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Research Article

ENTROPY METHOD FOR EARTHQUAKE VOLATILITY

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ABSTRACT

In this study, we obtained the volatility of 1. and 2. degree earthquake zones on the same fault line by using entropy method. The application of entropy in earthquake can be regarded as the extension of information entropy and probability theory. The entropy theory applied to derive the most likely univariate distributions subject to specified restriction by applying the principle of maximum entropy. These findings indicate the necessity of more detailed studies for a more comprehensive understanding the nature of Earthquake.
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1. INTRODUCTION

The past of the word entropy can be traced back to 1865 when the German physicist Rudolf Clausius tested to give a novel name to irreversible heat loss, what he beforehand called equivalent value. The word entropy was selected because in Greek, entropies average ingredient transformative or transformation ingredient [1]. [2] suggested a widening of the notion of entropy, which defines the statistical features of complicated systems. [3] determined the cumulative residual entropy, generalized measure of indefiniteness which applied in credibility and image placement and non-additive measures of entropy. [4] suggested a new method of describing entropy of a system, which gives a common condition that is non-extensive like Tsallis entropy, but is linearly dependent on component entropies, as Rényi entropy, which is wide, checked it numerically with the Tsallis and Shannon entropies and demonstrated restriction on the energy spectra imposed by the features of the Lambert function, which are absent in the Shannon condition. [5] submitted an analysis of the wind features of four stations (Elazig-Maden, Elazig-Keban, Elazig, Elazig-Agin) that have been investigated period of 1998–2005, used the probabilistic distributions of wind speed which are a very important part of information requirement in the evaluation of wind energy potential, which have been traditionally defined by various empirical correlations and regarded a theoretical approach to the analytical description of wind speed distributions through application of the maximum entropy principle (MEP). [6] indicated the use of approximate entropy (ApEn), a model-independent measure of sequential irregularity, towards this aim, via a few different applications, both empirical data and model

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based, drafted cross ApEn, concerned two variable measure of asynchrony that ensured a more robust and ubiquitous measure of bivariate assimilation than does correlation, and the resultant containment to diversification strategies, and demonstrated analytic expressions for and statistical properties of ApEn and compare ApEn to nonlinear measures, correlation and spectral analyses, and different entropy measures. [7] indicated that new entropy has the same features than the Shannon entropy outside additive and given that this entropy function satisfies the Lesche and thermodynamic steadiness criteria. [8] considered an analysis of wind features of four stations (Elazig, Elazig-Maden, Elazig-Keban, and Elazig-Agin) period of 1998–2005, investigated the probabilistic distributions of wind speed which are a critical part of information required in the evaluation of wind energy potential, described by diversified empirical correlations, used Weibull distribution and the M aximum Entropy Principle and calculated the parameters of the distributions which were estimated using the least squares method and Statistica software. [9] proposed a new method of applying the basis of maximum entropy to revoke the risk neutral density of future stock, or any other asset, returns from European call and create prices. [10] investigated the effect of renewable energies and different environmental and economic variables on electricity prices in Spain, used knowledge actual concerning renewable energies which is limited so when tried to estimate the electricity price model through regression methods a dimensionality problem emerged and used the Maximum Entropy Econometric approach which considered estimating models, when information limited. [11] investigated the parameters associated with the computation of the Rényi entropy in order to further the comprehension of its practice to assessing wind energy estimating errors. [12] submitted the impact of the liberalization process in the Spanish electricity market and the impact of RESE on domestic electricity prices and used a Maximum Entropy Econometric approximation is used that allows for the estimation, told that energy dependence also had an important effect on electricity prices. [13] proposed to use the exergy and entropy approach to improve the renewable energy systems and to use a link between entropy generation maximum principle and the exergy analysis of engineering and natural networks. [14] demonstrated the explication of entropy is the measure of indefiniteness concerning the system that maintains after observing its macroscopic properties (pressure, temperature or volume) in statistical mechanics. [15] considered the best significant features of Rényi divergence and Kullback– Leibler divergence, including convexity, continuity, limits of σ -algebras, and the relation of the special order 0 to the Gaussian dichotomy and contiguity and indicated how to generalize the Pythagorean inequality to orders various from 1. [16] investigated the wind speed data had been statistically examined usage Weibull distribution to find out wind energy conversion characteristics of Hatiya Island in Bangladesh, demonstrated two important parameters like Weibull shape factor and Weibull scale factor had been computed by four methods, find the probability density function f(x), cumulative distribution function or Weibull function F(x) had been used to describe the best wind distribution between observed and theoretically computed data. [17] used to study the complication of financial time series since the financial market was a complex evolved dynamic method and considered multi measure entropy in the complication of a time series and applied to the financial market. [18] obtained some integrated methods for modeling financial data and demonstrated solving determination making problems, based on risk theory and information theory, investigated several risk measures and entropy measures and crosschecked with respect to their analytical features and effectiveness in analysing real problems. [19] described a generalized cumulative remaining entropy based on the non-additive Tsallis entropy. [20] used entropy approach for volatility markets. [21] considered the effects of financial attacks on alien exchange (FX) markets, where entropy evolution was measured for varied exchange rates, using the time dependent complex entropy method. [22] submitted the applicability of Permutation Entropy based complication measure of a time series for finding of error in wind turbines, examined a set of electrical data from one faulty and one solid wind turbine using traditional Fast Fourier analysis in addition to Permutation Entropy analysis to compare the complication index of stage flows of the two turbines over time. [23]

submitted focuses on detecting the fitness and accuracy of the fitted distribution function to the measured wind speed data for Baburband site in Sindh Pakistan and made to comparison between the wind energy densities obtained using the fitted functions based on Maximum Entropy Principle and Weibull distribution. [24] performed like this entropy measure on the time series of prices and volatilities of six financial markets on data sampled over period 1999 - 2004 and indicated that the entropy of the volatility series depends on the individualistic market. [25] provided the weighted form of this measure with the Weighted Cumulative Residual Tsallis Entropy, reproduced ageing classes and shown that it can uniquely detect the survival function and Rayleigh distribution. [26] examined the question of proximity of the global earthquake population to the critical point characterised by the energy E and entropy S based on annual frequency data from the Harvard CMT catalogue and compared with a theoretical model corresponding to a Boltzmann probability density distribution.

