ENTROPY APPROACH FOR VOLATILITY OF WIND ENERGY

by

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In this study, we give the practice of entropy in wind energy. Firstly, we fit marginal distributions to each of the variables and later demonstrate the notion of entropy to perform a comparison the wind energy data of the stations (Bursa, Elazig, Istanbul, Mugla, Rize, Tokat, Van, and Zonguldak) that have been examined in a period 2015-2018. The results of probability distribution fitting to these wind energy variables show that the wind energy time series of Bursa, Elazıg, Istanbul, Mugla, Rize, Tokat, Van, and Zonguldak are best resubmitted by Gamma Burr and Lognormal distributions. Later, we calculate Shannon entropy for several various values, Tsallis entropy, Renyi entropy, and the approximate entropy. We form calculation outcomes with these entropies for daily data.

Key words: Shannon entropy, Tsallis entropy, approximate entropy, wind energy, Renyi entropy

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, Laidler [1]. Tsallis [2] suggested a widening for the entropy, which characterizes the statistical properties of complicated structure. Rao *et al.* [3] determined the cumulative residual entropy, generalized measure of indefiniteness which applied in credibility and image placement and non-additive measures of entropy. Shaffe [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 Renyi 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. Akpinar and Akpinar [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). Pincus [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 based, drafted cross

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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 non-linear measures, correlation and spectral analyses, and different entropy measures. Ubriaco [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. Akpinar and Akpinar [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 maximum entropy principle and calculated the parameters of the distributions which were estimated using the least squares method and STATISTICA software. Rompolis [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. Moreno and Garcia-Alvarez [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. Hodge *et al*. [11] investigated the parameters associated with the computation of the Renyi entropy in order to further the comprehension of its practice to assessing wind energy estimating errors. Wang *et al*. [12] defined the market performance in foreign exchange (FX) markets by using the multi-scale approximate entropy (MApEn) to assess the randomness in FX market, allocated 17 daily FX rates in the periods 1984-2011, Southeast Asia currency crisis and American sub-prime crisis and submitted that the developed FX markets was more efficient than emerging FX markets, and that the financial crisis promotes the market efficiency in FX markets significantly, especially in emerging markets, like China, Hong Kong, Korea, and African market. Moreno and Garcia-Alvarez [13] 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. Lucia [14] 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. Ormos and Zibriczky [15] 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. Van Erven and Harremos [16] considered the best significant features of Renyi 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. Azad *et al*. [17] investigated the wind speed data had been statistically examined usage Weibull distribution 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. Niu and Jang [18] 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. Dedu and Toma [19] obtained some integrated methods for modelling 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. Sati and Gupta [20] described a generalized cumulative remaining entropy based on the non-additive Tsallis entropy. Sheraz [21] used entropy approach for volatility markets. Stosic *et al*. [22] 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. Ram *et al.*, [23] 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 permutation entropy analysis to compare the complication index of stage flows of the two turbines over time. Shoaib *et al.*, [24] submitted focuses on detecting the fitness and accuracy of the fitted distribution function 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. Ponta and Carbone [25] 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. Khammar and Jahanshahi [26] 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. In this study, the method of analytical determination of wind energy distributions, and based on entropy approach was used for regions (Bursa, Elazıg, Istanbul, Mugla, Rize, Tokat, Van and Zonguldak) over a period of 3 years.

Material and method

The Shannon entropy

The Shannon entropy of probability measure p on finite set X is given:

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

where $p_i \geq 0$, $i = 1, 2..., n$, $\sum_{i=1}^{n}, p_i = 1$, and $0\ln0 = 0$. Given a continuous probability distribution with a density function $f(x)$, we can define the Shannon entropy:

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

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

$$|T| \leq \mathrm{e}^{n[H(\rho)+\varepsilon]} \tag{3}$$

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

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:

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

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.

