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A Comparative Analysis of Entropy Measures for Exponentiated Exponential and Truncated Exponentiated Exponential Distributions

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Abstract. Our research explores several entropy measurements for both EE (Exponentiated Exponential) and TEE (Truncated Exponentiated Exponential) lifetime models that scientists commonly use in their reliability projects. Our research develops various measures of entropy such as Shannon and Rényi to precisely measure uncertainty and unpredictability within these statistical distributions. The research analyzes entropy behavior across changing distribution parameters and contrasts EE with TEE results. The results show what exactly connects distribution parameters to their entropy measurements and shows why each distribution is special. This study enhances statistical and information theoretical methods for general use by showing all known uncertainty characteristics of EE and TEE distributions.

2020 Mathematics Subject Classifications: 16N60, 16W10, 47B47

Key Words and Phrases: Exponentiated Exponential Distribution, Truncated Exponenetiated, Exponential Distribution, Entropy

1. Introduction

In probability theory, information theory plays a vital role, which is the basis of reliability theory, communication systems, and financial characteristics. Claude Shannon gave the idea of information theory in 1948, which is also known as Shannon Entropy [1]. It is a connection point between several fields such as Mathematics, Statistics, Computer Science, Physics, Engineering, etc. In addition, it has diverse applications including natural language processing, linguistics, statistical Inference, fuzzy entropy, cryptography,

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bioinformatics, quantum computer science, plagiarism detection, human vision [2–4] and thermal physics [5]. Moreover, the subfields of information theory include algorithm complexity theory, theoretical information security, source coding, information measurements, and gray system.

In literature, many authors contributed to measuring entropies and their generalization. [6] defined the seven entropy measures of Truncated Rayleigh distribution instead of Rayleigh distribution and computed the relative loss of entropy. We initiated this investigation due to the increasing need to understand entropy measures for two special distribution types. Scientists and researchers depend heavily on Exponentiated Exponential and Truncated Exponentiated Exponential distributions because they handle lifetime data, reliability analysis, and survival studies effectively. Deep knowledge of the entropy measures for these distributions helps us better explain their randomness characteristics. This research examines entropy values of these distributions to show their actual performance characteristics for different applications. New statistical information will benefit areas of practical application while helping researchers understand distribution qualities better.

2. Several Entropy measures

The mathematical expression of Shannon entropy

$$\Xi_S(y) = -\int_{-\infty}^{+\infty} g(y) \ln g(y) dy \tag{1}$$

The only shortcoming of Shannon entropy is that it may produce negative results for some probability models, which is not possible for uncertainty measures. Many authors contributed to overcoming this problem and proposed different entropy measures.
[7] gave the idea of randomness and uncertainty and gave a new generalized entropy. The Renyi entropy [8] is as follows:

$$\Xi_R(y) = \frac{1}{1-\varsigma} log(\int_{-\infty}^{+\infty} [g(y)]^{\varsigma} dy), \quad \varsigma > 0, \varsigma \neq 1 \tag{2}$$

It gives a non-negative result due to the constant ς involved in the expression.
[7] discussed entropy as

$$\Xi_{\text{HC}}\left(y\right) = \frac{1}{2^{1-\varsigma}-1}\left[\int_{-\infty}^{+\infty}[g(y)]^{\varsigma}dy - 1\right] \quad \varsigma > 0, \varsigma \neq 0 \tag{3}$$

[9] investigated the entropy is

$$\Xi_{AR}(y) = \frac{1}{2^{\varsigma-1}-1}\left[\int_{-\infty}^{+\infty}[g(y)]^{\varsigma}dy\right]^{\varsigma} - 1 \quad \varsigma > 0, \varsigma \neq 0 \tag{4}$$

[10] used entropy as

$$\Xi_{SM}(y) = \frac{1}{2^{1-\varsigma}-1}\left[\exp\left\{(\varsigma-1)\int_{-\infty}^{+\infty} g(y)\ln g(y)dy\right\}-1\right] \quad \varsigma>0, \varsigma\neq 1 \tag{5}$$

[11] derived generalized entropy as

$$\Xi_{A1}(y) = -\int_{-\infty}^{+\infty} g(y)\ln\left[\frac{g(y)}{\delta}\right]dy; \delta = \mathrm{Sup}[g(y)] \tag{6}$$

[11] produced generalization of Renyi Entropy,

$$\Xi_{A2}(y) = \frac{1}{\varsigma-1}\ln\left[\int_{-\infty}^{+\infty}\frac{[g(y)]^{\varsigma}}{\delta^{\varsigma-1}}dy\right] \quad \varsigma>0, \varsigma\neq 1 \tag{7}$$

[7] derived the generalized of Havrda and Charvat Entropy,

$$\Xi_{A3}(y) = \frac{1}{2^{1-\varsigma}-1}\left[\int_{-\infty}^{+\infty}\frac{[g(y)]^{\varsigma}}{\delta^{\varsigma-1}}dy-1\right] \quad \varsigma>0, \varsigma\neq 1 \tag{8}$$

[12] defined the generalized entropy as

$$\Xi_{T}(y) = \frac{1}{\varsigma-1}\left[1-\int_{-\infty}^{+\infty}[g(y)]^{\varsigma}dy\right] \quad \varsigma>0, \varsigma\neq 1 \tag{9}$$

The aim of present study is to derive the entropy measures for Exponetiated Exponential distribution and truncated Exponetiated Exponential distribution, and compared the relative loss of entropy under different parametric values.

3. Exponentiated Exponential Distribution (EED) and Truncated Exponentiated Exponential Distribution (TEED):

Let ' y ' be a r.v has EED with β and γ are parameters having pdf and cdf as

$$g(y;\beta,\gamma) = \beta\gamma\left(1-e^{-\gamma y}\right)^{\beta-1}e^{-\gamma y} \tag{10}$$

$$G(y;\beta,\gamma) = \left(1-e^{-\gamma y}\right)^{\beta} \tag{11}$$

Let ' z ' be a r.v of TEED having cdf and pdf can be defined as:

$$G(z;t,\beta,\gamma) = \frac{\left(1-e^{-\gamma z}\right)^{\beta}}{\left(1-e^{-\gamma t}\right)^{\beta}} \tag{12}$$

and

$$g(z;t,\beta,\gamma) = \frac{\beta\gamma\left(1-e^{-\gamma z}\right)^{\beta-1}e^{-\gamma z}}{\left(1-e^{-\gamma t}\right)^{\beta}} \tag{13}$$

Suppose $\Xi_n(y)$ and $\Xi_n(z)$ are two corresponding entropies, the relative loss of entropy by using ' y ' otherthan ' z ' can be defined as:

$$L_{\Xi_n}(y) = \frac{\Xi_n(y) - \Xi_n(z)}{\Xi_n(y)} \tag{14}$$

3.1 Entropies of EED and TEED:

In this section, by following section 2.1, different entropies measures of EED and TEED are derived. Then, using these two distributions, the relative loss of entropy is obtained by using ' y ' instead of ' z '.

