Advancing Covid-19 Data Modeling: Introducing a Neutrosophic Extension of Ramous Louzada Distribution

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Abstract

In this research, we introduce a neutrosopic extension of the Ramous Louzada Distribution called the Inverse Ramous Louzada Distribution. We delve into several mathematical properties of this distribution, including the Survival function, Hazard Rate function, cumulative Hazard Rate function, and estimation technique. Moreover, we conduct a comparative analysis between the Inverse Weibull distribution and the traditional Ramous Louzada Distribution, which are two widely used distributions. Our aim is to assess the performance of the developed model through Maximum Likelihood Estimation (MLE), Standard Error (SE), and Goodness of Fit tests.

Keywords: Survival Function; Hazard Rate Function; neutrosophic ramous Louzada Distribution; Maximum Likelihood Estimation.

1. Introduction

In probability and reliability theory, the exponential family of distribution plays an important role in modeling real-life data in almost every field such as medicine, engineering, life experiments, etc. The two most common parameter distributions are exponential, and Lindley has great importance in distribution theory as a baseline for many generalizations. Both distributions may not be suitable for most life problems. In some cases, the Lindley distribution may overtake the exponential distribution. Ramos and Louzada (2019) suggested the one-parameter distribution called Ramos-Louzada (RL) to overcome this situation the communication theory, the topic of inverse probability is in some respects debatable.

Unfortunately, it takes cast general apprehension on the theorem of inverse probability, which is by itself entirely undebatable. Many authors proposed different inverse versions of the probability distribution. As [1] developed beta inverse Weibull distribution, [2] discussed the theoretical analysis of Inverse Weibull distribution, [3] fisher

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Information Matrix for the Inverse Weibull Distribution, [4] suggested the modified version of Inverse Weibul distribution and [5] Modified inverse Rayleigh distribution. For more studies[6-8]

2. Proposed Distribution

In this study, the life span distribution known as Inverse Ramous Louzda Distribution (IRLD) was introduced, which is an appropriate model for testing the study. It can be derived by the transformation of r.v that if the r.v 'X' a has a Ramous Louzada distribution, the r.v $Z = \left(\frac{1}{X}\right)$ has an Inverse Ramous Louzada distribution.

Suppose Z is r.v following IRLD with parameters φ and ς. Then its pdf and cdf can be defined as

$$h_z(z \mid \varphi,\varsigma) = \frac{-\varphi}{\varsigma(\varsigma-1)} z^{-\beta-1}\left[\varsigma + \frac{z^{-\varphi}}{\varsigma} - 2\right] e^{\frac{z^{-\varphi}}{\varsigma}}, \qquad z \geq 0$$

$$H_z(z \mid \varphi,\varsigma) = 1 - \frac{e^{\frac{z^{-\varphi}}{\varsigma}}}{(\varsigma-1)}\left[\varsigma + \frac{z^{-\varphi}}{\varsigma} - 1\right]$$

One can notice the cdf $H_z(z \mid \varphi,\varsigma)$ of the Subsequently mentioned distribution is known as IRLZ distribution is differentiable and it ranges from 0 to ∞ as

$$\lim_{z \to 0} H(z) = 0 \qquad (7)$$

$$\lim_{z \to \infty} G(z) = 1 \qquad (8)$$

The density plot can be shown in Figure 1

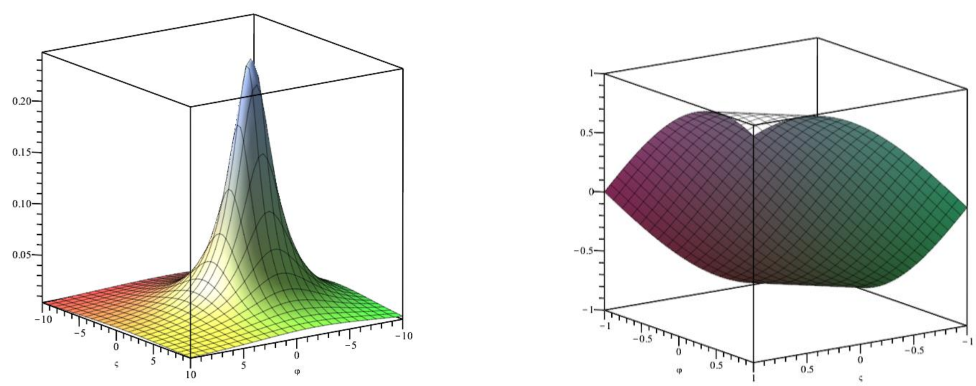

Figure 1: The pdf and cdf 3d plot of IRLD model

2.1. Survival Function

$$S_z(z \mid \varphi,\varsigma) = 1 - H_z(z \mid \varphi,\varsigma)$$

$$= \frac{e^{\frac{z^{-\varphi}}{\varsigma}}}{(\varsigma-1)}\left[\varsigma + \frac{z^{-\varphi}}{\varsigma} - 1\right]$$