Renyi entropy

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

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

– The scaling factor is conventional:

It makes H_β non-negative 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 Renyi 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:

$$H_0(\rho) = \log|\{i\in S \mid \rho(i) \succ 0\}| \tag{7}$$

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:

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

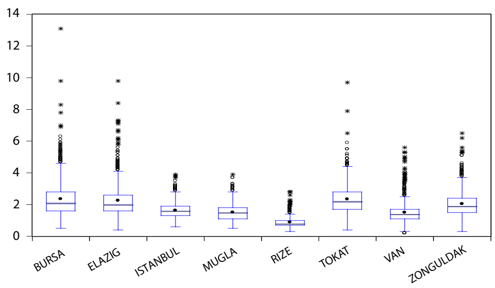

Figure 1. Box plot of change of Adana, Bitlis, Bursa, Elazıg, Igdır, Istanbul, MuGla, Rize, Sırnak, Tokat, Van, and Zonguldak wind energy data series

Results

Descriptive statistics

We use the daily wind energy data of Bursa, Elazıg, Istanbul, Mugla, Rize, Tokat, Van, and Zonguldak stations which receive from general directory of meteorology of Elazıg for the period 2015-2018. Table 1 summarizes statistics of Bursa, Elazıg, Istanbul, Mugla, Rize, Tokat, Van, and Zonguldak data. Table 1 shows different mean values for data set, and also the corresponding standard deviations are different. Skewness of data set is positive, that is, this data is skewed right. The high kurtosis of data set reveals that extreme value changes often occur when the tail of return distributions show fatness. The Jarque-Bera (JB) test denotes that the normality of each return series distribution is strongly rejected at 0.05 level, which means all price index distributions are non-normal. Graphical representations of the data employed are shown in figs. 1 and 2.

Table 1. Summary statistics

	Bursa	Elazıg	Istanbul	Mugla	Rize	Tokat	Van	Zonguldak
Mean	2,353	2,256	1,633	1,507	0,885	2,341	1,498	2,044
Median	2,100	2,000	1,600	1,500	0,800	2,200	1,400	1,900
Maksimum	13,10	9,800	3,900	3,900	2,800	9,700	5,600	6,500
Minumum	0,500	0,400	0,600	0,500	0,300	0,400	0,200	0,300
Std. Dev	1,153	0,989	0,469	0,511	0,329	0,8858	0,684	0,757
Skewness	2,066	2,046	1,101	0,681	1,568	1,5075	1,798	1,358
Kurtosis	12,47	10,38	4,870	3,826	7,559	9,005	9,084	6,339
Jarqure Bera	4990,8	3331,683	357,12	118,72	1430,5	2109,1	2333	865,7
Probability	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000

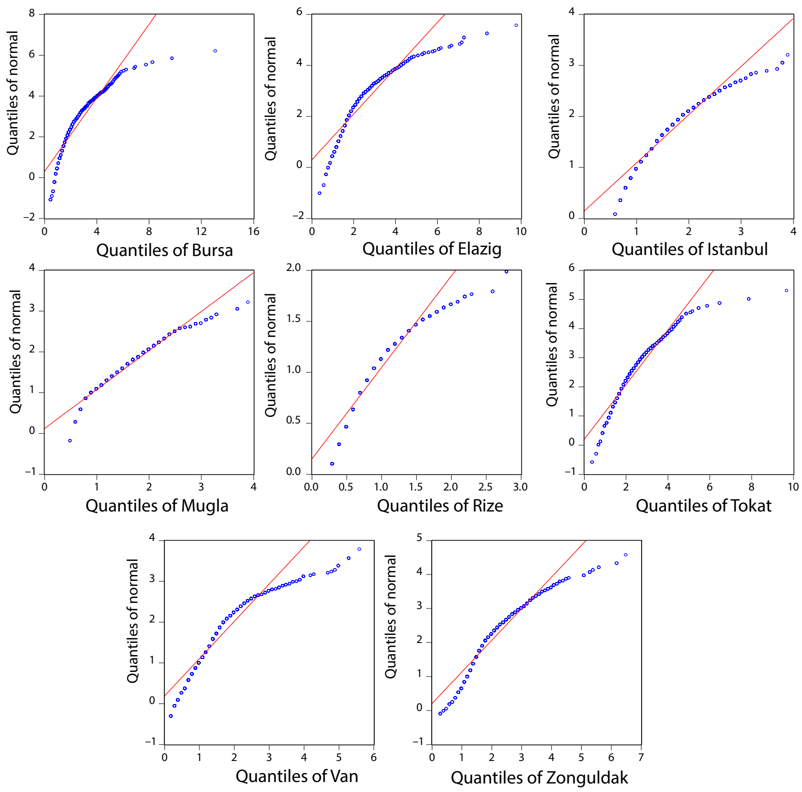

Figure 2. Quantile plot of change for wind energy data series of Adana, Bursa, Elazıg, Istanbul, Mugla, Rize, Tokat, Van, and Zonguldak