(i) Shannon Entropy of EED and TEED is given as:

$$\Xi_s(y) = -\int_0^\infty g(y)\ln g(y)dy$$

$$\Xi_S(y) = -\int_0^\infty \beta\gamma\left(1-e^{-\gamma_z}\right)^{\beta-1} e^{-\gamma_z} \ln\left[\beta\gamma\left(1-e^{-\gamma_z}\right)^{\beta-1} e^{-\gamma_z}\right] dy$$

Making transformation $e^{-\gamma z} = w$, finally Shannon entropy becomes,

$$\Xi_S(y) = -\log(\beta\gamma) - \varphi(1) + (1-\beta)\varphi(\beta) + \beta\varphi(\beta+1) \tag{15}$$

Where $\varphi(\square)$ is a digamma function.
The Shannon Entropy of TEED is as

$$\Xi_S(z) = -\int_0^\infty \frac{\beta\gamma\left(1-e^{-\gamma_z}\right)^{\beta-1} e^{-\gamma_z}}{\left(1-e^{-\gamma t}\right)^{\beta}} \ln\left\{\frac{\beta\gamma\left(1-e^{-\gamma_z}\right)^{\beta-1} e^{-\gamma_z}}{\left(1-e^{-\gamma t}\right)^{\beta}}\right\} dy \tag{16}$$

After making transformation and a little simplification, one can get

$$\Xi_S(z) = -\frac{\ln\beta\gamma}{\left(1-e^{-\gamma t}\right)^{\beta}} - \frac{\beta}{\left(1-e^{-\gamma t}\right)^{\beta}}\varphi(\beta) - \frac{\beta}{\left(1-e^{-\gamma t}\right)^{\beta}}\varphi(\beta+1) \tag{17}$$

Therefore, the final expression of Shannon entropy of TEED is

$$\Xi_S(z) = -\frac{1}{\left(1-e^{-\gamma t}\right)^{\beta}}\left[-\ln\beta - \beta\varphi(\beta) - \beta\varphi(\beta+1) - \ln G(z;t,\beta,\gamma)\right] \tag{18}$$

(ii) The Renyi Entropy of ' y ' and ' z ' is as follow

$$\Xi_R(y) = \frac{1}{1-\varsigma}\log\int_0^\infty [g(y)]^{\varsigma} dy$$

After simplification, we get the Renyi Entropy for EED as

$$\Xi_R(y) = -\log \beta\gamma + \frac{\log \beta + \log B(\varsigma, \varsigma(\beta-1)+1)}{1-\varsigma} \tag{19}$$

the Renyi Entropy for TEED as

$$\Xi_R(z) = \log\left(\frac{\beta\gamma}{(1-e^{-\gamma t})^{\beta}}\right) + \frac{\log \beta + \log B(\varsigma, \varsigma(\beta-1)+1)}{1-\varsigma} \tag{20}$$

(iv) Tsallis Entropy of EED and TEED is given as:

$$\Xi_T(y) = \frac{1}{1-\varsigma}\left[1 - \beta\gamma^{\varsigma-1} B(\varsigma, \varsigma(\beta-1)+1)\right] \tag{21}$$

$$\Xi_T(z) = \frac{1}{1-\varsigma}\left[1 - \frac{\beta\gamma^{\varsigma-1}}{(1-e^{-\gamma t})^{\beta}} B(\varsigma, \varsigma(\beta-1)+1)\right] \tag{22}$$

(v) The Havrda and Charvat Entropy of EED and TEED is given as:

$$\Xi_{HC}(y) = \frac{1}{2^{1-\varsigma}-1}\left[\beta^{\varsigma}\gamma^{\varsigma-1} B(\varsigma, \varsigma(\beta-1)+1) - 1\right] \tag{23}$$

$$\Xi_{HC}(z) = \frac{1}{2^{1-\varsigma}-1}\left[\frac{\beta^{\varsigma}\gamma^{\varsigma-1}}{(1-e^{-\gamma t})^{\beta\varsigma}} B(\varsigma, \varsigma(\beta-1)+1) - 1\right] \tag{24}$$

(vi) Arimoto's Entropy of EED and TEED is given as:

$$\Xi_{AR}(y) = \frac{1}{(2^{1-\varsigma}-1)}\left[\left\{\frac{(\beta^{\varsigma}\gamma)^{\frac{1}{\varsigma}}}{\varsigma} B\left(\frac{1}{\varsigma}, \frac{(\beta-1)}{\varsigma}+1\right)\right\} - 1\right] \tag{25}$$

$$\Xi_{AR}(z) = \frac{1}{(2^{1-\varsigma}-1)}\left[\left\{\frac{(\beta\gamma)^{\frac{1}{\varsigma}}}{\gamma\,(1-e^{-\gamma t})^{\frac{\beta}{\varsigma}}} B\left(\frac{1}{\varsigma}, \frac{(\beta-1)}{\varsigma}+1\right)\right\}^{\varsigma} - 1\right] \tag{26}$$

(vii) Sharma and Mittal's entropy of EED and TEED is given as:

$$\Xi_{SM}(y) = \frac{1}{(2^{1-\varsigma}-1)}[\exp(\varsigma-1)\{-\log(\beta\gamma) - \varphi(1) + (1-\beta)\varphi(\beta) + \beta\varphi(\beta+1)\} - 1] \tag{27}$$

$$\Xi_{SM}(z) = \frac{1}{(2^{1-\varsigma}-1)}[\exp(\varsigma-1)\{-\log(\beta\gamma) - \beta\varphi(\beta) + \beta\varphi(\beta+1) + \ln G(z;t,\beta,\gamma)\} - 1] \tag{28}$$

(viii) Awad's et al. entropy of EED and TEED is given as:

$$\Xi_{A1}(y) = \log(\delta) - \log(\beta\gamma) + \varphi(1) - (1-\beta)\varphi(\beta) + \beta\varphi(\beta+1) \tag{29}$$

$$\Xi_{A1}(z) = \log(\delta) + \frac{1}{(1-e^{-\gamma t})^{\beta}}[\log(\beta\gamma) + \beta\varphi(\beta) + \beta\varphi(\beta+1) - \ln G(z;t,\beta,\gamma)] \tag{30}$$

