}(x; \theta, b, \psi) \, dx = \sum_{k=0}^{\infty} \eta_{k+1} \int_M^\infty y \cdot g_{k+1}(y; \psi) \, dy. \]

### 3.3.2. Bonferroni and Lorenz Curves

In this subsection, we present Bonferroni and Lorenz curves for TL-GPS class of distributions. The Bonferroni and Lorenz curves are given by
\[
B(p) = \frac{1}{p\mu} \int_0^q x \cdot f_{TLP}(x; \theta, b, \psi) \, dx = \frac{1}{p\mu} \sum_{k=0}^{\infty} \eta_{k+1} \int_0^q x \cdot g_{k+1}(x; \psi) \, dx
\]
and
\[
L(p) = \frac{1}{\mu} \int_0^q x \cdot f_{TLP}(x; \theta, b, \psi) \, dx = \frac{1}{\mu} \sum_{k=0}^{\infty} \eta_{k+1} \int_0^q x \cdot g_{k+1}(x; \psi) \, dx,
\]
respectively, where \( \int_0^q x \cdot g_k(x; \psi) \, dx \) is the first incomplete moment of the Exp-G distribution with power parameter \( k+1 \) and \( \eta_{k+1} \) is given by equation (11).

### 3.4. Order Statistics and Rényi Entropy

In this section, we present the distribution of the order statistic and Rényi entropy of the TL-GPS class of distributions.

#### 3.4.1. Distribution of Order Statistics

Let \( X_1, X_2, \ldots, X_n \) be a random sample from the TL-GPS distribution and let \( X_{(i)} \) be the corresponding \( i^{th} \) order statistic. The pdf of the \( i^{th} \) order statistic, \( X_{(i)} \) is given by
\[
f_{X_{(i)}}(x) = \frac{1}{B(i, n-i+1)} f(x) \sum_{k=0}^{\infty} (-1)^k \binom{n-i}{k} [F(x)]^{k+i-1}, \tag{16}
\]
where \( B(\cdot, \cdot) \) is the beta function. Substituting the pdf and cdf of the TL-GPS family of distributions, we write
\[
f(x) [F(x)]^{k+i-1} = \sum_{n=1}^{\infty} \frac{n a_n \theta^n}{C(\theta)} [1 - (1 - \tilde{G}(x; \psi)^2)^{b} n^{-1} 2 \tilde{g}(x; \psi) \tilde{G}(x; \psi)]
\times [1 - \tilde{G}(x; \psi)^2]^{b-1} \left[ 1 - \frac{C(\theta(1 - (1 - \tilde{G}(x; \psi)^2)^{b}))}{C(\theta)} \right]^{k+i-1}.
\]

Using the generalized binomial expansion
\[
\left[ 1 - \frac{C(\theta(1 - (1 - \tilde{G}(x; \psi)^2)^{b}))}{C(\theta)} \right]^{k+i-1} = \sum_{j=0}^{\infty} (-1)^j \binom{k+i-1}{j} \left[ \frac{C(\theta(1 - (1 - \tilde{G}(x; \psi)^2)^{b}))}{C(\theta)} \right]^{j},
\]
and applying the result on power series raised to a positive integer, we get
\[
f(x) [F(x)]^{k+i-1} = \sum_{j=0}^{\infty} \sum_{n=1}^{\infty} \binom{k+i-1}{j} \left( -1 \right)^j \frac{n a_n \theta^{n+m}}{C(b+1)} b_{m,j} \tilde{g}(x; \psi) \tilde{G}(x; \psi)
\times [1 - (1 - \tilde{G}(x; \psi)^2)]^{m+n-1} [1 - \tilde{G}(x; \psi)^2]^{b-1},
\]
where \( b_{m,j} = (ma_0)^{-1} \sum_{l=1}^{m_1} (l(j+1) - m)a_0 b_{m-l} \) and \( b_{0,j} = a_0^j \) (Gradshetyn (2000)). Also, using the following generalized binomial expansion
\[
[1 - (1 - \tilde{G}(x; \psi)^2)]^{m+n-1} = \sum_{p=0}^{\infty} (-1)^p \binom{m+n-1}{p} \left[ 1 - \tilde{G}(x; \psi)^2 \right]^{bp},
\]
The Topp-Leone-G Power Series Class of Distributions with Applications
we obtain
\[ f(x)[F(x)]^{k+i-1} = \sum_{j,p=0}^{\infty} \sum_{n=1}^{\infty} \binom{k+i-1}{j} \binom{m+n-1}{p} (-1)^{j+p} \frac{n a_n \theta^{n+m}}{C^{j+1}(\theta)} b_{m,j} \]
\times [1 - \bar{G}(x; \psi)^2]^{b(p+1)-1} 2b g(x; \psi) \bar{G}(x; \psi).