Fitting marginal distributions to wind energy

Now, marginal distributions are fitted to each of the variables. For wind energy of Bursa, Elazıg, Istanbul, Mugla, Rize, Tokat, Van, and Zonguldak, we use the most popular distributions, namely Burr, Gamma, Log logistic, Lognormal and Weibull distribution. The performance estimation for the distribution fitting of wind energy at all the stations is carried out using cumulative distribution function plots and statistical ındicators as shown in fig. 3, tabs. 2-4. Here, we attain the estimates using the method of maximum likelihood. In addition, we make simulation study from parameter specified in tab. 2 of the selected distribution for the wind energy and as a result of this study, we determine the most suitable distributions for this data set, depending on the RMSE values. From tab. 2, wind energy of Bursa, Tokat, Van and Zonguldak time series are best Gamma distribution; wind energy of Elazıg, Istanbul, and Rize time series are best Lognormal distribution and wind energy of Mugla time series are best Burr distribution.

Table 2. Parameters of the probability distributions fitted to wind energy

	Burr			Gamma		Log logistic		Lognormal		Weibull	
	α	c	k	a	b	μ	σ	μ	σ	a	b
Bursa	1.899	4.459	0.755	5.147	0.456	0.744	0.350	0.754	0.440	2.661	2.142
Elazıg	1.797	5.652	0.635	6.522	0.346	0.0001241	2.052	0.735	0.387	2.546	2.344
Istanbul	1.559	6.3960	0.977	12.96	0.125	0.449	0.157	0.451	0.278	1.806	3.507
Mugla	1.893	4.079	2.303	8.762	0.171	0.363	0.200	0.351	0.346	1.683	3.110
Rize	0.792	5.451	0.859	8.283	0.106	–0.188	0.194	–0,184	0.347	0.991	2.716
Tokat	2.242	4.796	1.074	7.764	0.301	0.785	0.204	0.784	0.363	2.625	2.684
Van	1.557	3.790	1.382	5.352	0.279	0.324	0.239	0.307	0.451	1.690	2.264
Zonguldak	1.810	5.444	0.832	8.031	0.254	0.646	0.197	0.651	0.359	2.292	2.755

Table 3. For real data performance evaluation of different probability distributions fitted to wind energy

	Burr	Gamma	Log logistic	Lognormal	Weibull
Bursa, log*l*	–1524.01	–1556.01	–1536.7	–1519.36	–1652.4
Elazıg, log*l*	–1332.83	–1392.44	–1341.69	–1352.12	–1513.76
Istanbul, log*l*	–667.977	–675,121	–667.995	–664.034	–772.054
Mugla, log*l*	–800.852	–790,616	–816.345	–796.147	–833.045
Rize, log*l*	–193.429	–221.939	–194.338	–199.785	–330.726
Tokat, log*l*	–1335.3	–1346.93	–1335.47	–1337.27	–1437.92
Van, log*l*	–996.111	–1030.94	–1001	–1043.49	–1101.81
Zonguldak, log*l*	–1150.54	–1177.54	–1151.73	–1174.36	–1265.89

Table 4. For simulated data performance evaluation of different probability distributions fitted to wind energy

	Burr	Gamma	Log logistic	Lognormal	Weibull
Bursa RMSE	1.3932	1.0352	1,2330	1.0820	1.1750
Elazig RMSE	1.1194	0.8936	1.8410	0.8917	1.0153
Istanbul RMSE	0.5254	0.4444	0.4721	0.4306	0.5021
Mugla RMSE	0.4844	0.5187	0.5362	0.5434	0.5184
Rize RMSE	0.3448	0.3191	0.3370	0.3050	0.3592
Tokat RMSE	0.9182	0.8548	0.9507	0.8864	0.9290
Van RMSE	0.6660	0.6169	0.7396	0.6878	0.6920
Zonguldak RMSE	0.7980	0.7111	0.7546	0.7367	0.8210