2. MATERIAL AND METHOD

2.1. The Shannon Entropy

The Shannon Entropy of probability measure p on finite set X is given by;

$$S_n(P) = -\sum_{i=1}^{n} p_i \ln p_i \tag{1}$$

where $p_i \geq 0$, $i = 1, 2..., \mathrm{n}$, $\sum_{i=1}^{n} p_i = 1$. Given a continuous probability distribution with a density function $f(x)$, we can define The Shannon Entropy;

$$H = -\int_{-\infty}^{+\infty} f(x) \ln f(x) dx \tag{2}$$

where $\int_{-\infty}^{+\infty} f(x)dx = 1$ and $f(x) \geq 0$. The Shannon; in information theory applications, the answer is given by the asymptotic equipartition property; there is $T \subseteq S^n$ $T \subseteq S^n$ with,

$$\left|T\right| \leq e^{n\left(H(\rho)+\varepsilon\right)} \tag{3}$$

such that sampling n times from p yields an element of T with probability $\succ 1-\varepsilon$, and $\varepsilon \to 0$ as $n \to \infty$.

2.2. The Tsallis Entropy

The Tsallis Entropy, for any positive real number α, the Tsallis Entropy of order α of probability measure p on finite set X is defined as

$$H_\alpha(p) = \begin{cases} \dfrac{1}{\alpha-1}\left(1-\sum_{i\in X} p_i^{\alpha}\right), & if\, \alpha \neq 1 \\ -\sum_{i\in X} p_i \ln p_i, & if\, \alpha = 1 \end{cases} \tag{4}$$

The characterization of the Tsallis entropy is the same as that of the Shannon entropy except that for the Tsallis entropy, the degree of homogeneity under convex linearity condition is α instead of 1.

2.3. Rényi Entropy

For $\beta \in [0,\infty]$, the Rényi entropy of order β is given by

$$H_\beta(\rho) = \frac{1}{1-\beta}\log\left(\sum_{i\in S}\rho_i^\beta\right). \tag{5}$$

- The scaling factor is conventional: it makes H_β nonnegative for all β and ensures $H_\beta(u_n) = \log n$, where u_n is the uniform distribution on an *n*- element set.
- The main property which the Rényi entropies have in common with Shannon entropy is additivity:

$$H_\beta(\rho \times r) = H_\beta(\rho) + H_\beta(r). \tag{6}$$

Interesting special cases;

- For $\beta = 0$, we obtain the max entropy , which is cardinality of the support of ρ :

$$H_0(\rho) = \log\left|\left\{i \in S \,\middle|\, \rho(i) \succ 0\right\}\right|. \tag{7}$$

- For $\beta = 1$, we recover Shannon entropy:

$$H_1(\rho) = \lim_{\beta\to 1} H_\beta(\rho)$$
$$= \frac{d}{d\beta}\left(\frac{1}{1-\beta}\log\left(\sum_i \rho(i)^\beta\right)\right)_{\beta=1} = -\sum_i \rho(i)\log\rho(i). \tag{8}$$

- For $\beta = \infty$, we obtain the min entropy:

$$H_\infty(\rho) = -\log\max_i \rho(i) = \log\min_i \frac{1}{\rho(i)}. \tag{9}$$

3. RESULTS

3.1. Descriptive Statistics

We use size and depth of Eastern Anatolian fault line and North Anatolian fault line data of stations the period 1999- 2019. Table 1 and Table 2 summarizes statistics of size and depth of Eastern Anatolian fault line and North Anatolian fault line data. In Table 1 and Table 2 shows different mean values for the for data set, and the corresponding standard deviations are different. Skewness of data set is positive, indicating that this data is skewed right. The high kurtosis of data set reveals that extreme value changes often occur when the tail of return distributions shows fatness. The Jarque-Bera (JB) test shows that the normality of each return series distribution is strongly rejected at 0.05 level, which means all price index distributions are non-normal.

Table 1. Summary Statistics for Eastern Anatolian fault line

	Adıyaman	Elazığ	K.Maraş	Malatya	Şırnak
Depth					
Mean	8,243636	16,15455	18,00909	17,65455	15,19273
Median	8,000000	8,800000	10,80000	15,00000	11,00000
Maksimum	15,35000	45,40000	64,20000	45,40000	35,00000
Minumum	2,600000	2,000000	6,900000	9,500000	5,000000
Std.Dev	3,393636	15,43421	16,86265	11,13008	10,19934
Skewness	0,344330	0,929670	2,087951	1,594602	1,348772
Kurtosis	3,165211	2,248423	6,270340	4,557203	3,287966
Jarqure Bera	0,229876	1,843424	12,89442	5,773121	3,373180
Probability	0,891421	0,397837	0,001585	0,055768	0,185150
Size					
Mean	4,500000	4,309091	4,145455	4,318182	4,300000
Median	4,300000	4,200000	4,100000	4,100000	4,100000
Maksimum	5,500000	5,100000	4,500000	5,100000	5,100000
Minumum	4,000000	4,000000	4,000000	4,000000	4,000000
Std.Dev	0,473286	0,311302	0,180907	0,345885	0,354965
Skewness	0,908170	1,601171	0,874018	1,192958	1,097454
Kurtosis	2,771923	4,845286	2,344167	3,250882	3,163643
Jarqure Bera	1,535924	6,260866	1,597635	2,637954	2,220351
Probability	0,463958	0,043699	0,449861	0,267409	0,329501