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2.2. Reliability Function

The $R(z\mid\varphi,\varsigma)=1-H(z\mid\varphi,\varsigma)$ regulates reliability function and is defined as the probability of a lifetime of a certain device (without failure) during a particular time interval (say 'z'). the reliability function of ETBXII distribution is given as

$$R(z\mid\varphi,\varsigma)=\frac{e^{\frac{z^{-\varphi}}{\varsigma}}}{(\varsigma-1)}\left[\varsigma+\frac{z^{-\varphi}}{\varsigma}-1\right]$$

2.3. Hazard Rate Function:

In lifetime analysis, another useful function is Hazard Rate Function defined as the expeditious failure rate of a random variable T is the probability that the device tumble as it has persevered to the present time (say 'z') is given as

$$\pi_z(z\mid\varphi,\varsigma)=\frac{h_z(z\mid\varphi,\varsigma)}{H_z(z\mid\varphi,\varsigma)}$$

By simplifying, we get

$$\pi_z(z\mid\varphi,\varsigma)=\frac{-\varphi z^{-\varphi-1}\left[\varsigma+\frac{z^{-\varphi}}{\varsigma}-2\right]}{\varsigma\left[\varsigma+\frac{z^{-\varphi}}{\varsigma}-1\right]}$$

2.4 Cumulative Hazard Rate Function

The cumulative Hazard Rate Function of proposed model is defined as

$$\Lambda_z(z_z\mid\varphi,\varsigma)=\int_0^z h_z(z\mid\varphi,\varsigma)dz$$

Therefore,

$$\Lambda_z(z_z\mid\varphi,\varsigma)=-\log\left|\frac{-\varphi z^{-\varphi-1}\left[\varsigma+\frac{z^{-\varphi}}{\varsigma}-2\right]e^{\frac{z^{-\varphi}}{\varsigma}}}{\varsigma(\varsigma-1)}\right|$$

2.5 Hazard Rate & Shape of the model

The significance tool which gives an image about the model is referred as shape of the model. By following Glaser, the shape of the Hazard Rate Function can be defined as

$$\xi(z)=\frac{h_z'(z\mid\varphi,\varsigma)}{h_z(z\mid\varphi,\varsigma)}$$

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Where $h_z(z|\varphi,\varsigma)$ and $h_z'(z|\varphi,\varsigma)$ are the density function and its first derivative respectively.

Theorem. 1. (a). If $\psi(t)<0$ for all $t>0$, then model has "Decreasing Failure Rate (DFR)".

(b) $h_z(z|\varphi,\varsigma)$ is called unimodal if there exist $t_0>0$ and $\psi'(t)<0$ for all $t>t_0$.

Proof:

For $\xi(z)$ the subject distribution is suggested as

$$\xi(z)=\frac{h_z'(z|\varphi,\varsigma)}{h_z(z|\varphi,\varsigma)}$$

where

$$h_z'(z|\varphi,\varsigma)=\frac{-\varphi z^{-\varphi-2}\left[\varsigma+\dfrac{z^{-\varphi}}{\varsigma}-2\right]e^{\frac{z^{-\varphi}}{\varsigma}}\left[\varphi z^{-\varphi}-\dfrac{\varsigma}{z}(\varsigma+1)-\varphi z^{-\varphi-1}\right]}{\varsigma^2(\varsigma-1)}$$

Therefore

$$\xi(z)=\frac{\varphi z^{-\varsigma-2}(z-1)}{\varsigma}-\frac{\varphi+1}{\varsigma^2}$$

$$\xi'(z)=\frac{\varphi z^{-\varphi+1}-\varphi^2(\varphi-2)z^{-\varphi}(z-1)+2\varsigma(\varphi+1)}{\varsigma z^3}$$

To attain z_0

$$\varphi z_0^{-\varphi+1}-\varphi^2(\varphi-2)z_0^{-\varphi}(z_0-1)+2\varsigma(\varphi+1)=0$$

The graph of hazard rate function can be shown in Figure 2.