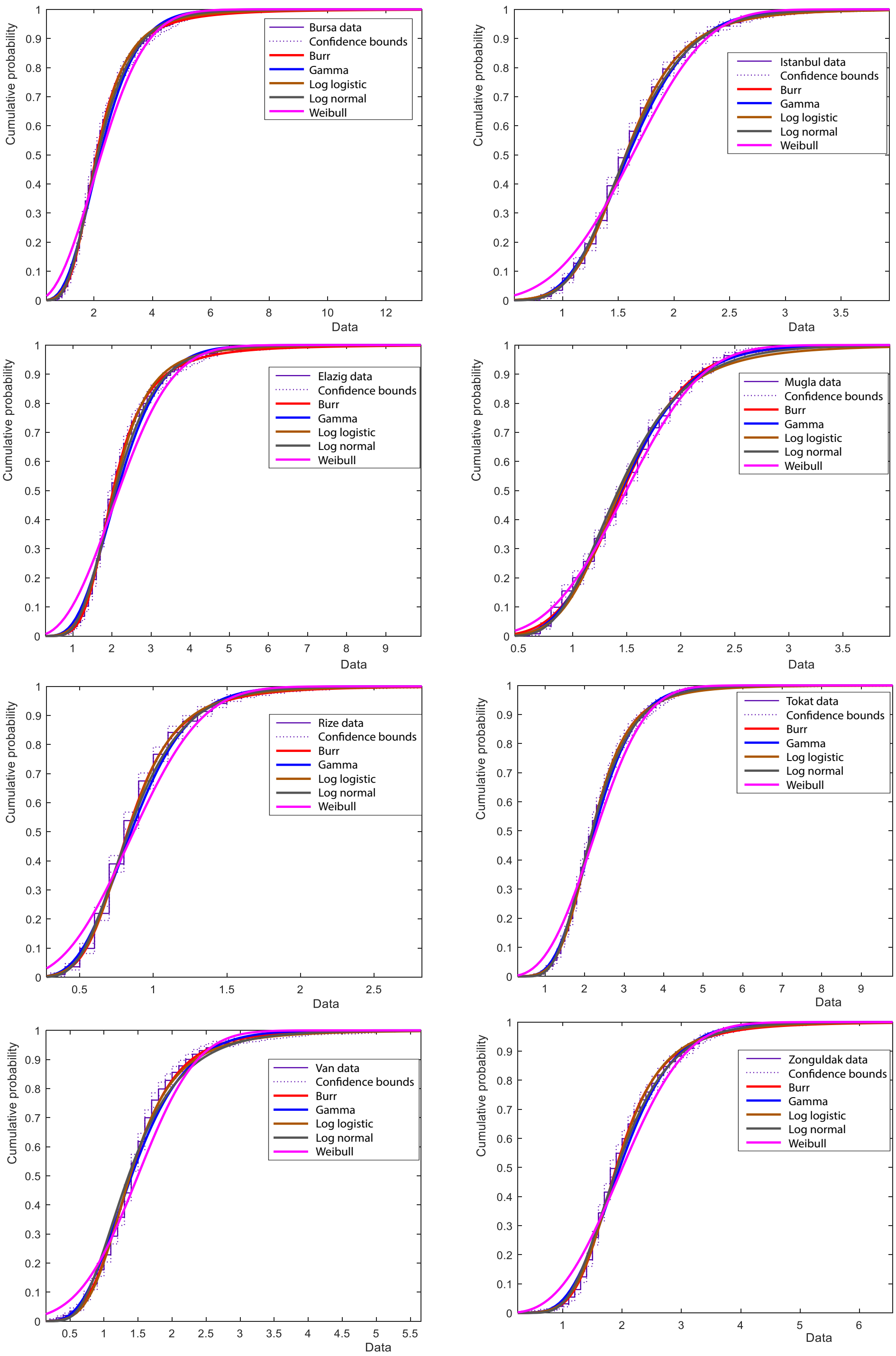

Figure 3. Cumulative distribution function of Burr, Gamma, Log logistic, Lognormal, and Weibull distributions fitted to wind energy