Furthermore, applying the generalized binomial expansion
\[ [1 - \bar{G}(x; \psi)^2]^{b(p+1)-1} = \sum_{q=0}^{\infty} (-1)^q \binom{b(p+1)-1}{q} \bar{G}(x; \psi)^{2q} \]
yields
\[ f(x)[F(x)]^{k+i-1} = \sum_{j,p=0}^{\infty} \sum_{n=1}^{\infty} \binom{k+i-1}{j} \binom{m+n-1}{p} \binom{b(p+1)-1}{q} \]
\times (-1)^{j+p+q} \frac{2b a_n \theta^{n+m}}{C^{j+1}(\theta)} b_{m,j} g(x; \psi) \bar{G}(x; \psi)^{2q+1}.

Also, applying the binomial expansion
\[ \bar{G}(x; \psi)^{2q+1} = \sum_{r=0}^{\infty} (-1)^r \binom{2q+1}{r} G(x; \psi)^r \]
yields
\[ f(x)[F(x)]^{k+i-1} = \sum_{j,p,q,r=0}^{\infty} \sum_{n=1}^{\infty} \binom{k+i-1}{j} \binom{m+n-1}{p} \binom{b(p+1)-1}{q} \binom{2q+1}{r} \]
\times (-1)^{j+p+q+r} \frac{2b a_n \theta^{n+m}}{C^{j+1}(\theta)} \frac{b_{m,j}}{r+1} g(x; \psi) G(x; \psi)^r \quad (17)
= \sum_{r=0}^{\infty} a_{r+1} g_{r+1}(x; \psi),

where \( g_{r+1}(x; \psi) = (r+1) g(x; \psi) G(x; \psi)^r \) is the Exp-G distribution with power parameter \((r+1), and
\[ a_{r+1} = \sum_{j,p,q,r=0}^{\infty} \sum_{n=1}^{\infty} \binom{k+i-1}{j} \binom{m+n-1}{p} \binom{b(p+1)-1}{q} \binom{2q+1}{r} \]
\times (-1)^{j+p+q+r} \frac{2b a_n \theta^{n+m}}{C^{j+1}(\theta)(r+1)} b_{m,j}.

Therefore, substituting equation (17) in (16) we obtain
\[ f_{Eq}(x) = \frac{1}{B(i,n-i+1)} \sum_{r=0}^{\infty} \sum_{k=0}^{n-i} (-1)^k \binom{n-i}{k} a_{r+1} g_{r+1}(x; \psi). \quad (18) \]

It follows that the distribution of the \( i^{th} \) order statistic from the TL-GPS class of distributions can be obtained directly from the distribution of the \( i^{th} \) order statistic from the Exp-G distribution.

### 3.4.2. Rényi Entropy

In this subsection, Rényi entropy of the TL-GPS class of distributions is derived. Entropy measures the uncertainty or variation of a random variable. Rényi entropy (Rényi (1960)) is a generalization of Shannon entropy (Shannon
Rényi entropy of the TL-GPS class of distributions is defined as
\[ I_R(v) = \frac{1}{1-v} \log \left( \int_0^\infty (f_{TL-GPS}(x; \theta, b, \psi))^v dx \right), \quad v \neq 1, \quad v > 0. \] (19)

Note that \( f_{TL-GPS}^v(x; \theta, b, \psi) \) can be written as
\[ f_{TL-GPS}^v(x; \theta, b, \psi) = \left[ \theta 2b g(x; \psi) \tilde{G}(x; \psi)[1 - \tilde{G}(x; \psi)]^{2(b-1)} \right] \frac{C'(\theta)}{C'(\theta)^2} \].