Table 2. Summary Statistics for North Anatolian fault line

	Çankırı	Düzce	Erzincan	İzmit	Sakarya
Depth					
Mean	11,04286	20,00000	27,87143	13,51429	17,64286
Median	10,00000	10,00000	22,20000	10,00000	10,00000
Maksimum	22,30000	65,60000	66,10000	22,60000	56,00000
Minumum	7,000000	10,00000	7,000000	7,000000	3,700000
Std.Dev	5,110074	20,70394	23,37404	5,863852	17,79671
Skewness	1,791256	1,828218	0,512661	0,553095	1,668841
Kurtosis	4,681279	4,624956	1,852352	1,783947	4,292637
Jarqure Bera	4,567817	4,669584	0,690778	0,788212	3,736549
Probability	0,101885	0,096831	0,707945	0,674283	0,154390
Size					
Mean	4,042857	4,685714	5,200000	4,928517	4,300000
Median	4,000000	4,300000	4,700000	4,600000	4,200000
Maksimum	4,200000	7,100000	6,600000	7,600000	4,500000
Minumum	4,000000	4,000000	4,600000	4,000000	4,100000
Std.Dev	0,078680	1,080785	0,797914	1,237894	0,163299
Skewness	1,357727	1,916392	0,822842	1,652398	0,248039
Kurtosis	3,233728	4,893136	2,175256	4,331803	1,421875
Jarqure Bera	2,166593	5,329972	0,988305	3,702817	0,798167
Probability	0,338478	0,069600	0,610088	0,157016	0,670935

3.2. Fitting marginal distributions to wind energy

Before evaluating the volatility, marginal distributions were fitted to each of the variables. For size and depth of Eastern Anatolian fault line and North Anatolian fault line data, the most popular distributions were used, namely Gamma, Log logistic, Lognormal, Weibull and Generalized Extreme distribution. The performance evaluation for the distribution fitting size and depth of Eastern Anatolian fault line and North Anatolian fault line data at all the stations was carried out using statistical ındicators as shown in Table 3, 4, 5, 6, 7, 8. All cases, the estimates were obtained using the method of maximum likelihood. In addition, we made simulation study from parameter specified in table 3, 4 of the selected distribution for the w Eastern Anatolian fault line and North Anatolian fault line data and as a result of this study, we determined the most suitable distributions for this data set, depending on the RMSE values. From Table 7, 8, North Anatolian fault line depth data of Çankırı, Erzincan time series are best Generalized Extreme Distrubution, Düzce, Sakarya time series is best Lognormal distribution and İzmit time series is best Loglogistic distribution, similarly for North Anatolian fault line size data of Düzce, Sakarya time series are best Gamma, Erzincan, İzmit time series is best Log logistic distribution and Çankırı time series is best Lognormal distribution. Eastern Anatolian fault line depth data of Adıyaman, Elazığ, Kahramanmaraş, Şırnak time series are best Log logistic, Malatya time series is best Generalized Extreme Distribution, similarly for Eastern Anatolian fault line size data of Adıyaman, Kahramanmaraş time series are best Weibull, Elazığ, Malatya time series is best Log logistic distribution and Şırnak time series is best Lognormal distribution.

Table 3. Parameters of the probability distributions fitted to North Anatolian fault line

	Gamma		**Loglogistic**		**Lognormal**		**Weibull**		**GEV**		
	α	b	μ	σ	μ	σ	α	b	k	σ	μ
DEPTH											
Çankırı	7,57479	1,45784	2,27742	0,168245	2,33433	0,36814	12,4871	2,42487	0,427318	1,89218	8,73707
Düzce	2,45774	4,19415	2,14797	0,29097	2,11591	0,639759	11,4015	1,35277	0,156383	3,90913	7,07004
Erzincan	1,93419	6,58885	2,25451	0,379494	2,26482	0,720763	13,9128	1,27492	0,307504	4,82201	7,64687
İzmit	9,68489	1,26787	2,4307	0,181619	2,45539	0,323902	13,7464	3,05386	0,171856	2,76348	10,1593
Sakarya	1,92051	6,61245	2,29203	0,428388	2,25915	0,789646	13,9859	1,37074	0,238941	5,5169	7,87354
SIZE											
Çankırı	3129,96	0,0029166	1,39304	0,00942366	1,39679	0,0192303	4,08242	47,8028	2,38264	5,66563	4
Düzce	83,1689	0,0519945	1,44107	0,0432012	1,45823	0,105041	4,58325	5,71838	4,01341	0,0116405	4,00289
Erzincan	81,3394	0,0536737	1,44677	0,0502042	1,46764	0,107711	4,61679	6,72814	1,07792	0,121789	4,07594
İzmit	42,1921	0,10705	1,46939	0,0687983	1,49588	0,149217	4,86207	4,76556	1,37876	0,143237	4,08056
Sakarya	183,669	0,0233144	1,43973	0,0363209	1,45173	0,0729423	4,44982	10,2441	0,582183	0,134767	4,10097

Table 4. Parameters of the probability distributions fitted to Eastern Anatolian fault line

	Gamma		**Loglogistic**		**Lognormal**		**Weibull**		**GEV**		
	α	b	μ	σ	μ	σ	α	b	k	σ	μ
DEPTH											
Adıyaman	5,65907	1,45671	2,0669	0,247356	2,01849	0,476894	9,26366	2,73949	-0,188324	3,04801	6,97496
Elazığ	1,65088	6,97069	2,07711	0,478011	2,11055	0,819321	12,4639	1,25279	0,561682	4,15867	5,87078
K.Maraş	2,63618	5,79964	2,45447	0,276479	2,52563	0,578575	17,0699	1,41708	0,342317	4,42132	9,97418
Malatya	1,98498	6,2627	2,32931	0,445362	2,24766	0,839527	13,7823	1,49928	0,0872541	5,98654	8,42375
Şırnak	3,44918	4,37979	2,51918	0,287828	2,56323	0,552812	17,1402	1,77906	0,288117	4,80729	10,5055
SIZE											
Adıyaman	104,671	0,0429917	1,489	0,0561534	1,49929	0,10136	4,71528	9,54297	0,460204	0,246842	4,22846
Elazığ	84,386	0,0523718	1,45991	0,0552714	1,48008	0,107696	4,6623	7,55233	0,710996	0,169153	4,13448
K.Maraş	378,498	0,0110818	1,4255	0,02857	1,43244	0,0524107	4,30703	16,6238	3,86936	0,00437798	4,00113
Malatya	148,874	0,0289895	1,44478	0,0427808	1,45892	0,0815862	4,4984	10,0946	0,708279	0,131685	4,10252
Şırnak	172,8	0,0247396	1,43847	0,042196	1,44989	0,0784177	4,44104	11,5106	5,15769	0,0472993	4,00917