(ix) Awad's entropy of EED and TEED is given as:

$$\Xi_{A2}(y) = \frac{1}{\varsigma-1}\ln\left[\frac{1}{\delta^{\varsigma}-1}\left\{\log(\beta\gamma) + \frac{\log\beta + \log B(\varsigma, \varsigma(\beta-1)+1)}{1-\varsigma}\right\}\right] \tag{31}$$

$$\Xi_{A2}(z) = \frac{1}{\varsigma-1}\ln\left[\frac{1}{\delta^{\varsigma}-1}\left\{\log\left(\frac{\beta\gamma}{(1-e^{-\gamma t})^{\beta}}\right) + \frac{\log\beta + \log B(\varsigma, \varsigma(\beta-1)+1)}{1-\varsigma}\right\}\right] \tag{32}$$

(x) Awad's Entropy of EED and TEED is given as:

$$\Xi_{A3}(y) = \frac{1}{2^{\varsigma-1}-1}\left[\frac{1}{\delta^{\varsigma}-1}\left\{\log(\beta\gamma) + \frac{\log\beta + \log B(\varsigma, \varsigma(\beta-1)+1)}{1-\varsigma}\right\}\right] \tag{33}$$

$$\Xi_{A3}(z) = \frac{1}{2^{\varsigma-1}-1}\left[\frac{1}{\delta^{\varsigma}-1}\left\{\log\left(\frac{\beta\gamma}{(1-e^{-\gamma t})^{\beta}}\right) + \frac{\log\beta + \log B(\varsigma, \varsigma(\beta-1)+1)}{1-\varsigma}\right\}\right] \tag{34}$$

4. Results and Discussion

In this section, the results of entropies using different parametric values of (β, γ, ς and t) are discussed. In table (1) and (2), the combination of different parametric values are to be chosen as ($\beta =$), ($\gamma =$) and ($\varsigma =$). On the basis of these combinations of parametric values, the relative loss function is calculated. In table (3) and (4) illustrate that relative loss of all entropies for Exponnetiated Exponential and Trucated Expoenentiated Exponential distribution. The result reveal that with an increasing in the value of shape parameter t, the entropy measures show a decreasing behavior and same in the same of parameter t. Table (3) and (4) shows that as ' t ' increases, the Shannon entropy decreases, whereas with the increase of truncated parameter ' t ' decreases Renyi, Tsalli, Havdra and increases.

In table (1) and (2), shows clear findings but requires deeper exploration of entropy behavior changes across different parameter adjustments. The conclusion needs to show how parameter t makes Shannon entropy grow since the study does not explain this pattern clearly. An examination of the parameter t and its effects on the PDF reveals how changes in t affect the distribution shape to influence uncertainty as measured by Shannon entropy. Examining this behavior in specific settings such as reliability tests and survival experiments will provide useful practical interpretation for the results. The additional analysis would improve our interpretation of outcomes while showing exactly how t affects the entropy level.

Table. 1 Entropy values for Exponentiated Exponential distribution using $\gamma = 0.5, \varsigma = 0.5$

t	$\Xi_S(y)$	$\Xi_R(y)$	$\Xi_T(y)$	$\Xi_{HC}(y)$	$\Xi_{AR}(y)$	$\Xi_{SM}(y)$	$\Xi_{A1}(y)$	$\Xi_{A2}(y)$	$\Xi_{A3}(y)$
0.2	1.657	1.963	2.643	2.924	3.745	4.856	3.928	4.665	5.093
0.4	1.342	1.874	2.316	2.782	3.548	4.623	3.109	4.762	5.006
0.6	1.137	1.509	2.078	2.663	3.337	4.098	3.095	3.817	4.298
0.8	0.793	1.148	1.940	2.516	3.286	3.827	3.100	2.629	2.647
1.0	0.649	0.746	1.877	1.732	2.647	2.573	2.645	2.109	2.194
1.5	0.385	0.274	1.574	1.504	2.554	2.674	2.193	1.846	2.167
2.0	0.174	0.203	1.483	1.184	2.108	2.105	1.746	1.239	1.738

Table. 2 Entropy values for truncated Exponentiated Exponential distribution using $\beta = 0.5, \gamma = 0.5, \varsigma = 0.5$

t	$\Xi_S(z)$	$\Xi_R(z)$	$\Xi_T(z)$	$\Xi_{HC}(z)$	$\Xi_{AR}(z)$	$\Xi_{SM}(z)$	$\Xi_{A1}(z)$	$\Xi_{A2}(z)$	$\Xi_{A3}(z)$
0.2	2.115	2.376	3.147	3.667	2.873	4.095	4.868	3.017	3.029
0.4	2.120	2.101	2.885	2.920	2.665	4.092	4.782	2.774	2.894
0.6	1.742	1.939	2.638	2.830	2.483	3.759	4.692	2.648	2.777
0.8	1.093	1.254	2.440	2.755	2.387	3.284	4.553	2.371	2.474
1.0	0.877	1.093	2.143	2.163	2.194	3.119	4.284	2.531	2.389
1.5	0.289	1.035	1.873	1.934	2.003	2.648	3.298	1.783	1.586
2.0	0.093	0.727	1.443	1.932	1.903	2.465	3.266	1.367	1.382

Table. 3 Entropy values for Exponentiated Exponential distribution using $\gamma = 1, \varsigma = 0.5$

t	$\Xi_S(y)$	$\Xi_R(y)$	$\Xi_T(y)$	$\Xi_{HC}(y)$	$\Xi_{AR}(y)$	$\Xi_{SM}(y)$	$\Xi_{A1}(y)$	$\Xi_{A2}(y)$	$\Xi_{A3}(y)$
0.2	1.657	1.966	2.678	2.967	3.775	4.886	3.968	4.625	5.396
0.4	1.342	1.874	2.416	2.682	3.548	4.623	3.759	4.592	5.106
0.6	1.137	1.489	2.383	2.563	3.437	4.098	3.355	3.817	4.598
0.8	0.593	1.133	2.001	2.416	3.386	3.827	3.180	2.399	2.511
1.0	0.449	0.564	1.977	1.432	2.447	2.573	2.954	2.299	2.135
1.5	0.225	0.255	1.774	1.274	2.354	2.674	2.138	1.743	2.163
2.0	0.134	0.225	1.383	1.214	2.158	2.105	1.746	1.295	1.908