Considering the following series expansions
\[ [C'(\theta(1 - [1 - \tilde{G}(x; \psi)]^2)])^v = \sum_{k=0}^\infty d_k,v \theta^k (1 - [1 - \tilde{G}(x; \psi)]^2)^k, \]
where \( d_{k,v} = (kb_0)^{-1} \sum_{l=1}^k [v(l + 1) - k] b_l d_{k-l,v} \) and \( d_{0,v} = b_0^v \),
\[ (1 - [1 - \tilde{G}(x; \psi)]^2)^k = \sum_{m=0}^\infty (-1)^m \left( \begin{array}{c} k \\ m \end{array} \right) [1 - \tilde{G}(x; \psi)]^2 m, \]
\[ [1 - \tilde{G}(x; \psi)]^{2(m+v)} = \sum_{n=0}^\infty (-1)^n \left( \begin{array}{c} b(m+v) - v \\ n \end{array} \right) \tilde{G}(x; \psi)^{2n}, \]
and
\[ \tilde{G}(x; \psi)^{2n+v} = \sum_{q=0}^\infty (-1)^q \left( \begin{array}{c} 2n+v \\ q \end{array} \right) \tilde{G}(x; \psi)^q, \]
we get
\[ f_{TL-GPS}^v(x; \theta, b, \psi) = \sum_{k,m,n,q=0}^{\infty} \left[ \frac{2b}{C'(\theta)} \right]^v (-1)^{m+n+q} \left( \begin{array}{c} k \\ m \end{array} \right) \left( \begin{array}{c} b(m+v) - v \\ n \end{array} \right) \left( \begin{array}{c} 2n+v \\ q \end{array} \right) d_{k,v} \theta^{v+k} g(x; \psi) G^q(x; \psi). \]

Therefore, the Rényi entropy of the TL-GPS class of distributions is given by
\[ I_R(v) = \frac{1}{1-v} \log \left( \sum_{q=0}^\infty \eta_{q+1} e^{(1-v)I_{REG}} \right), \] (20)
where
\[ \eta_{q+1} = \sum_{k,m,n=0}^{\infty} \left[ \frac{2b}{C'(\theta)} \right]^v (-1)^{m+n+q} \left( \begin{array}{c} k \\ m \end{array} \right) \left( \begin{array}{c} b(m+v) - v \\ n \end{array} \right) \left( \begin{array}{c} 2n+v \\ q \end{array} \right) d_{k,v} \theta^{v+k} \left( \frac{q+1}{v+1} \right). \] (21)

and
\[ I_{REG} = \frac{1}{1-v} \int_0^{\infty} \left[ \frac{q}{v+1} \right] g(x; \psi) G(x; \psi)^{\frac{q}{v}} dx \]
is the Rényi entropy of the Exp-G distribution with parameter \( \left( \frac{q}{v} + 1 \right) \). As such, we can directly derive the Rényi entropy of the TL-GPS family of distributions from the Rényi entropy of the Exp-G distribution.
4. Estimation

In this section, we derive the maximum likelihood estimates of the parameter vector \((\theta, b, \psi)^T\) of the TL-GPS class of distributions. Let \(X_i \sim \text{TL-GPS}(\theta, b, \psi)\) and \(\Delta = (\theta, b, \psi)^T\) be the parameter vector. The log-likelihood \(\ell = \ell(\Delta)\) based on a random sample of size \(n\) is given by

\[
\ell(\Delta) = n \ln(2b\theta) + (b - 1) \sum_{i=1}^{n} \ln[1 - G(x_i; \psi)] + \sum_{i=1}^{n} \ln[G(x_i; \psi)] \\
+ \sum_{i=1}^{n} \ln[g(x_i; \psi)] - n \ln(C(\theta)) + \sum_{i=1}^{n} \left(C'\left(\theta \left(1 - \frac{1}{\Delta} G(x_i; \psi)^2\right)^b\right)\right).
\]

The elements of the score vector are given by

\[
\frac{\partial \ell}{\partial \theta} = \frac{nC'(\theta)}{C(\theta)} + \sum_{i=1}^{n} \left(C''\left(\theta \left(1 - \frac{1}{\Delta} G(x_i; \psi)^2\right)^b\right)\right) 1 - \left(1 - G(x_i; \psi)^2\right)^b, \\
\frac{\partial \ell}{\partial b} = \frac{n}{b} + \sum_{i=1}^{n} \ln[1 - G(x_i; \psi)^2] + \sum_{i=1}^{n} \left(C''\left(\theta \left(1 - \frac{1}{\Delta} G(x_i; \psi)^2\right)^b\right)\right) \left(1 - \left(1 - G(x_i; \psi)^2\right)^b\right), \\
\times \left[1 - \left(1 - G(x_i; \psi)^2\right)^b\ln[1 - G(x_i; \psi)^2]\right], \\
\frac{\partial \ell}{\partial \psi_k} = (b - 1) \sum_{i=1}^{n} \left(\frac{1}{1 - G(x_i; \psi)^2}\right) \frac{\partial[1 - G(x_i; \psi)^2]}{\partial \psi_k} + \sum_{i=1}^{n} \frac{\partial G(x_i; \psi)}{\partial \psi_k} + \sum_{i=1}^{n} \frac{\partial g(x_i; \psi)}{\partial \psi_k}.
\]