Table 5. For real data performance evaluation of different probability distributions fitted to North Anatolian fault line

	Gamma	Loglogistic	Lognormal	Weibull	GEV
Size					
Çankırı $\log l$	8,46023	8,64881	8,44878	6,98007	76,1976
Düzce $\log l$	-24,7433	-14,3531	-22,5794	-40,0169	45,5824
Erzincan $\log l$	-52,3877	-41,1454	-49,529	-74,3952	-2,3876
İzmit $\log l$	-25,1436	-20,9302	-23,799	-32,2161	-7,88323
Sakarya $\log l$	-14,8403	-9,68461	-13,6445	-30,5986	6,15514
Depth					
Çankırı $\log l$	-19,3398	-18,3081	-18,7778	-20,3712	-17,2275
Düzce $\log l$	-116,636	-109,382	-113,763	-120,017	-111,411
Erzincan $\log l$	-261,34	-252,08	-254,58	-265,323	-253,024
İzmit $\log l$	-66,1498	-65,7905	-65,4283	-68,2574	-64,7098
Sakarya $\log l$	-192,481	-191,57	-192,248	-193,937	-191,672

Table 6. For real data performance evaluation of different probability distributions fitted to Eastern Anatolian fault line

	Gamma	Loglogistic	Lognormal	Weibull	GEV
Size					
Adıyaman $\log l$	-6,53852	-6,61377	-6,42073	-8,086	-4,75412
Elazığ $\log l$	-24,5984	-22,2162	-23,6406	-32,6543	-7,02298
K.Maraş $\log l$	2,09318	2,32224	2,25079	-1,5103	31,6568
Malatya $\log l$	-14,3422	-12,4789	-13,6269	-22,7693	2,28368
Şırnak $\log l$	-3,52469	-3,36359	-3,37745	-5,7428	19,7909
Depth					
Adıyaman $\log l$	-28,6021	-28,9682	-29,1667	-28,374	-28,4133
Elazığ $\log l$	-121,594	-120,438	-119,388	-122,461	-119,448
K.Maraş $\log l$	-63,4059	-59,3404	-60,6528	-65,1369	-58,8637
Malatya $\log l$	-129,446	-131,18	-132,184	-129,428	-129,841
Şırnak $\log l$	-40,9339	-40,0283	-40,1731	-41,785	-39,8114

Table 7. For simulated data performance evaluation of different probability distributions fitted to North Anatolian fault line

Depth	Gamma	Loglogistic	Lognormal	Weibull	GEV
Çankırı RMSE	8.5888	2.2123	5.8243	3.0758	1.5077
Düzce RMSE	9.6871	3.8128	8.9935	7.8908	5.4653
Erzincan RMSE	11.9596	7.0107	8.2929	9,1774	6.9818
İzmit RMSE	5.2557	3.8158	4.8141	4.2423	6.6078
SakaryaRMSE	12.5127	15.8355	8.0651	8.5803	9.8016

Size	Gamma	Loglogistic	Lognormal	Weibull	GEV
Çankırı RMSE	0.1236	0.0857	0.0792	0.1236	9.3928
Düzce RMSE	0.0648	0.3059	0.4329	0.8010	736.4667
Erzincan RMSE	0.5453	0.3049	0.4834	0.8057	0.7230
İzmit RMSE	0.8616	0.3100	0.4839	1.0933	60.3437
SakaryaRMSE	0.0622	0.5817	0.2489	0.4788	0.5055

Table 8. For simulated data performance evaluation of different probability distributions fitted to Eastern Anatolian fault line

Depth	Gamma	Loglogistic	Lognormal	Weibull	GEV
Adıyaman RMSE	5.7738	2.5850	3.3594	2.7476	3.1164
Elazığ RMSE	13.0300	6.1049	15.4311	9.2866	7.5691
K.Maraş RMSE	14.0761	5.0212	11.5263	9.7360	5.8151
Malatya RMSE	13.1147	7.7100	17.9086	8.4790	7.3752
Şırnak RMSE	14.6209	5.3859	6.2141	7.6567	7.8400

Size	Gamma	Loglogistic	Lognormal	Weibull	GEV
Adıyaman RMSE	0.5469	0.4579	0.5483	0.3780	0.7105
Elazığ RMSE	0.5195	0.3308	0.5506	0.6871	0.3720
K.Maraş RMSE	0.2804	0.1755	0.2410	0.2350	8.8344
Malatya RMSE	0.4221	0.2693	0.3898	0.4723	0.4922
Şırnak RMSE	0.4665	0.3294	0.2328	0.2937	5.6289

3.3. Entropy Approach

We use the entropy method for volatility of the depth and size of Eastern Anatolian fault line and North Anatolian fault line data. For this, we calculate to Shannon, Tsallis, Rényi and approximate entropies. In Table 9-18, firstly, we have obtained various several estimators for the Shannon entropy measure. Later, we obtained the Tsallis entropy for various several values of parameter and Rényi entropy measures for various several values of parameter. Eventually, we have calculated approximate entropy. When whole probable incidents are same probability, the entropy obtains maximum value. In our empirical results, volatility doesn't show different; this model indicates linear and nonlinear dynamics. We obtain from the numerical results that all entropies are positive so, characters of our data series are nonlinear. In the daily data series, we obtain that in North Anatolian fault line data series, for depth and size data series, Erzincan, Düzce, Sakarya, İzmit, Çankırı have great value of approximate entropy respectively. It concludes in this case that Erzincan data series is higher than volatility other data series. For the Shannon entropy estimators, it is clear that Erzincan series has larger value, similarly for the Tsallis and Rényi entropy measures, we take attention that q and r close to 1, we get the Shannon entropy value. The conduct of Erzincan, Düzce, Sakarya, İzmit, Çankırı series volatility is based on q and r. Similarly, we obtain that in Eastern Anatolian fault line data series, for depth data series, Elazığ, Kahramanmaraş, Adıyaman, Şırnak and Malatya have great value of approximate entropy respectively, and for size data series, Elazığ, Malatya, Kahramanmaraş, Şırnak and Adıyaman have great value of approximate entropy respectively. It concludes in this case that, for depth and size data, Elazığ data series is higher than volatility other data series. For the Shannon entropy estimators, it is clear that Elazığ series has larger value, similarly for the Tsallis and Rényi entropy measures, we take attention that q and r close to 1, we get the Shannon entropy value. The conduct of Elazığ, Malatya, Kahramanmaraş, Şırnak and Adıyaman series volatility is based on q and r.