Table. 4 Entropy values for truncated Exponentiated Exponential distribution using $\beta = 1, \gamma = 0.5, \varsigma = 0.5$

t	$\Xi_S(z)$	$\Xi_R(z)$	$\Xi_T(z)$	$\Xi_{HC}(z)$	$\Xi_{AR}(z)$	$\Xi_{SM}(z)$	$\Xi_{A1}(z)$	$\Xi_{A2}(z)$	$\Xi_{A3}(z)$
0.2	2.875	2.576	3.147	3.467	2.874	4.198	4.848	3.298	3.328
0.4	2.120	2.101	2.885	2.920	2.835	4.000	4.782	2.981	2.894
0.6	1.772	1.939	2.638	2.995	2.383	3.399	4.392	2.859	2.782
0.8	1.871	1.254	2.440	2.834	2.297	3.194	4.153	1.671	2.445
1.0	0.763	1.093	2.143	2.163 s	2.138	3.023	4.004	1.531	2.348
1.5	0.588	1.035	1.873	1.934	2.107	2.578	3.549	1.295	1.993
2.0	0.210	0.727	1.443	1.932	1.903	2.480	3.103	1.609	1.758

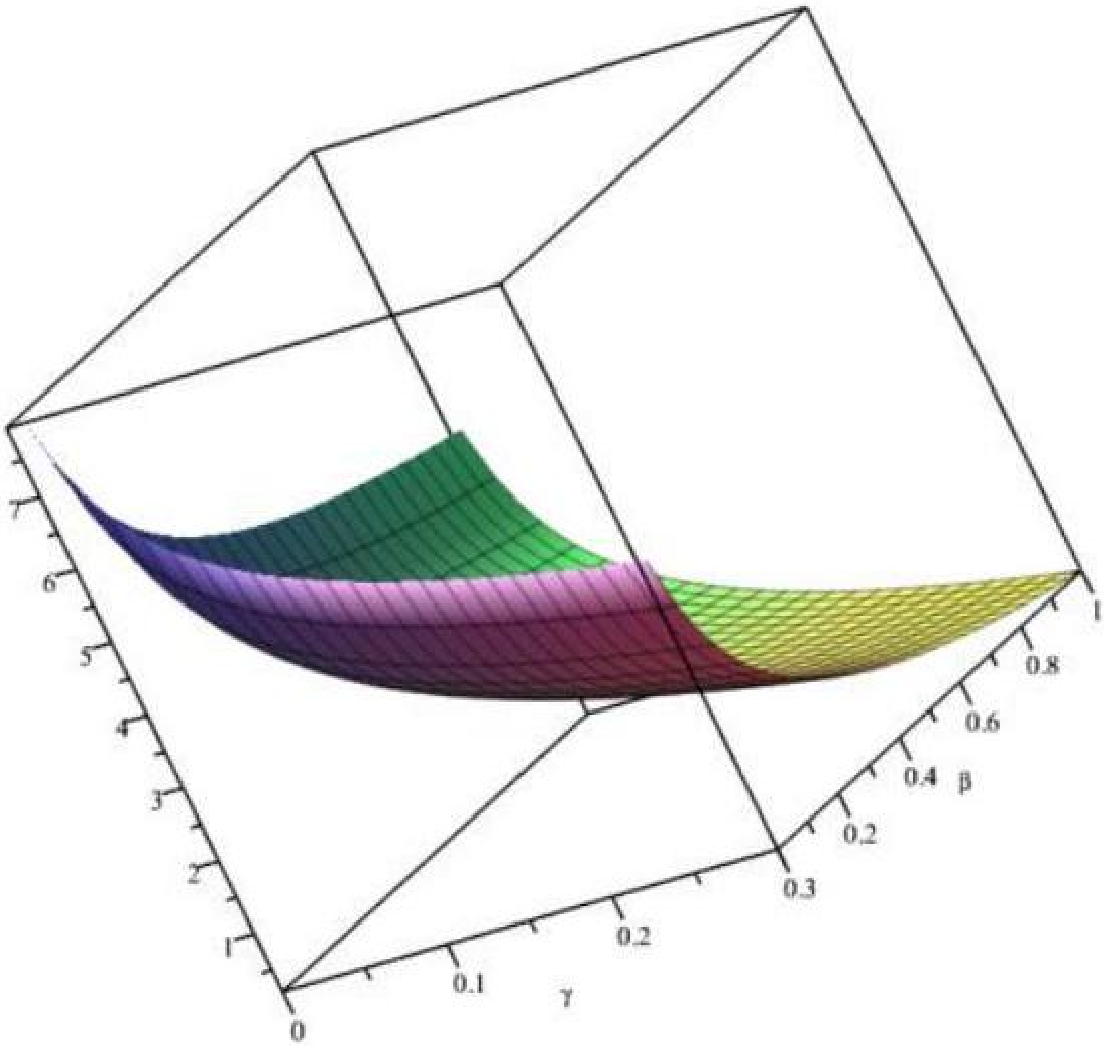
Table. 5 Relative loss for $\beta = 0.4, \gamma = 0.3, \varsigma = 0.5$

t	$\Xi_S(y)$	$\Xi_R(y)$	$\Xi_T(y)$	$\Xi_{HC}(y)$	$\Xi_{AR}(y)$	$\Xi_{SM}(y)$	$\Xi_{A1}(y)$	$\Xi_{A2}(y)$	$\Xi_{A3}(y)$
0.2	-1.927	1.827	1.109	1.763	1.393	1.983	1.837	1.368	1.537
0.4	-1.812	1.667	0.983	1.348	1.225	1.683	1.636	1.183	1.793
0.6	-1.766	1.553	0.788	1.391	1.193	1.356	1.368	1.109	1.348
0.8	-1.598	1.428	0.639	1.164	0.683	1.227	1.311	0.924	1.039
1.0	-1.172	1.198	0.535	1.093	0.663	1.184	0.667	0.832	0.799
1.5	-0.411	0.873	0.283	0.673	0.274	0.378	0.394	0.735	0.676
2.0	-0.298	0.374	0.016	0.336	0.738	0.274	0.297	0.338	0.448

Table. 6 Relative loss for $\beta = 0.8, \gamma = 0.7, \varsigma = 0.25$

t	$\Xi_S(z)$	$\Xi_R(z)$	$\Xi_T(z)$	$\Xi_{HC}(z)$	$\Xi_{AR}(z)$	$\Xi_{SM}(z)$	$\Xi_{A1}(z)$	$\Xi_{A2}(z)$	$\Xi_{A3}(z)$
0.2	-1.209	1.387	1.092	1.009	1.293	2.784	2.564	2.831	2.009
0.4	-1.109	1.293	1.002	0.927	1.109	1.937	2.106	2.645	1.998
0.6	-1.100	1.104	0.919	0.683	1.038	1.648	1.834	2.194	1.646
0.8	-0.937	0.928	0.783	0.554	0.839	1.467	1.749	2.177	1.344
1.0	-0.910	0.904	0.615	0.309	0.378	1.392	1.664	1.748	0.978
1.5	-0.745	0.778	0.567	0.298	0.239	0.923	1.548	1.478	0.347
2.0	-0.329	0.276	0.275	0.222	0.196	0.451	1.063	1.390	0.227