The equations obtained by setting the partial derivatives equal to zero are not in closed form. The maximum likelihood estimates of the parameters denoted by \(\hat{\Delta}\) are obtained by solving the non-linear equation \(\left(\frac{\partial \ell}{\partial \theta}, \frac{\partial \ell}{\partial b}, \frac{\partial \ell}{\partial \psi_k}\right)^T = 0\) using numerical methods such as the Newton-Raphson procedure. The multivariate normal distribution \(N(\hat{\theta}, J^{-1}(\hat{\Delta}))\), where the mean vector \(\hat{\theta} = (0, 0, 0)^T\) and \(J^{-1}(\hat{\Delta})\) is the observed Fisher information matrix evaluated at \(\hat{\Delta}\) can be used to construct confidence intervals and confidence regions for the individual model parameters and for the survival and hazard rate functions.

5. Simulation Study

In this section, a simulation study was conducted to assess consistency of the maximum likelihood estimators. We considered a special case of the TL-LLP distribution. We simulated for the sample sizes \(n = 25, 50, 100, 200, 400, 800,\) and \(1000\), for \(N=1000\) for each sample. We estimate the mean, root mean square error (RMSE), and average bias. The bias and RMSE for the estimated parameter, say, \(\hat{\Delta}\), are given by

\[
\text{Bias}(\hat{\Delta}) = \frac{1}{N} \sum_{i=1}^{N} (\hat{\Delta}_i - \Delta_i), \quad \text{and} \quad \text{RMSE}(\hat{\Delta}) = \sqrt{\frac{\sum_{i=1}^{N} (\hat{\Delta}_i - \Delta)^2}{N}},
\]

respectively. We consider simulations for the following sets of initial parameters values (I: \(\theta = 0.5, b = 1.5, c = 1.0\), (II: \(\theta = 1.5, b = 1.5, c = 0.5\), (III: \(\theta = 0.5, b = 1.0, c = 1.5\), and (IV: \(\theta = 1.0, b = 1.5, c = 0.5\). If the model performs better, we except the mean to approximate the true parameter values, the RMSE, and bias to decay toward zero for an
increase in sample size. From the results in Table 6, the mean values approximate the true parameter values, RMSE and bias decay towards zero for all the parameter values.

6. Applications

In this section, we present examples to illustrate the usefulness and applicability of the TL-GPS class of distributions. This is achieved by applying the special case of Topp-Leone-Log-Logistic Poisson to two real data sets and comparing it to several equal-parameter non-nested models. Model parameters were estimated via the maximum likelihood estimation technique using the R software. The performance of the models were assessed using the following several goodness-of-fit statistics: -2loglikelihood (-2 log L), Akaike Information Criterion (AIC), Consistent Akaike Information Criterion (CAIC), Bayesian Information Criterion (BIC), Cramer von Mises ($W^*$) and Andersen-Darling ($A^*$) (as described by Chen and Balakrishnan (1995)), Kolmogorov-Smirnov (K-S) statistic and its p-value. The model that has smaller values of these above mentioned goodness-of-fit statistics and larger p-value of the K-S statistics is deemed as the best model.

Tables 7 and 8 show the model parameters estimates (standard errors in parenthensis) and the goodness-of-fit-statistics for the two data sets considered. Plots of the fitted densities, the histogram of the data and probability plots (Chambers et al. (1983)) are also presented to show how well our model fits the observed data set compared to the selected non-nested models.