Table 9. Different Entropy measures of Depth and Size of İzmit

Entropy	Shannon	Tsallis		Renyi		Approximate
Method Value	**Value**	**q**	**Value**	**r**	**Value**	
Depth						
ML	3.123662	0	23.0000000	0	3.178054	
MM	3.162684	0.2	14.5043181	0.25	3.164790	
Jefferys	3.127764	0.4	9.4101183	0.5	3.151277	
Laplace	3.131415	0.6	6.2987958	1	3.123662	
SG	3.124023	0.8	4.3595312	2	3.067478	0.1813953
Minimax	3.129387	1	3.1236616	4	2.963467	
CS	3.123907	1.2	2.3169731	8	2.828634	
Shrink	3.171758	1.4	1.7768906	16	2.720733	
		1.6	1.4056426	32	2.649561	
		1.8	1.1435213	64	2.608757	
		2	0.9534616	Infinite	2.568008	
Size						
ML	3.16483	0	23.0000000	0	3.178054	
MM	3.270919	0.2	14.6075085	0.25	3.175001	
Jefferys	3.167225	0.4	9.5195337	0.5	3.171786	
Laplace	3.169022	0.6	6.3859519	1	3.164830	
SG	3.165059	0.8	4.4213451	2	3.148564	0.4384662
Minimax	3.166947	1	3.1648302	4	3.105187	
CS	3.201647	1.2	2.3433387	8	2.988672	
Shrink	3.178054	1.4	1.7933343	16	2.833580	
		1.6	1.4157056	32	2.743406	
		1.8	1.1495933	64	2.699865	
		2	0.9570863	Infinite	2.65768	

Table 10. Different Entropy measures of Depth and Size of Sakarya

Entropy	Shannon	Tsallis		Renyi		Approximate
Method	**Value**	**q**	**Value**	**r**	**Value**	**Value**
Depth						
ML	3.350109	0	55.0000000	0	4.025352	
MM	3.397303	0.2	28.6829299	0.25	3.956132	
Jefferys	3.371641	0.4	15.7997565	0.5	3.889244	
Laplace	3.39034	0.6	9.2223345	1	3.760480	
SG	3.351356	0.8	5.7155727	2	3.521067	0.4272776
Minimax	3.37275	1	3.350109	4	3.169154	
CS	3.366881	1.2	2.6194381	8	2.873814	
Shrink	3.395068	1.4	1.9220583	16	2.708063	
		1.6	1.4759951	32	2.623467	
		1.8	1.1779271	64	2.581888	
		2	0.9704321	Infinite	2.541546	
Size						
ML	3.60417	0	55.0000000	0	4.025352	
MM	3.71667	0.2	30.0302009	0.25	4.024663	
Jefferys	3.605435	0.4	16.9744892	0.5	4.023961	
Laplace	3.606374	0.6	10.0004050	1	4.022512	
SG	3.604249	0.8	6.1792302	2	4.019427	0.5162339
Minimax	3.605077	1	3.60417	4	4.012443	
CS	3.652922	1.2	2.7631806	8	3.994817	
Shrink	3.610918	1.4	1.9995425	16	3.947774	
		1.6	1.5173355	32	3.871518	
		1.8	1.1998586	64	3.816203	
		2	0.9820367	Infinite	3.757039	

Table 11. Different Entropy measures of Depth and Size of Düzce

	Shannon	Tsallis		Renyi		Approximate Entropy
Method	**Value**	**q**	**Value**	**r**	**Value**	**Value**
Depth						
ML	3.76048	0	36.0000000	0	3.610918	
MM	3.799149	0.2	20.4304786	0.25	3.555130	
Jefferys	3.780621	0.4	12.1041608	0.5	3.494609	
Laplace	3.79832	0.6	7.5111657	1	3.350109	
SG	3.761247	0.8	4.8938114	2	2.954672	0.739165
Minimax	3.779722	1	3.76048	4	2.336804	
CS	3.778703	1.2	2.4060501	8	2.011701	
Shrink	3.819162	1.4	1.8065780	16	1.877625	
		1.6	1.4111145	32	1.817056	
		1.8	1.1402366	64	1.788214	
		2	0.9479042	Infinite	1.760273	
Size						
ML	4.022512	0	36.0000000	0	3.610918	
MM	4.13719	0.2	21.1910674	0.25	3.609370	
Jefferys	4.023065	0.4	12.8582439	0.5	3.607734	
Laplace	4.02347	0.6	8.0815507	1	3.604170	
SG	4.022535	0.8	5.2837693	2	3.595674	0.6526635
Minimax	4.022839	1	4.022512	4	3.571358	
CS	4.078511	1.2	2.5675168	8	3.486254	
Shrink	4.025352	1.4	1.9079196	16	3.321470	
		1.6	1.4743790	32	3.215564	
		1.8	1.1796931	64	3.164525	
		2	0.9725578	Infinite	3.115079	

Table 12. Different Entropy measures of Depth and Size of Erzincan

	Shannon	Tsallis		Renyi		Approximate Entropy
Method	**Value**	**q**	**Value**	**r**	**Value**	**Value**
Depth						
ML	4.019788	0	75.0000000	0	4.330733	
MM	4.058506	0.2	36.9204490	0.25	4.259023	
Jefferys	4.04162	0.4	19.2249763	0.5	4.183498	
Laplace	4.061034	0.6	10.6593211	1	4.019788	
SG	4.020398	0.8	6.3235454	2	3.670147	0.8184741
Minimax	4.03786	1	4.0197882	4	3.195393	
CS	4.032217	1.2	2.7308981	8	2.889068	
Shrink	4.065918	1.4	1.9703291	16	2.735479	
		1.6	1.4970538	32	2.656553	
		1.8	1.1871806	64	2.615292	
		2	0.9745273	Infinite	2.574441	
Size						
ML	4.324118	0	75.0000000	0	4.330733	
MM	4.437138	0.2	38.6641389	0.25	4.329166	
Jefferys	4.325369	0.4	20.7038693	0.5	4.327542	
Laplace	4.326296	0.6	11.6122229	1	4.324118	
SG	4.324156	0.8	6.8762572	2	4.316510	0.685758
Minimax	4.324767	1	4.3241178	4	4.297912	
CS	4.382174	1.2	2.8937649	8	4.247453	
Shrink	4.330733	1.4	2.0561148	16	4.141903	
		1.6	1.5418591	32	4.040794	
		1.8	1.2104958	64	3.979592	
		2	0.9866536	Infinite	3.917463	