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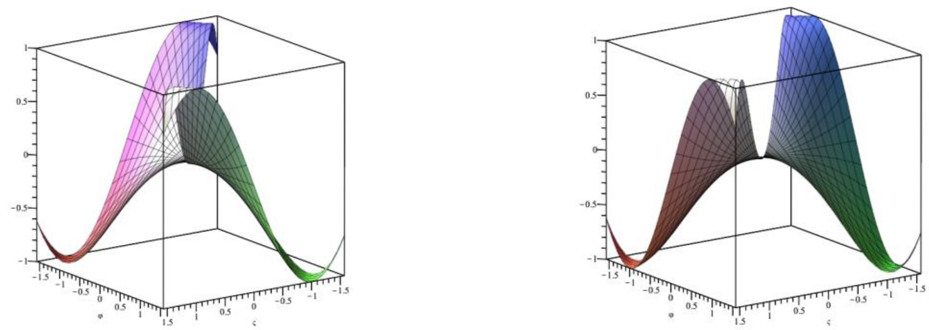

Figure 2: The graph of hazard rate function

2.6 Harmonic Mean:

The harmonic mean of proposed distribution can be defined as:

$$H.M_z(z\,|\,\varphi,\varsigma)=\int_0^\infty \frac{1}{z}h_z(z\,|\,\varphi,\varsigma)dz$$

$$H.M_z(z\,|\,\varphi,\varsigma)=\int_0^\infty \frac{1}{z}\left[\frac{-\varphi}{\varsigma(\varsigma-1)}z^{-\beta-1}\left[\varsigma+\frac{z^{-\varphi}}{\varsigma}-2\right]e^{\frac{z^{-\varphi}}{\varsigma}}\right]dz$$

$$H.M_z(z\,|\,\varphi,\varsigma)=\frac{1}{\varsigma^{\frac{1}{\varphi}}(\varsigma-1)}\Gamma\left(1-\frac{1}{\varphi}\right)\left[\varsigma-\frac{1}{\varphi}-1\right]$$

1. Moment Generating Function:

The moment generating function and Characteristic of LBRL distribution is given by

$$M_z\left(t\right)=E\left(e^{tz}\right)=\int_0^\infty e^{tz}h_z(z\,|\,\varphi,\varsigma)dz$$

$$M_z\left(t\right)=\int_0^\infty e^{tz}\frac{-\varphi}{\varsigma(\varsigma-1)}z^{-\beta-1}\left[\varsigma+\frac{z^{-\varphi}}{\varsigma}-2\right]e^{\frac{z^{-\varphi}}{\varsigma}}dz$$

Using taylor series, we can write

$$M_z\left(t\right)=\int_0^\infty\left(1+tz+\frac{(tz)^2}{2}+.......\right)h_z(z\,|\,\varphi,\varsigma)dz$$

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$$M_z(t)=\int_0^\infty \sum_{j=0}^\infty \frac{t^j}{j!} z^j h_z(z\mid\varphi,\varsigma)dz$$

$$M_z(t)=\sum_0^\infty \frac{t^j}{j!} z^j E(Z^j)$$

$$M_z(t)=\sum_0^\infty \frac{t^r}{r!}\frac{r\varsigma^{\frac{r}{\beta}}}{\varphi(\varsigma-1)}\left(\varsigma+\frac{r}{\varphi}-2\right)\Gamma\left(1-\frac{1}{\varphi}\right) \tag{16}$$

Similarly, the characteristics function of LBRL distribution can be obtained as

$$\phi_z(t)=\sum_0^\infty \frac{(it)^r}{r!}\frac{r\varsigma^{\frac{r}{\beta}}}{\varphi(\varsigma-1)}\left(\varsigma+\frac{r}{\varphi}-2\right)\Gamma\left(1-\frac{1}{\varphi}\right) \tag{17}$$

3. Estimation Technique:

In this section, we used maximum likelihood technique to estimate the parameters of the proposed model IRLD. The likelihood function can be defined as

$$\ln L\left[h_z(z)\right]=-n\log\varphi-n\log\varsigma-n\log(\varsigma-1)-(\varphi+1)\log\sum_i z_i$$
$$+\log\left[\varsigma+\frac{\sum_i z_i^{-\varphi}}{\varsigma}-2\right]-\frac{\sum_i z_i^{-\varphi}}{\varsigma}$$