The non-nested models considered are the Weibull-Poisson (Mahmoudi and Seahdar (2013)), Topp-Leone generalized exponential (TL-GE) (Sangsanit and Bodhisuwan (2016)), alpha power Weibull (APW) (Nassar et al. (2016)), Marshall-Olkin Extended Weibull (MOEW) (Cordeiro and Lemonte (2013)) and Marshall-Olkin log-logistic (MOLL) (Gui (2013)), Topp-Leone Weibull-Lomax (WLP) (Jamal et al. (2019)), Marshall-Olkin-Log-Logistic Poisson (Mohie Ud-Din et al. (2015)) distributions. The pdfs of the non-nested models are as follows:

\[
 f_{MOLL}(x; \alpha, \beta, \gamma) = \alpha \beta \gamma \frac{x^{\beta-1}}{(\beta + \gamma \alpha x)^2},
\]

for $\alpha, \beta, \gamma > 0$, and $x > 0$,

\[
 f_{WP}(x; \theta, \beta, \gamma) = \frac{\theta \gamma \beta x^{\gamma-1} \exp(-x\beta \gamma) \exp(\theta(1 - \exp(-x\beta \gamma)))}{\exp(\theta) - 1},
\]

for $\theta, \beta, \gamma > 0$, and $x > 0$,

\[
 f_{TL-GE}(x; \alpha, \beta, \lambda) = 2 \alpha \beta \lambda e^{-\lambda x} \left(1 - (1 - e^{-\lambda x})^\beta \right) \left(1 - e^{-\lambda x} \right)^{\alpha - 1} \left(2 - (1 - e^{-\lambda x}) \right)^{\alpha - 1},
\]

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

\[
 f_{APW}(x; \alpha, \beta, \theta) = \frac{\log(\alpha)}{\alpha - 1} \beta \alpha \beta - 1 e^{-\theta x \beta} \alpha^{1 - e^{-\theta x \beta}},
\]

for $\alpha, \beta, \theta > 0$ and $x > 0$,

\[
 F_{MOEW}(x; \alpha, \lambda, \gamma) = \frac{\alpha \gamma \lambda x^{\gamma-1} e^{-\lambda x \gamma}}{(1 - (1 - \alpha) e^{-\lambda x \gamma})^2},
\]

for $\alpha, \lambda, \gamma > 0$, and $x > 0$,

\[
 f_{WLP}(x; a, b, \alpha) = \alpha \beta (1 + bx)^{\alpha - 1} \left(1 - (1 + bx)^{-a} \right)^{\alpha - 1} e^{-\left(\frac{1 - (1 + bx)^{-a}}{1 + bx} \right)^2},
\]

and

\[
 F_{TW}(x; \lambda, \beta, \alpha) = \alpha \beta \lambda x^{\beta - 1} e^{-\lambda x \beta} \left(1 - \lambda + 2 \lambda e^{-\lambda x \beta} \right),
\]

for $\lambda, \beta, \alpha > 0$ and $x > 0$. 

The Topp-Leone-G Power Series Class of Distributions with Applications
Table 6: Monte Carlo Simulation Results for TL-LLP Distribution: Mean, RMSE and Average Bias