Table 13. Different Entropy measures of Depth and Size of Çankırı

Entropy	Shannon	Tsallis		Renyi		Approximate
Method	**Value**	**q**	**Value**	**r**	**Value**	**Value**
Depth						
ML	1.869135	0	6.0000000	0	1.945910	
MM	1.907945	0.2	4.6136770	0.25	1.928456	
Jefferys	1.875266	0.4	3.5993564	0.5	1.909821	
Laplace	1.880682	0.6	2.8500541	1	1.869135	
SG	1.870967	0.8	2.2908823	2	1.777395	0.08972572
Minimax	1.883214	1	1.8691352	4	1.600047	
CS	1.869351	1.2	1.5475043	8	1.419710	
Shrink	1.918077	1.4	1.2994185	16	1.325980	
		1.6	1.1058312	32	1.283208	
		1.8	0.9529964	64	1.262839	
		2	0.8309220	Infinite	1.243107	
Size						
ML	1.945749	0	6.0000000	0	1.945910	
MM	2.051756	0.2	4.6789437	0.25	1.945870	
Jefferys	1.945783	0.4	3.6899537	0.5	1.945830	
Laplace	1.945806	0.6	2.9445563	1	1.945749	
SG	1.94576	0.8	2.3786760	2	1.945586	0.0487275
Minimax	1.945796	1	1.9457491	4	1.945251	
CS	1.970942	1.2	1.6118143	8	1.944551	
Shrink	1.94591	1.4	1.3520048	16	1.943034	
		1.6	1.1480370	32	1.939608	
		1.8	0.9864076	64	1.932336	
		2	0.8570965	Infinite	1.907777	

Table 14. Different Entropy measures of Depth and Size of Elaziğ

	Shannon	Tsallis		Renyi		Approximate Entropy
Method	**Value**	**q**	**Value**	**r**	**Value**	**Value**
Depth						
ML	3.416266	0	35.0000000	0	3.583519	
MM	3.455428	0.2	19.5856591	0.25	3.500261	
Jefferys	3.434645	0.4	11.5458120	0.5	3.417739	
Laplace	3.450529	0.6	7.1832992	1	3.416266	
SG	3.417307	0.8	4.7162571	2	3.004626	0.5910899
Minimax	3.43707	1	3.416266	4	2.708118	
CS	3.429138	1.2	2.3649952	8	2.483608	
Shrink	3.485454	1.4	1.7903026	16	2.353448	
		1.6	1.4067045	32	2.282188	
		1.8	1.1409589	64	2.246125	
		2	0.9504427	Infinite	2.211030	
Size						
ML	3.634101	0	35.0000000	0	3.583519	
MM	3.746905	0.2	20.7050945	0.25	3.582016	
Jefferys	3.634776	0.4	12.6222366	0.5	3.580475	
Laplace	3.635273	0.6	7.9670262	1	3.634101	
SG	3.634142	0.8	5.2282449	2	3.570412	0.5282481
Minimax	3.63458	1	3.634101	4	3.554791	
CS	3.682541	1.2	2.5545068	8	3.517414	
Shrink	3.637586	1.4	1.9016338	16	3.443121	
		1.6	1.4713465	32	3.363462	
		1.8	1.1782326	64	3.312936	
		2	0.9718558	Infinite	3.261244	

Table 15. Different Entropy measures of Depth and Size of Malatya

	Shannon	Tsallis		Renyi		Approximate Entropy
Method	**Value**	**q**	**Value**	**r**	**Value**	**Value**
Depth						
ML	2.323709	0	37.0000000	0	3.637586	
MM	2.354049	0.2	20.7650882	0.25	3.573532	
Jefferys	2.333575	0.4	12.2619099	0.5	3.516378	
Laplace	2.342534	0.6	7.6179647	1	2.323709	
SG	2.325422	0.8	4.9775834	2	2.321000	0.2344464
Minimax	2.344595	1	2.323709	4	2.307595	
CS	2.324383	1.2	2.4566634	8	2.269581	
Shrink	2.368452	1.4	1.8440115	16	2.298345	
		1.6	1.4380441	32	2.217851	
		1.8	1.1592065	64	2.179472	
		2	0.9610609	Infinite	2.142293	
Size						
ML	3.577278	0	37.0000000	0	3.637586	
MM	3.687272	0.2	21.6851485	0.25	3.636738	
Jefferys	3.578457	0.4	13.1027503	0.5	3.635874	
Laplace	3.57933	0.6	8.2027485	1	3.634101	
SG	3.577354	0.8	5.3439462	2	3.630364	0.3378808
Minimax	3.578142	1	3.577278	4	3.622123	
CS	3.6215	1.2	2.5824293	8	3.602810	
Shrink	3.583519	1.4	1.9153628	16	3.559403	
		1.6	1.4781008	32	3.497115	
		1.8	1.1815575	64	3.448719	
		2	0.9734935	Infinite	3.395118	