To solve the implicit form of likelihood function, we get the MLEs of the parameters φ and ς, by taking derivative w.r.t the parameters involved. We get the score vector's component as $\Theta_{\varphi,\varsigma}=\left(\Theta_\varphi,\Theta_\varsigma\right)$

$$\Theta_\varphi=\frac{\partial L}{\partial\varphi}=\frac{-n}{\varphi}-\log\sum_i z_i-\frac{\varphi\sum_i z_i^{-\varphi-1}}{\left[\varsigma+\frac{\sum_i z_i^{-\varphi}}{\varsigma}-2\right]}+\frac{\varphi}{\varsigma}\sum_i z_i^{-\varphi-1}=0$$

$$\Theta_\varsigma=\frac{\partial L}{\partial\varsigma}=\frac{-n}{\varsigma}-\frac{-n}{\varsigma-1}+\frac{\left[1-\frac{\sum_i z_i^{-\varphi}}{\varsigma^2}\right]}{\left[\varsigma+\frac{\sum_i z_i^{-\varphi}}{\varsigma}-2\right]}+\frac{\sum_i z_i^{-\varphi}}{\varsigma^2}=0$$

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MLEs of the parameters φ and ς of the IRLD model can be obtained by setting $\Theta_{\varphi} = \Theta_{\varsigma} = 0$. Newton Raphson method is required to solve them numerically by an iterative process. The performance of MLEs of IRLD model examined through sample size. The following steps are required for simulation study.

i. Simulate 2000 samples having size (n=25, 100, 200, 300) from IRLD.

ii. Different combination of Hyperparameters are to be chosen as $\{(0.2, 0.4) to (2, 4)\}$

iii. 2000 MLEs can be obtained (say $\hat{\varphi}_m$ and $\hat{\varsigma}_m$), as m=1,2,….,2000.

iv. Compute MLEs, absolute biases and MSEs (Mean Square Error) as:

$$MLEs = \frac{\sum_{m=1}^{2000} \hat{\Theta}}{2000}$$

$$Absolute\ Bias = \frac{\sum_{m=1}^{2000} \left|\hat{\Theta} - \Theta\right|}{2000}$$

$$MSE = \frac{\sum_{m=1}^{2000} \left(\hat{\Theta} - \Theta\right)^2}{2000}$$

In table 1. To 10. we can observed that the MSEs of IRLD model are less as compared to other two models IW (Inverse Weibul) and Traditional RLD (Ramous Louzada Distribution). It is also observed that from selecting small values of the parameters, smaller values of MSEs can be obtained, vice versa. It is noted that MSEs are decreased by increasing sample size “n”.

Table 1: The MLEs, Bias and MSEs of IRLD $(\hat{\varphi} = 0.2, \hat{\varsigma} = 0.4)$

N	Model	MLE	Bias	MSE
25	**IW**	0.0387	0.0118	0.0073
	RLD	0.0198	0.0111	0.0038
	IRLD	0.0116	0.0108	0.0037
100	**IW**	0.0317	0.0110	0.0059
	RLD	0.0124	0.0109	0.0034
	IRLD	0.0153	0.0106	0.0029
200	**IW**	0.0334	0.0110	0.0060
	RLD	0.0110	0.0106	0.0032
	IRLD	0.0104	0.0102	0.0026
300	**IW**	0.0319	0.0107	0.0052
	RLD	0.0108	0.0104	0.0011
	IRLD	0.0101	0.0098	0.0005

Table 2:The MLEs, Bias and MSEs of IRLD $(\hat{\varphi} = 0.5, \hat{\varsigma} = 1)$

N	Model	MLE	Bias	MSE
25	**IW**	0.1109	0.0394	0.0163
	RLD	0.1097	0.0290	0.0161
	IRLD	0.1048	0.0289	0.0133
	IW	0.1093	0.0374	0.0194

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100	**RLD**	0.1035	0.0320	0.0162
	IRLD	0.1020	0.0274	0.0158
	IW	0.1076	0.0365	0.0187
200	**RLD**	0.1082	0.0310	0.0167
	IRLD	0.1081	0.0302	0.0138
	IW	0.1078	0.0329	0.0164
300	**RLD**	0.1072	0.0284	0.0155
	IRLD	0.1045	0.0251	0.0135