<table>
<thead>
<tr>
<th>samplesize</th>
<th>I: $\theta = 0.5, b = 1.5, c = 1.0$</th>
<th>II: $\theta = 1.5, b = 1.5, c = 0.5$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>RMSE</td>
</tr>
<tr>
<td>25</td>
<td>1.5971</td>
<td>1.6131</td>
</tr>
<tr>
<td>50</td>
<td>1.4729</td>
<td>1.5153</td>
</tr>
<tr>
<td>100</td>
<td>1.2283</td>
<td>1.3343</td>
</tr>
<tr>
<td>$\theta$</td>
<td>200</td>
<td>0.8945</td>
</tr>
<tr>
<td></td>
<td>400</td>
<td>0.6985</td>
</tr>
<tr>
<td></td>
<td>800</td>
<td>0.5767</td>
</tr>
<tr>
<td></td>
<td>1000</td>
<td>0.5582</td>
</tr>
<tr>
<td>III</td>
<td>25</td>
<td>2.1429</td>
</tr>
<tr>
<td></td>
<td>50</td>
<td>2.0972</td>
</tr>
<tr>
<td></td>
<td>100</td>
<td>1.9571</td>
</tr>
<tr>
<td>$b$</td>
<td>200</td>
<td>1.7545</td>
</tr>
<tr>
<td></td>
<td>400</td>
<td>1.6238</td>
</tr>
<tr>
<td></td>
<td>800</td>
<td>1.5459</td>
</tr>
<tr>
<td></td>
<td>1000</td>
<td>1.5336</td>
</tr>
<tr>
<td>c</td>
<td>25</td>
<td>0.9534</td>
</tr>
<tr>
<td></td>
<td>50</td>
<td>0.9260</td>
</tr>
<tr>
<td></td>
<td>100</td>
<td>0.9364</td>
</tr>
<tr>
<td></td>
<td>200</td>
<td>0.9588</td>
</tr>
<tr>
<td></td>
<td>400</td>
<td>0.9774</td>
</tr>
<tr>
<td></td>
<td>800</td>
<td>0.9915</td>
</tr>
<tr>
<td></td>
<td>1000</td>
<td>0.9946</td>
</tr>
<tr>
<td>III: $\theta = 0.5, b = 1.0, c = 1.5$</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>50</td>
<td>1.3213</td>
</tr>
<tr>
<td></td>
<td>100</td>
<td>1.0529</td>
</tr>
<tr>
<td>$\theta$</td>
<td>200</td>
<td>0.7617</td>
</tr>
<tr>
<td></td>
<td>400</td>
<td>0.6205</td>
</tr>
<tr>
<td></td>
<td>800</td>
<td>0.5378</td>
</tr>
<tr>
<td></td>
<td>1000</td>
<td>0.5307</td>
</tr>
<tr>
<td>IV: $\theta = 1.0, b = 1.5, c = 0.5$</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>50</td>
<td>1.3771</td>
</tr>
<tr>
<td></td>
<td>100</td>
<td>1.2557</td>
</tr>
<tr>
<td>$b$</td>
<td>200</td>
<td>1.1193</td>
</tr>
<tr>
<td></td>
<td>400</td>
<td>1.0549</td>
</tr>
<tr>
<td></td>
<td>800</td>
<td>1.0168</td>
</tr>
<tr>
<td></td>
<td>1000</td>
<td>1.0126</td>
</tr>
<tr>
<td>c</td>
<td>25</td>
<td>1.4752</td>
</tr>
<tr>
<td></td>
<td>50</td>
<td>1.4338</td>
</tr>
<tr>
<td></td>
<td>100</td>
<td>1.4436</td>
</tr>
<tr>
<td></td>
<td>200</td>
<td>1.4684</td>
</tr>
<tr>
<td></td>
<td>400</td>
<td>1.4827</td>
</tr>
<tr>
<td></td>
<td>800</td>
<td>1.4971</td>
</tr>
<tr>
<td></td>
<td>1000</td>
<td>1.4989</td>
</tr>
</tbody>
</table>
6.1. Growth Hormone Data

The data consists of the estimated time since growth hormone medication until the children reached the targeted age. This data was used by Alizadeh et al. (2017) and are as follows: 2.15, 2.20, 2.55, 2.63, 2.74, 2.81, 2.90, 3.05, 3.41, 3.43, 3.43, 3.84, 4.16, 4.18, 4.36, 4.42, 4.51, 4.60, 4.61, 4.75, 5.03, 5.10, 5.44, 5.90, 5.96, 6.77, 7.82, 8.00, 8.16, 8.21, 8.72, 10.40, 13.20, 13.70. The estimated variance-covariance matrix for the TL-LLP model on growth hormone data is

\[
\begin{bmatrix}
0.0107 & 0.0001 & -0.0013 \\
0.0001 & 322.661 & 2.4121 \\
-0.0013 & 2.4121 & 0.0240 
\end{bmatrix}
\]

and the 95% confidence intervals for the model parameters are given by \( \theta \in [(6.5265 \times 10^{-5}) \pm 0.2025], b \in [5.2422 \times 10 \pm 35.2075] \) and \( c \in [1.3853 \pm 0.3036] \). Based on the results shown in Table 7, we observe that the TL-LLP model has the smallest values of all the goodness-of-fit statistics and bigger value for the K-S p-value. We therefore conclude that the TL-LLP distribution performs better than the several models considered in this paper. The fitted densities and probability plots for the growth hormone data are shown in Figure 5:

![Figure 5: Fitted Densities and Probability Plots for the Growth Hormone Data](image)

Table 7: Parameter estimates and goodness-of-fit statistics for various fitted models for growth hormone data