Shannon Entropy of EED



Shannon Entropy of TEED

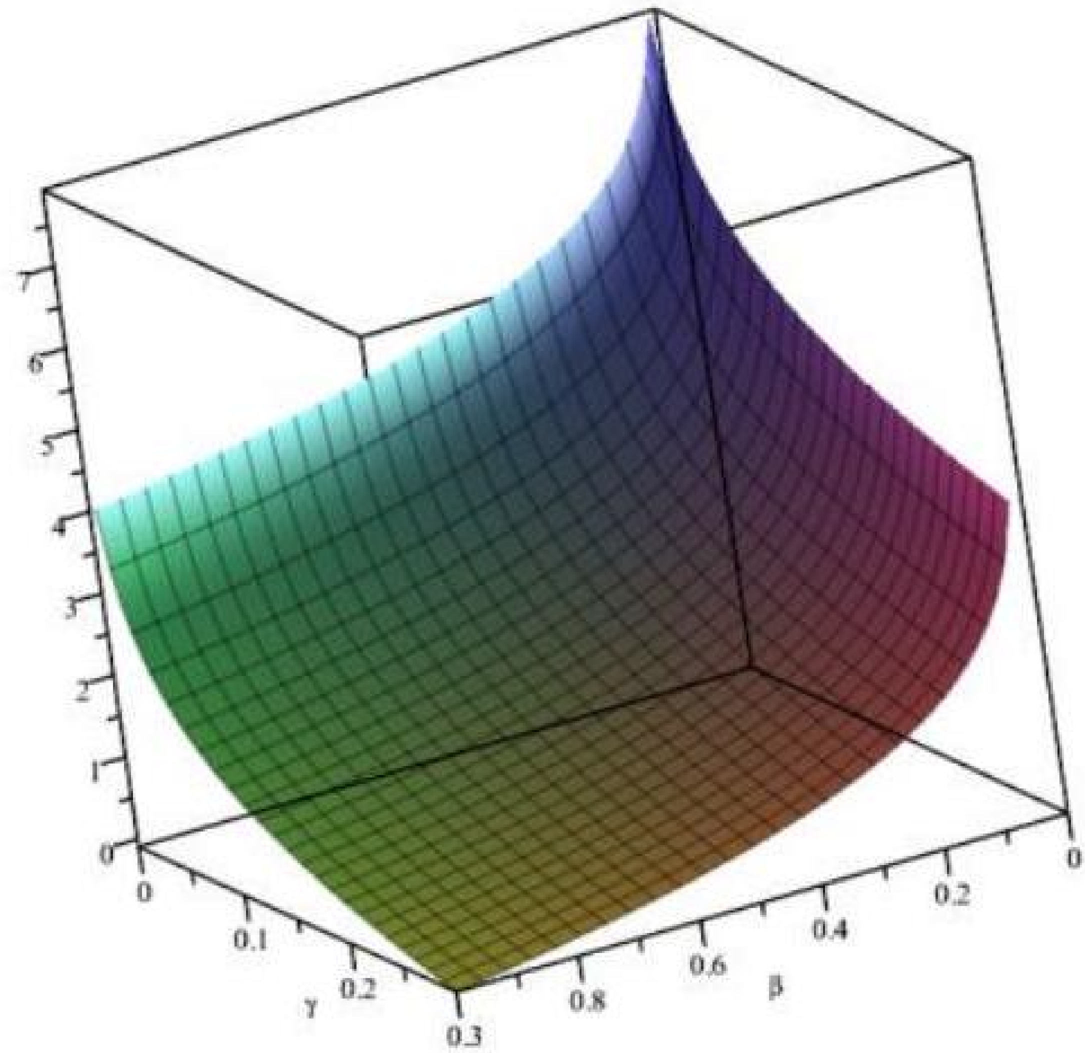


Figure. 1 Shannon Entropy of EED and TEED

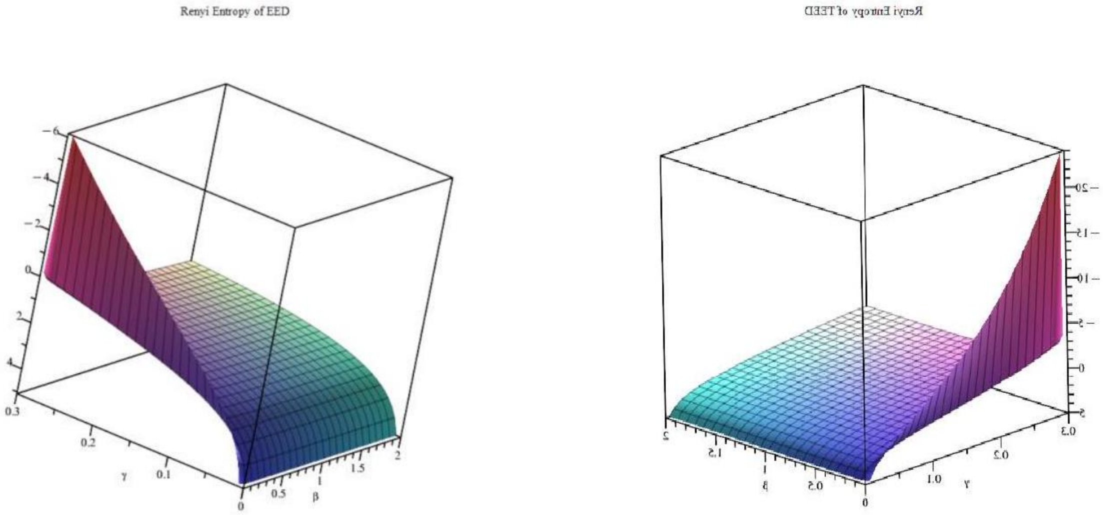