Table 3: The MLEs, Bias and MSEs of IRLD $\left(\hat{\varphi}=1,\hat{\varsigma}=0.5\right)$

N	**Model**	**MLE**	**Bias**	**MSE**
	IW	0.1183	0.0676	0.0234
25	**RLD**	0.1175	0.0682	0.0210
	IRLD	0.1146	0.0670	0.0205
	IW	0.1193	0.0651	0.0195
100	**RLD**	0.1169	0.0659	0.0200
	IRLD	0.1141	0.0651	0.0174
	IW	0.1156	0.0623	0.0187
200	**RLD**	0.1164	0.0630	0.0162
	IRLD	0.1147	0.0621	0.0148
	IW	0.1132	0.0610	0.0147
300	**RLD**	0.1146	0.0619	0.0121
	IRLD	0.1120	0.0604	0.0111

Table 4: The MLEs, Bias and MSEs of IRLD $\left(\hat{\varphi}=1,\hat{\varsigma}=2\right)$

N	**Model**	**MLE**	**Bias**	**MSE**
	IW	0.1293	0.0681	0.9304
25	**RLD**	0.1269	0.0681	0.8210
	IRLD	0.1241	0.0676	0.8205
	IW	0.1293	0.0663	0.9193
100	**RLD**	0.1269	0.0664	0.8207
	IRLD	0.1221	0.0661	0.7172
	IW	0.1249	0.0659	0.5180
200	**RLD**	0.1244	0.0633	0.8165
	IRLD	0.1241	0.0620	0.4142
	IW	0.1233	0.0616	0.6144
300	**RLD**	0.1291	0.0613	0.4512
	IRLD	0.1211	0.0607	0.4011

Table 5: The MLEs, Bias and MSEs of IRLD $\left(\hat{\varphi}=1.5,\hat{\varsigma}=2\right)$

N	**Model**	**MLE**	**Bias**	**MSE**
	IW	0.1533	0.1063	0.6920
25	**RLD**	0.1591	0.1081	0.5489
	IRLD	0.1511	0.1083	0.5259
	IW	0.1520	0.1048	0.5159

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100	**RLD**	0.1518	0.1051	0.5202
	IRLD	0.1510	0.1049	0.5149
	IW	0.1516	0.1023	0.5159
200	**RLD**	0.1513	0.1021	0.5103
	IRLD	0.1511	0.1020	0.5083
	IW	0.1503	0.1030	0.5139
300	**RLD**	0.1501	0.1036	0.5166
	IRLD	0.1501	0.1027	0.5042

Table 6: The MLEs, Bias and MSEs of IRLD $(\hat{\varphi}=1.5, \hat{\varsigma}=2.5)$

N	Model	MLE	Bias	MSE
	IW	0.1592	0.1160	0.3017
25	**RLD**	0.1595	0.1169	0.3026
	IRLD	0.1587	0.1155	0.3011
	IW	0.1585	0.1158	0.2990
100	**RLD**	0.1580	0.1157	0.2997
	IRLD	0.1579	0.1151	0.2879
	IW	0.1589	0.1157	0.3193
200	**RLD**	0.1571	0.1155	0.3154
	IRLD	0.1570	0.1149	0.3012
	IW	0.1547	0.1136	0.2127
300	**RLD**	0.1552	0.1135	0.2121
	IRLD	0.1538	0.1124	0.2092

Table 7: The MLEs, Bias and MSEs of IRLD $(\hat{\varphi}=1.5, \hat{\varsigma}=3)$

N	Model	MLE	Bias	MSE
	IW	0.1620	0.1192	0.6022
25	**RLD**	0.1605	0.1199	0.5012
	IRLD	0.1601	0.1187	0.4025
	IW	0.1609	0.1188	0.5391
100	**RLD**	0.1581	0.1176	0.4671
	IRLD	0.1559	0.1177	0.4482
	IW	0.1575	0.1182	0.5485
200	**RLD**	0.1587	0.1189	0.3900
	IRLD	0.1570	0.1172	0.2348
	IW	0.1556	0.1156	0.6039
300	**RLD**	0.1551	0.1158	0.5946
	IRLD	0.1547	0.1151	0.5227