Table 16. Different Entropy measures of Depth and Size of Kahramanmaraş

	Shannon	Tsallis		Renyi		Approximate Entropy
Method	**Value**	**q**	**Value**	**r**	**Value**	**Value**
Depth						
ML	3.260807	0	17.0000000	0	2.890372	
MM	3.303049	0.2	10.9541133	0.25	2.837191	
Jefferys	3.287351	0.4	7.2892168	0.5	2.778127	
Laplace	3.310532	0.6	5.0188772	1	3.260807	
SG	3.262383	0.8	3.5789839	2	2.336337	0.4196655
Minimax	3.290559	1	3.260807	4	1.915563	
CS	3.279512	1.2	2.0171956	8	1.663118	
Shrink	3.325421	1.4	1.5881032	16	1.552528	
		1.6	1.2855003	32	1.502446	
		1.8	1.0662831	64	1.478598	
		2	0.9033189	Infinite	1.455495	
Size						
ML	2.889026	0	17.0000000	0	2.890372	
MM	3.001608	0.2	11.3693168	0.25	2.890040	
Jefferys	2.889295	0.4	7.7711923	0.5	2.889705	
Laplace	2.889491	0.6	5.4416314	1	2.889026	
SG	2.88906	0.8	3.9110998	2	2.887630	0.2046015
Minimax	2.889287	1	2.8890256	4	2.884690	
CS	2.928872	1.2	2.1942025	8	2.878225	
Shrink	2.890372	1.4	1.7126628	16	2.863410	
		1.6	1.3720532	32	2.833426	
		1.8	1.1259644	64	2.798804	
		2	0.9442919	Infinite	2.755517	

Table 17. Different Entropy measures of Depth and Size of Şirnak

Shannon		Tsallis		Renyi		Approximate Entropy
Method	**Value**	**q**	**Value**	**r**	**Value**	**Value**
Depth						
ML	2.318028	0	11.0000000	0	2.484907	
MM	2.373167	0.2	7.6530493	0.25	2.446213	
Jefferys	2.327427	0.4	5.4628373	0.5	2.406227	
Laplace	2.335212	0.6	4.0030050	1	2.318028	
SG	2.319877	0.8	3.0111345	2	2.162664	0.2827701
Minimax	2.333256	1	2.318028	4	1.938469	
CS	2.327975	1.2	1.8375239	8	1.780378	
Shrink	2.391575	1.4	1.4865704	16	1.708131	
		1.6	1.2280413	32	1.675390	
		1.8	1.0337776	64	1.659799	
		2	0.8849817	Infinite	1.644695	
Size						
ML	2.481933	0	11.0000000	0	2.484907	
MM	2.589145	0.2	7.8712145	0.25	2.484178	
Jefferys	2.482516	0.4	5.7302779	0.5	2.483439	
Laplace	2.482943	0.6	4.2500308	1	2.481933	
SG	2.482044	0.8	3.2148695	2	2.478804	0.09531018
Minimax	2.482609	1	2.4819325	4	2.472099	
CS	2.512179	1.2	1.9559949	8	2.457189	
Shrink	2.484907	1.4	1.5731736	16	2.425544	
		1.6	1.2903102	32	2.379891	
		1.8	1.0780256	64	2.345044	
		2	0.9161565	Infinite	2.308450	

Table 18. Different Entropy measures of Depth and Size of Adiyaman

	Shannon	Tsallis		Renyi		Approximate Entropy
Method	**Value**	**q**	**Value**	**r**	**Value**	**Value**
Depth						
ML	2.642531	0	10.0000000	0	2.397895	
MM	2.673418	0.2	7.1421623	0.25	2.375916	
Jefferys	2.656565	0.4	5.2151368	0.5	2.355370	
Laplace	2.669384	0.6	3.8936156	1	2.642531	
SG	2.644156	0.8	2.9718841	2	2.254606	0.3105278
Minimax	2.667448	1	2.642531	4	2.153324	
CS	2.643352	1.2	1.8462898	8	2.012277	
Shrink	2.67728	1.4	1.5001651	16	1.894395	
		1.6	1.2419278	32	1.833519	
		1.8	1.0460613	64	1.804415	
		2	0.8950851	Infinite	1.776221	
Size						
ML	2.392999	0	10.0000000	0	2.397895	
MM	2.494009	0.2	7.2553094	0.25	2.396692	
Jefferys	2.39392	0.4	5.3508093	0.5	2.395475	
Laplace	2.394603	0.6	4.0161537	1	2.392999	
SG	2.393189	0.8	3.0706743	2	2.387889	0.1053605
Minimax	2.394131	1	2.3929987	4	2.377129	
CS	2.416439	1.2	1.9011246	8	2.354427	
Shrink	2.397895	1.4	1.5393076	16	2.312860	
		1.6	1.2694005	32	2.264836	
		1.8	1.0651107	64	2.231974	
		2	0.9081767	Infinite	2.197225	

4. CONCLUSION

In this article we have considered fitted to each of the Eastern Anatolian fault line and North Anatolian fault line data marginal distributions and the entropy approach to explain for volatility of Eastern Anatolian fault line and North Anatolian fault line data. An earthquake is the shaking of the surface of the Earth, resulting from the sudden release of energy in the Earth. The analysis of the results of this study, for Eastern Anatolian fault line depth time series, Adıyaman, Elazığ, Kahramanmaraş and Şırnak are best represented Log logistic distribution, Malatya are best represented Generalized Extreme Value, and for the Eastern Anatolian fault line size time series, Elazığ, Kahramanmaraş, Malatya are best represented Log logistic, Adıyaman is best represented Weibull, Şirnak is best represented Lognormal. Smilarly, for the North Anatolian fault line depth, Düzce and İzmit are best represented Log logistic, Çankırı and Erzincan are best represented Generalized Extreme Value, Sakarya is best represented Lognormal and for the North Anatolian fault line size, Düzce and Sakarya are best represented Gamma, Erzincan and İzmit are best represented Log logistic, Çankırı is best represented Lognormal. Later, we have employed the entropy approximation to evaluate the volatile of depth and size of the Eastern Anatolian fault line and North Anatolian fault line. We employed the Tsallis, Shannon and Rényi entropy and the approximate entropy. Our results demonstrated that for depth and size of North Anatolian fault line, Erzincan is more volatile than other other stations in daily data series for the period 1990 to 2019 and for depth and size of Eastern Anatolian fault line, Elazığ is more volatile than other other stations in daily data series for the period 1990 to 2019.

REFERENCES

[1] Laidler, K.J., (1995) Thermodynamics, *In The World of Physical Chemistry, Oxford University Press, New York, NY, USA,* 156–240.