<table>
<thead>
<tr>
<th>Model</th>
<th>Estimates</th>
<th>Statistics</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>( \theta )</td>
<td>( b )</td>
</tr>
<tr>
<td>TL-LLP</td>
<td>6.5265 \times 10^{-5}</td>
<td>5.2422 \times 10^{-17}</td>
</tr>
<tr>
<td>WP</td>
<td>8.8353 \times 10^{-9}</td>
<td>0.159</td>
</tr>
<tr>
<td>APW</td>
<td>6.4700 \times 10^{-4}</td>
<td>0.8444</td>
</tr>
<tr>
<td>MOEW</td>
<td>0.3280</td>
<td>3.4077</td>
</tr>
<tr>
<td>WLx</td>
<td>0.2548</td>
<td>2.4039</td>
</tr>
<tr>
<td>TW</td>
<td>0.6092</td>
<td>2.1722</td>
</tr>
</tbody>
</table>

The Topp-Leone-G Power Series Class of Distributions with Applications
probability plots in Figure 5 also shows that the TL-LLP model fit the growth hormone data set better than the selected non-nested models.

6.2. Repair Lifetimes Data

The second data set represents maintenance on active repair times (in hours) for an airborne communication transceiver reported by Leiva et al. (2009) and Chhikara and Folks (1977) and are as follows: 0.2, 0.3, 0.5, 0.5, 0.5, 0.5, 0.6, 0.6, 0.7, 0.7, 0.8, 0.8, 1.0, 1.0, 1.1, 1.3, 1.5, 1.5, 1.5, 2.0, 2.0, 2.2, 2.5, 2.7, 3.0, 3.0, 3.3, 3.3, 4.0, 4.0, 4.5, 4.7, 5.0, 5.4, 5.4, 7.0, 7.5, 8.8, 9.0, 10.3, 22.0, 24.5. The estimated variance-covariance matrix for the TL-LLP model

Table 8: Parameter estimates and goodness of fit statistics for various fitted models for repair lifetimes data set

<table>
<thead>
<tr>
<th>Model</th>
<th>Estimates</th>
<th>Statistics</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$\theta$</td>
<td>$b$</td>
</tr>
<tr>
<td>TL-LLP</td>
<td>0.0001 (0.2035)</td>
<td>4.4081 (0.6894)</td>
</tr>
<tr>
<td>WP</td>
<td>$3.9697 \times 10^{-8}$ (0.0219)</td>
<td>0.2953 (0.0516)</td>
</tr>
<tr>
<td>WLx</td>
<td>0.2222 (0.1093)</td>
<td>7.0310 (11.2084)</td>
</tr>
<tr>
<td>APW</td>
<td>$0.0295 (0.0566)$</td>
<td>1.1011 (0.1201)</td>
</tr>
<tr>
<td>MOEW</td>
<td>0.0332 (0.0540)</td>
<td>1.4861 (0.2084)</td>
</tr>
<tr>
<td>TW</td>
<td>$2.1603 \times 10^{-6}$ (4.2209 $\times 10^{-7}$)</td>
<td>$4.4317 \times 10^{-3}$ (2.8118 $\times 10^{-8}$)</td>
</tr>
<tr>
<td>MOLL</td>
<td>$0.9457 (114.6974)$</td>
<td>1.5439 (0.1858)</td>
</tr>
</tbody>
</table>

Figure 6: Fitted Densities and Probability Plots for the Repair Lifetimes Data

on repair times data set is

\[
\begin{bmatrix}
0.0414 & 0.0459 & -0.0030 \\
0.0459 & 0.4753 & -0.0073 \\
-0.0030 & -0.0073 & 0.0082
\end{bmatrix}
\]

and the 95% confidence intervals for the model parameters are given by $\theta \in [0.0001 \pm 0.3988]$, $b \in [4.4081 \pm 1.3512]$ and $c \in [0.8102 \pm 0.1773]$. Based on the results shown in Table 8, we observe that the TL-LLP model has the smallest values of all the goodness-of-fit statistics and bigger value for the K-S p-value. We therefore, conclude that the TL-
LLP distribution performs better than the several models considered in this paper. The fitted densities and probability plots in Figure 6 also shows that the TL-LLP model fit the repair times data set better than the selected models.

7. Concluding Remarks

We developed a new class of distributions, called the Topp-Leone-G Power Series (TL-GPS) class of distributions. We presented some sub-classes and some special cases of the new proposed distribution. Structural properties were also derived including moments, mean deviations, distribution of order statistics, Rényi entropy, and maximum likelihood estimates. We also presented two real data examples to show the usefulness of the new class of distributions. The proposed model performs better than the several models on the selected data sets.

References