Table 8: The MLEs, Bias and MSEs of IRLD $(\hat{\varphi}=2, \hat{\varsigma}=3)$

N	Model	MLE	Bias	MSE
	IW	0.1958	0.1459	0.5922
25	**RLD**	0.1961	0.1467	0.5812
	IRLD	0.1941	0.1405	0.5725
	IW	0.1946	0.1145	0.5801

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100	**RLD**	0.1951	0.1129	0.5791
	IRLD	0.1946	0.1187	0.5482
	IW	0.1935	0.1202	0.6005
200	**RLD**	0.1937	0.1209	0.6030
	IRLD	0.1930	0.1207	0.5098
	IW	0.1926	0.1202	0.6209
300	**RLD**	0.1929	0.1009	0.5906
	IRLD	0.1917	0.1001	0.5729

Table 9: The MLEs, Bias and MSEs of IRLD $\left(\hat{\varphi}=2,\hat{\varsigma}=3.5\right)$

N	Model	MLE	Bias	MSE
	IW	0.2381	0.1432	0.3822
25	**RLD**	0.2399	0.1424	0.4312
	IRLD	0.2373	0.1420	0.3700
	IW	0.2377	0.1359	0.4390
100	**RLD**	0.2368	0.1367	0.4402
	IRLD	0.2364	0.1347	0.3983
	IW	0.2366	0.1302	0.7393
200	**RLD**	0.2359	0.1303	0.8209
	IRLD	0.2350	0.1285	0.6304
	IW	0.2354	0.1184	0.6938
300	**RLD**	0.2358	0.1134	0.6389
	IRLD	0.2350	0.1123	0.6301

Table 10: The MLEs, Bias and MSEs of IRLD $\left(\hat{\varphi}=2,\hat{\varsigma}=4\right)$

N	Model	MLE	Bias	MSE
	IW	0.4810	0.1354	0.8238
25	**RLD**	0.4809	0.1328	0.9138
	IRLD	0.4803	0.1347	0.8057
	IW	0.4856	0.1448	0.8930
100	**RLD**	0.4867	0.1573	0.7020
	IRLD	0.4853	0.1431	0.7859
	IW	0.4822	0.1419	0.8995
200	**RLD**	0.4834	0.1424	0.7034
	IRLD	0.4856	0.1407	0.6022
	IW	0.4788	0.1284	0.5938
300	**RLD**	0.4793	0.1288	0.7389
	IRLD	0.4759	0.1173	0.5301

4 Real Data Application

In order to illustrate the efficiency of proposed model, we used different data sets, which makes it valuable in a range of domains markedly those dealing with lifetime analysis. Therefore, this section demonstrates how the proposed models works by applying the subject model to the Covid-19 pandemic lifespan data of countries including, China, Europe, and Italy. This aspect is demonstrated here by comparing suggested model with Inverse Weibul distribution and traditional Ramous Louzada Distribution. The "best fit" of the proposed model can be demonstrated by choosing the specific measures for comparison. The standardized goodness of fit measures including LL (Likelihood), AIC (Akaike Information Criteria), CAIC (Corrected Akaike Information Criteria, and HQIC (Hannan Quinn Information

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Criteria) are implemented on the suggested model and existing mentioned models. The best model might be the one with lower values of those benchmarks. The revealed that the suggested model is better than all existing models in all respects. The value of the considered measures is given in Table ().

Data-I: The first data set represents the "no of death" due to the second wave of coronavirus known as "Beta Coronavirus" in France. This wave outbreak during the period 1st July to 15th August 2020. The data is reported in (WHO,2020), which represents sent the daily deaths due to this pandemic.

Data-II: The second data set represents the "Total no. of deaths" during the second wave of the pandemic from the period 1st July to 15th August 2020 in India.

Data-III: The third data set are taken from (WHO,2020), which represents the "Total no. of deaths" in Italy from 1st July to 15th August 2020.

Data-IV: This data set is taken from (WHO,2020), which represents the "Total no. of deaths" in Europe from 1st July to 15th August 2020. The data contain the region of Europe with an area (L:55.3781, -3.436).