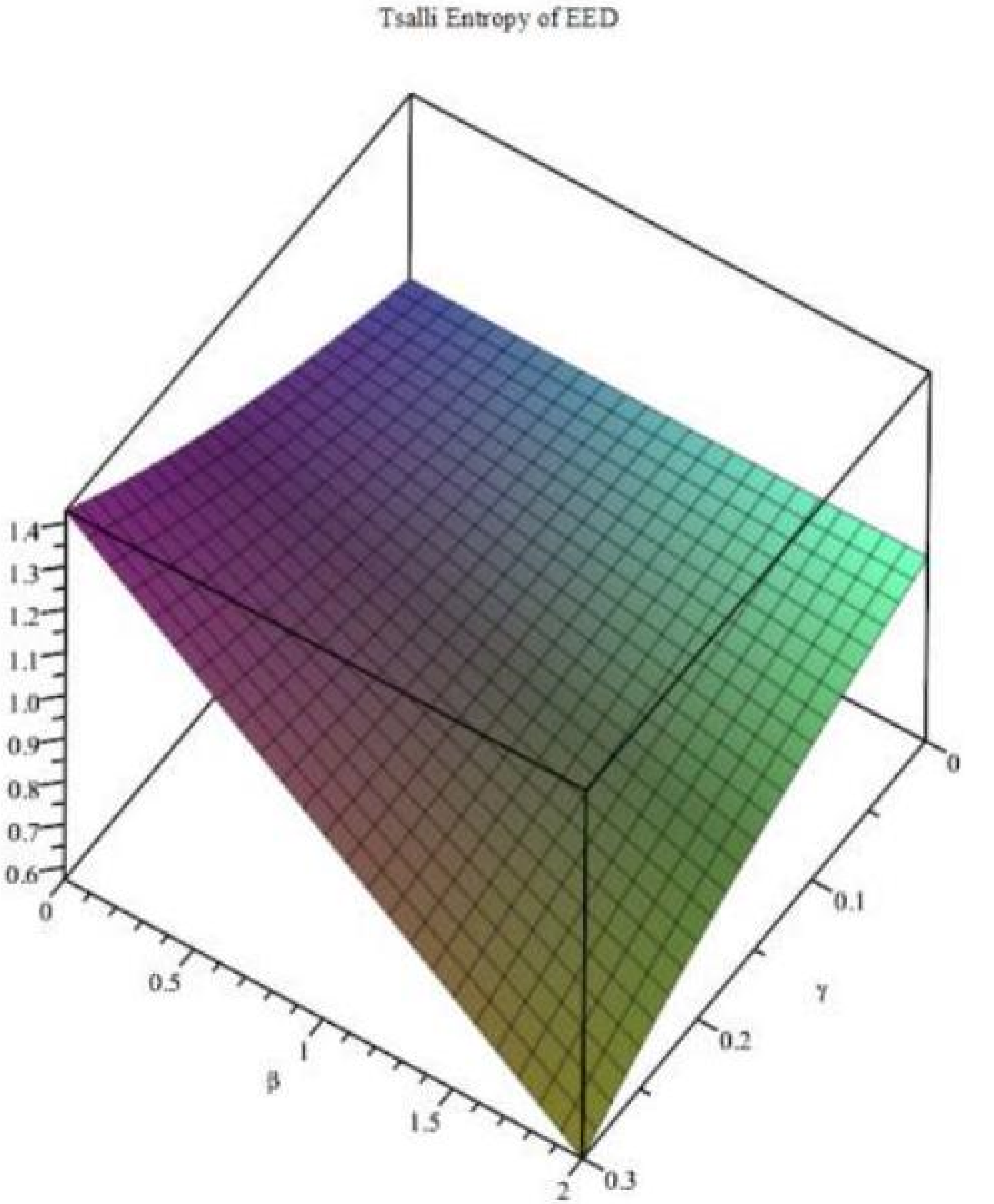


Figure. 2 Renyi Entropy of EED and TEED


Tsalli Entropy of EED
1.4
1.3
1.2
1.1
1.0
0.9
0.8
0.7
0.6
0
0.5
1
β
1.5
2
0
0.1
γ
0.2
0.3