[2] Tsallis, C. (1988) Possible generalization of Boltzmann-Gibbs statistics, *Journal of Statistical Physics, 52,* 479-487. https://link.springer.com/content/pdf/10.1007%2FBF01016429.pdf

[3] Rao, M.,Chen, Y.,Vemuri, B.C., Wang, F. (2004) Cumulative residual entropy: a new measure of information , *IEEE transactions on Information Theory*, 50 6, 1220-1228. DOI: 10.1109/TIT.2004.828057

[4] Shafee, F. (2007) Lambert function and a new non-extensive form of entropy, *IMA journal of applied mathematics*, 72, 6, 785-800. https://doi.org/10.1093/imamat/hxm039

[5] Akpinar, S., Akpinar, E. K. (2006) Wind energy analysis based on maximum entropy principle (MEP)-type distribution function, *Energy Conversion and Management*, 48(4),1140-1149. https://doi.org/10.1016/j.enconman.2006.10.004.

[6] Pincus, S. (2008) Approximate entropy as an irregularity measure for financial data, *Econometric Reviews*, 27, 4-6, 329-362. https://doi.org/10.1080/07474930801959750

[7] Ubriaco, M. R. (2009) Entropies based on fractional calculus, *Physics Letters A*, 373, 30, 2516-2519. https://doi.org/10.1016/j.physleta.2009.05.026

[8] Akpinar, S., Akpinar, E. K. (2009) Estimation of wind energy potential using finite mixture distribution models, *Energy Conversion and Management*, 50, 4, 877-884. https://doi.org/10.1016/j.enconman.2009.01.007

[9] Rompolis, L. S. (2010) Retrieving risk neutral densities from European option prices based on the principle of maximum entropy, *Journal of Empirical Finance*, 17, 5, 918-937. https://doi.org/10.1016/j.jempfin.2010.04.007

[10] Moreno, B., García-Álvarez, M. T. (2011) Analyzing the effect of Renewable Energy Sources on Electricity Prices in Spain, *A Maximum Entropy Econometric Approach*. https://hrcak.srce.hr/107272

[11] Wang, G. J., Xie, C., Han, F. (2012) Multi-scale approximate entropy analysis of foreign exchange markets efficiency, *Systems Engineering Procedia*, 3, 201-208. https://doi.org/10.1016/j.sepro.2011.10.030

[12] Moreno, B., Garcia-Alvarez, M. T. (2013) The role of renewable energy sources on electricity prices in Spain. A maximum entropy econometric model, *Strojarstvo: časopis za teoriju i praksu u strojarstvu*, 55, 2, 149-159 https://hrcak.srce.hr/107272

[13] Lucia, U. (2013) Entropy and exergy in irreversible renewable energy systems, *Renewable and Sustainable Energy Reviews*, 20, 559-564. https://doi.org/10.1016/j.rser.2012.12.017

[14] Ormos, M., Zibriczky, D. (2014) Entropy-based financial asset pricing, *PloS one*, 9, 12, e115742. https://doi.org/10.1371/journal.pone.0115742

[15] Van Erven, T., Harremos, P. (2014) Rényi divergence and Kullback-Leibler divergence, *IEEE Transactions on Information Theory*, 60, 7, 3797-3820. https://10.1109/TIT.2014.2320500

[16] Azad, A. K., Rasul, M. G., Alam, M. M., Uddin, S. A., Mondal, S. K. (2014) Analysis of wind energy conversion system using Weibull distribution *Procedia Engineering*, 90,725-732 https://doi.org/10.1016/j.proeng.2014.11.803

[17] Niu, H., Wang, J. (2015) Quantifying complexity of financial short-term time series by composite multiscale entropy measure *Communications in Nonlinear Science and Numerical Simulation*, 22, 1-3, 375-382. https://doi.org/10.1016/j.cnsns.2014.08.038

[18] Dedu, S., Toma, A. (2015) An Integrated Risk Measure and Information Theory Approach for Modeling Financial Data and Solving Decision Making Problems, *Procedia Economics and Finance*, 22, 531-537. https://doi.org/10.1016/S2212-5671(15)00252-X

[19] Sati, M. M., Gupta, N. (2015) Some characterization results on dynamic cumulative residual Tsallis entropy, *Journal of Probability and Statistics*. http://dx.doi.org/10.1155/2015/694203

[20] Sheraz, M., Dedu, S., Preda, V. (2015) Entropy measures for assessing volatile markets. *Procedia Economics and Finance*, 22, 655-662. https://doi.org/10.1016/S2212-5671(15)00279-8

[21] Stosic, D., Stosic, D., Ludermir, T., Oliveira, W., Stosic, T., (2016) Foreign exchange rate entropy evolution during financial crises, *Physica A: Statistical Mechanics and its Applications*, 449,233-239. https://doi.org/10.1016/j.physa.2015.12.124

[22] Ram, S. K., Kulia, G., Molinas, M., (2016) On wind Turbine failure detection from measurements of phase currents: a permutation entropy approach, *arXiv preprint arXiv:1601.05387*. https://arxiv.org/pdf/1601.05387.pdf

[23] Shoaib, M., Siddiqui, I., Rehman, S., Rehman, S. U., Khan, S., Lashin, A. (2016) Comparison of wind energy generation using the maximum entropy principle and the Weibull distribution function. *Energies*, 9,10, 842 https://doi.org/10.3390/en9100842

[24] Ponta, L., Carbone, A. (2018) Information measure for financial time series: quantifying short-term market heterogeneity, *Physica A: Statistical Mechanics and its Applications*. https://doi.org/10.1016/j.physa.2018.06.085

[25] Khammar, A. H., Jahanshahi, S. M. A. (2018) On weighted cumulative residual Tsallis entropy and its dynamic version, *Physica A: Statistical Mechanics and its Applications*, 491, 678-692 https://doi.org/10.1016/j.physa.2017.09.079

[26] Main, I. G., Al-Kindy, F. H. (2002). Entropy, energy, and proximity to criticality in global earthquake populations, *Geophysical Research Letters*, 29, 7, 1-25. https://doi.org/10.1029/2001GL014078