Table 11: Descriptive measures for Data sets

Datasets	Min	Max	Mean	Median	Q_1	Q_3	Range	SD	Skew	Kutosis
I	0	86	11.13	10	0	16	86	14.15	3.39	16.62
II	379	1129	714.36	711	553	857	750	182.62	0.12	-0.82
III	2	158	13.42	9	5	13	156	22.67	5.96	38.01
IV	0	57	19.33	17	10	26	57	13.80	1.03	0.65

Table 12: MLEs and Goodness of Fit for Data-I

Models	-2LL	AIC	CAIC	BIC	HQIC
IW	264.217	578.040	578.472	589.146	576.342
RLD	277.024	571.277	571.035	582.980	571.996
IRLD	256.275	570.289	570.766	581.193	571.864

Table 13: MLEs and Goodness of Fit for Data-II

Models	-2LL	AIC	CAIC	BIC	HQIC
IW	239.103	563.237	564.238	581.117	599.375
RLD	231.568	559.669	560.664	587.364	604.496
IRLD	231.005	538.496	548.690	581.100	597.361

Table 14: MLEs and Goodness of Fit for Data-III

Models	-2LL	AIC	CAIC	BIC	HQIC
IW	195.827	320.539	326.822	321.115	322.829
RLD	180.639	310.187	309.684	316.572	319.118
IRLD	178.392	308.028	308.115	313.099	311.744

Table 15: MLEs and Goodness of Fit for Data-IV

Models	-2LL	AIC	CAIC	BIC	HQIC
IW	260.564	464.194	463.287	489.283	400.279
RLD	267.267	458.153	459.468	479.124	498.004
IRLD	260.145	458.076	458.109	476.265	475.475

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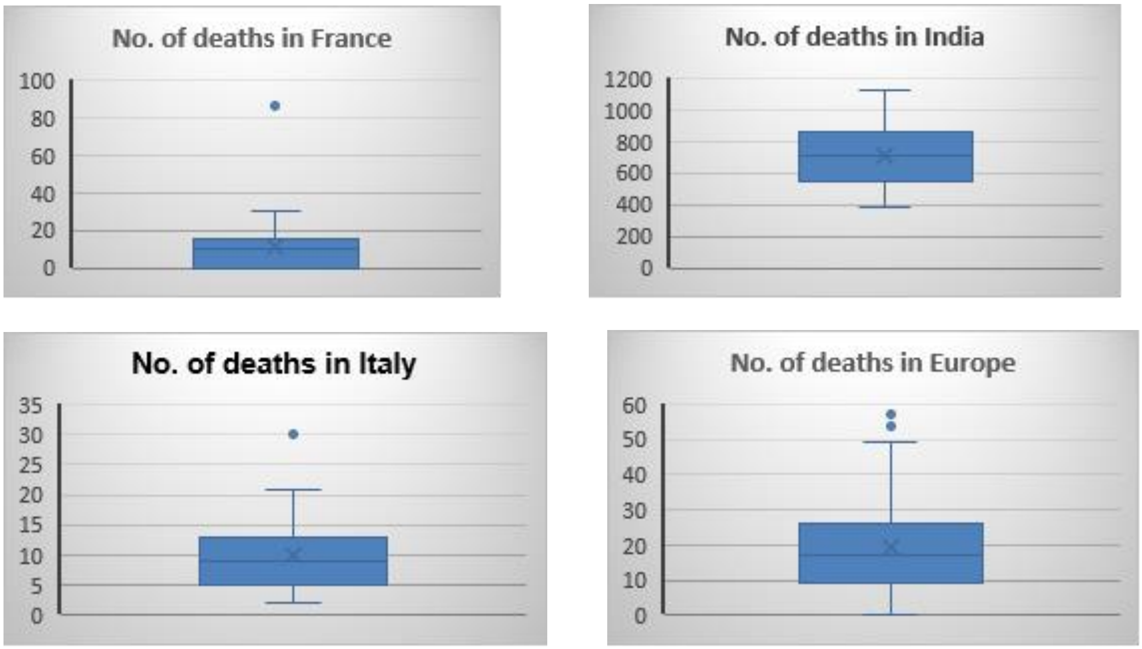

Figure 3: summary statistics plots for data set I, II, III and IV

4. Conclusion

In this study, a new generalization of Ramous Louzada distribution is presented known as Inverse Ramous Louzada Distribution. It is specially designed for modeling COVID-19 data set. The data set comprises "no of deaths" in four major countries France, India, UK and Italy. Besides this, some of the common properties has been discussed. Moreover, simulation study has been carried out to check the performance of the proposed model. The results revealed that the developed model is better in performance compared to existing models (Inverse Weibul and Ramous Louzada Distribution).

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