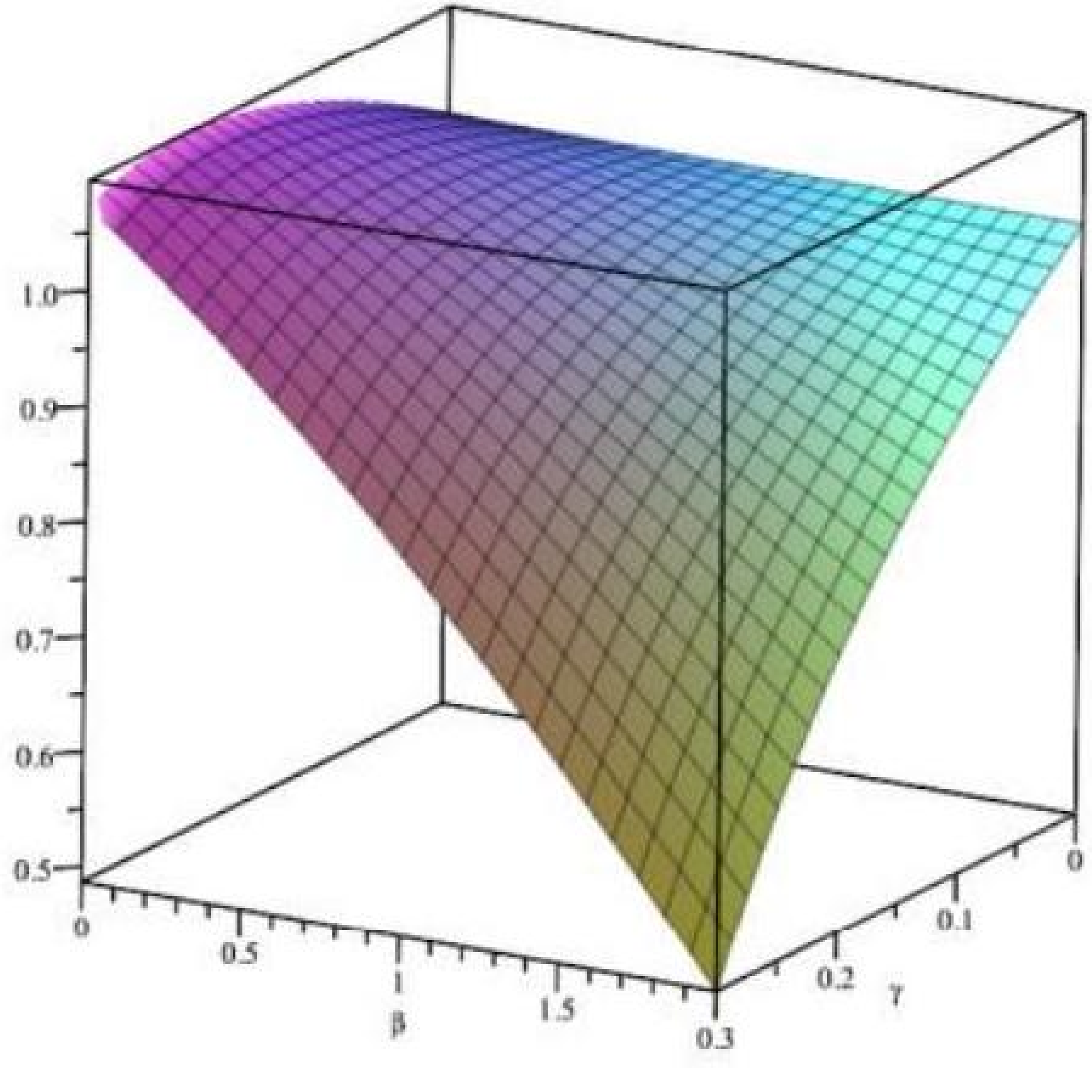


Figure. 3 Tsalli Entropy of EED and TEED

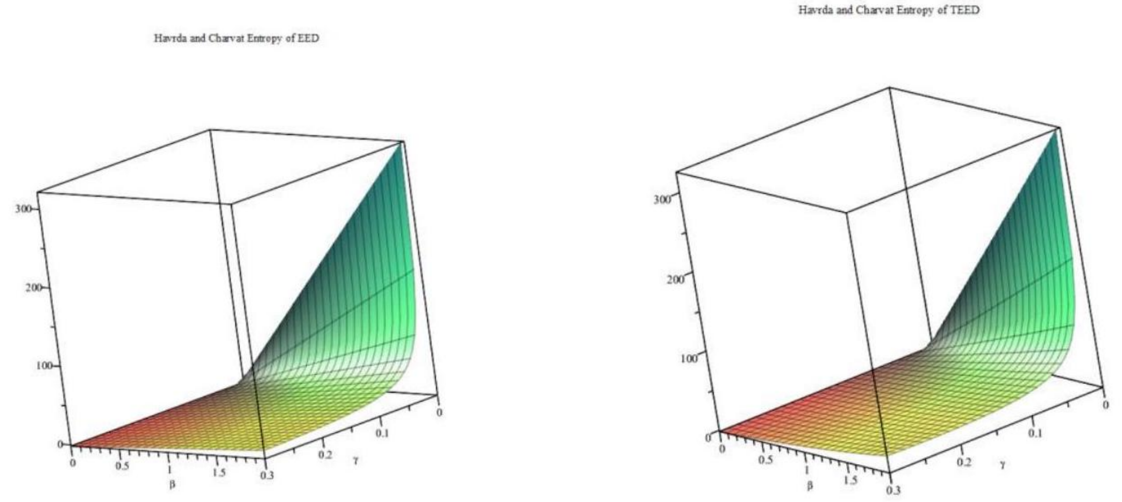


Figure. 4 Havrda and Charvat Entropy of EED and TEED

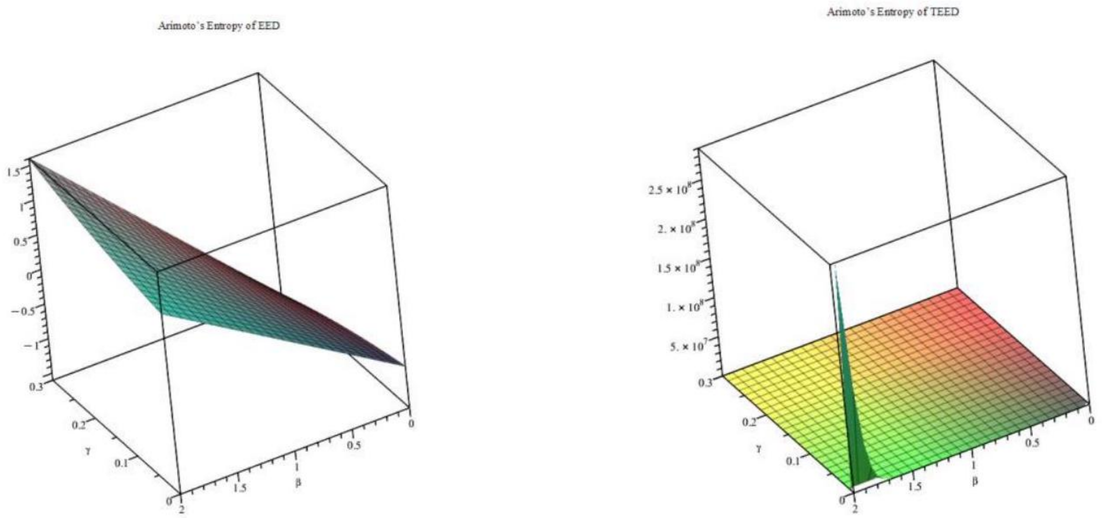


Figure. 5 Arimoto's Entropy of EED and TEED

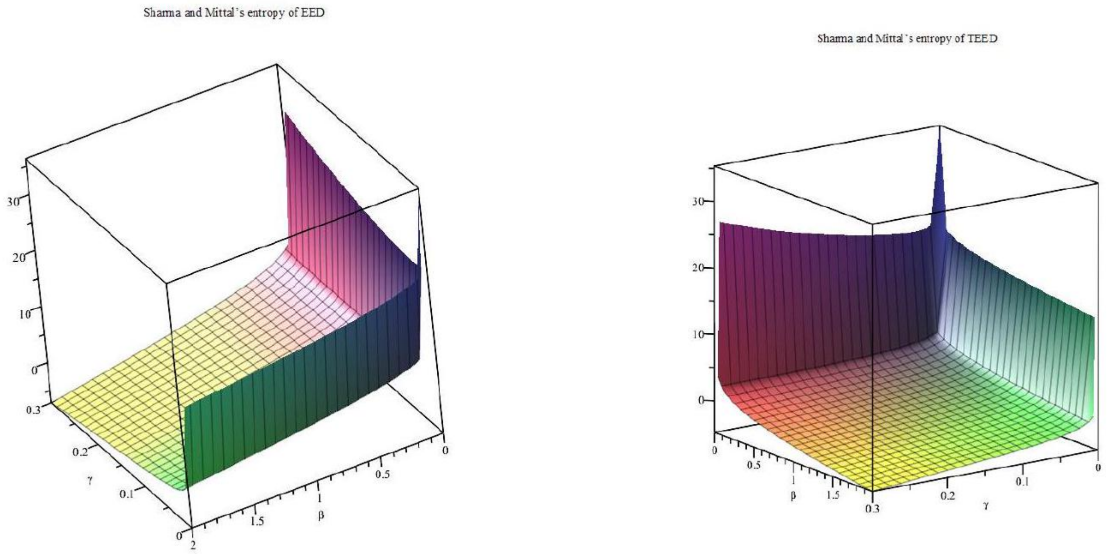


Figure. 6 Sharma and Mittal's entropy of EED and TEED

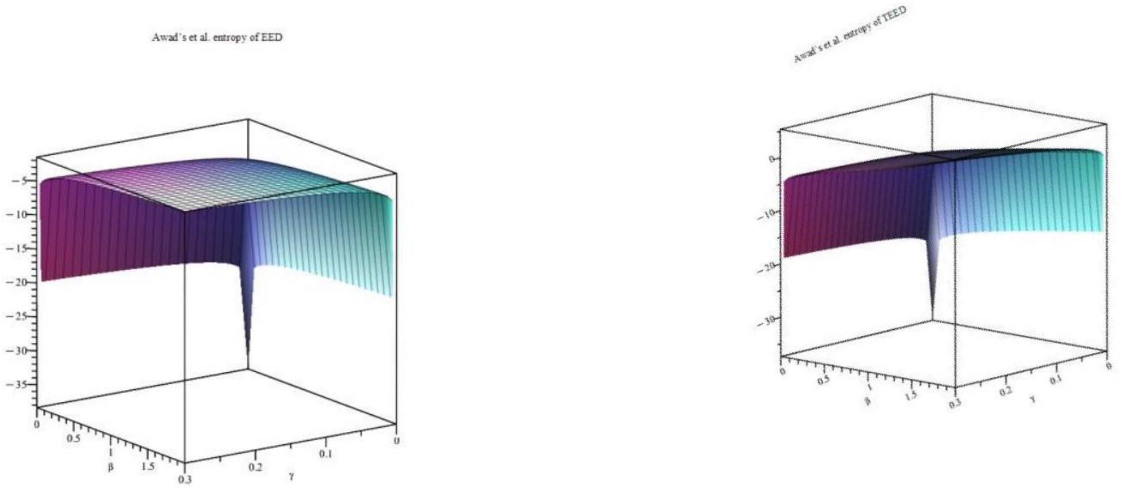


Figure. 7 Awad's et al. entropy of EED and TEED

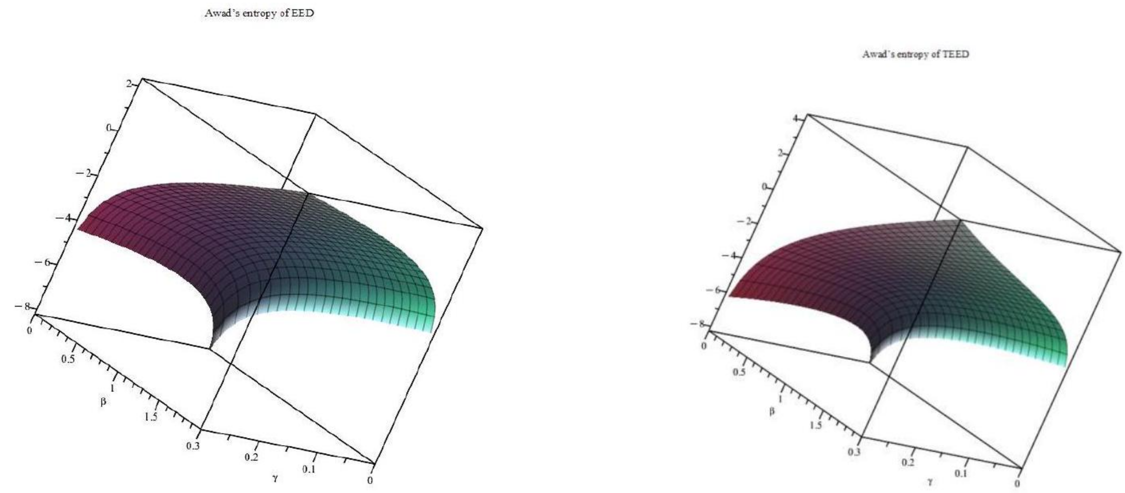


Figure. 8 Awad's entropy of EED and TEED

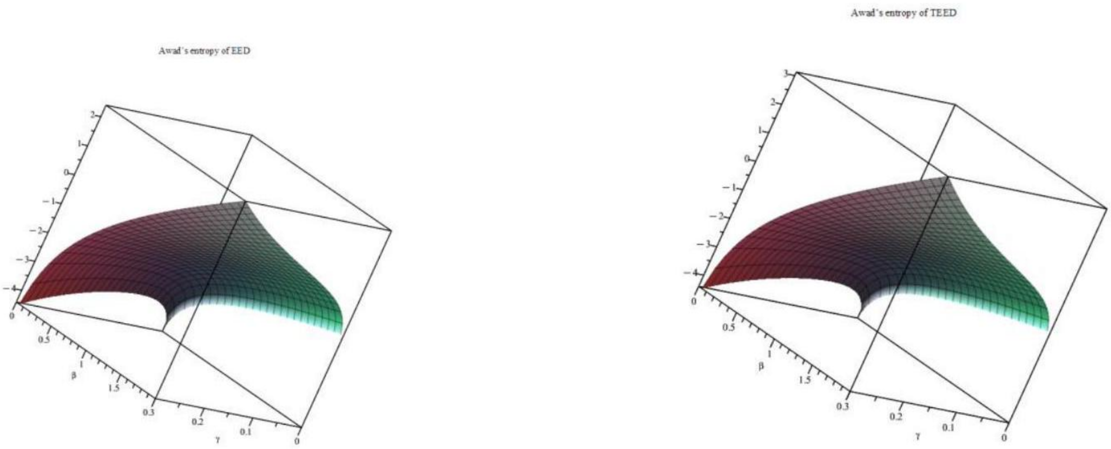


Figure. 9 Awad's entropy of EED and TEED

5. Conclusion

This research examines most entropy measures for EE and TEE models to show how well they represent distribution uncertainty. Our analysis uses Shannon entropy plus Rényi entropy and similar tools to inspect model parameter changes versus entropy results. Our tests show entropy measures behave correctly to detect how these step-like distributions work and how they handle specific data patterns. As the parameter values grow the model produces more uncertain results. Because its range is limited the truncated distribution shows distinct entropy behavior which expands our abilities to represent real-world measurements with specified upper and lower boundaries. These results benefit fields that require accurate modeling of uncertain data since reliability studies and information theory rely on precise knowledge of data uncertainty. Our research adds essential knowledge about entropy measurements for popular statistical distributions and creates new directions for engineering biology machine learning and other related studies.

Conflict of Interest: The authors declare that they have no Conflict of interest

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