Entropy approach

We use the entropy method for volatility of the wind energy of Bursa, Elazıg, Istanbul, Mugla, Rize, Tokat, Van, and Zonguldak. For this, we calculate to the entropies of Shannon-, Tsallis, Rényi and approximate. In tabs. 5-12, firstly, we have obtained several various estimators for the Shannon entropy. Later, we attain the Tsallis entropy for various several values of parameter and Renyi entropy measures for several various values of parameter. Eventually, we have calculated approximate entropy. When the whole probable incidents are same probability, the entropy takes maximum value. In our empirical results, volatility does not show differentness; this model indicates linear and non-linear dynamics. From the results, we obtain that entropies are positive so, characters of our data series are non-linear. In the daily data series, we obtain that Tokat, Zonguldak, Rize, Mugla, Elazıg, Bursa, Istanbul, and Van series has great value of approximate entropy, respectively. It concludes in this case that Tokat data series are higher volatility than other data series. For the Shannon entropy estimators, it is clear that Tokat series have larger value. Similarly for the Tsallis and Renyi, if α and β close to 1, we get the value of Shannon entropy. Volatility for Tokat, Zonguldak, Rize, Mugla, Elazıg, Bursa, Istanbul, and Van series is conditioned by α and β.

Table 5. Different measures of wind energy of Bursa

Shannon		Tsallis		Renyi		Approximate entropy
Method		α		β		
ML	6.954647	0	1120.0000000	0	7.021976	
MM	7.24824	0.2	338.8670010	0.25	7.004193	1.50267
Jefferys	6.982708	0.4	109.0709907	0.5	6.987160	
Laplace	6.996261	0.6	38.2924034	1	6.954647	
SG	6.954724	0.8	15.1444296	2	6.893237	
Minimax	6.957835	1	6.9546466	4	6.777054	
CS	8.546349	1.2	3.7526438	8	6.568408	
Shrink	7.022868	1.4	2.3436360	16	6.311575	
		1.6	1.6404040	32	6.133102	
		1.8	1.2450137	64	6.038328	
		2	0.9989854	∞	5.944058	

Table 6. Different measures of wind energy of Elazıg

Shannon		Tsallis		Renyi		Approximate entropy
Method		α		β		
ML	6.956969	0	1121.0000000	0	7.022868	
MM	7.170355	0.2	339.4219177	0.25	7.006435	1.510556
Jefferys	6.978	0.4	109.2491176	0.5	6.989999	
Laplace	6.990273	0.6	38.3397891	1	6.956969	
SG	6.957019	0.8	15.1555918	2	6.889192	
Minimax	6.959463	1	6.9569690	4	6.735413	
CS	7.805384	1.2	3.7530396	8	6.350171	
Shrink	7.022868	1.4	2.3436722	16	5.972166	
		1.6	1.6403931	32	5.782001	
		1.8	1.2450048	64	5.690268	
		2	0.9989813	∞	5.601358	

Table 7. Different measures of wind energy of Istanbul

Shannon		Tsallis		Renyi		Approximate entropy
Method		α		β		
ML	6.919184	0	1121.0000000	0	7.022868	
MM	7.131607	0,2	337.5101501	0,25	6.997599	1.349244
Jefferys	6.951732	0,4	108.2989577	0,5	6.971909	
Laplace	6.970873	0,6	37.9835230	1	6.919184	
SG	6.919261	0,8	15.0361331	2	6.807588	
Minimax	6.923039	1	6.9191840	4	6.549772	
CS	7.813447	1,2	3.7414930	8	6.037212	
Shrink	7.022868	1,4	2.3402191	16	5.658377	
		1,6	1.6393746	32	5.476530	
		1,8	1.2447070	64	5.389604	
		2	0.9988946	∞	5.305392	

Table 8. Different measures of wind energy of Mugla

Shannon		Tsallis		Renyi		Approximate entropy
Method		α		β		
ML	6.959424	0	1121.0000000	0	7.022868	
MM	7.203789	0.2	339.5497412	0,25	7.007026	1.525615
Jefferys	6.981774	0.4	109.3133127	0,5	6.991214	
Laplace	6.994002	0.6	38.3637567	1	6.959424	
SG	6.959479	0.8	15.1635140	2	6.894239	
Minimax	6.961992	1	6.9594236	4	6.757099	
CS	8.113825	1.2	3.7537722	8	6.498266	
Shrink	7.022868	1.4	2.3438862	16	6.219607	
		1.6	1.6404549	32	6.048530	
		1.8	1.2450226	64	5.958478	
		2	0.9989864	∞	5.866119	

Table 9. Different measures of wind energy of Rize

Shannon		Tsallis		Renyi		Approximate entropy
Method		α		β		
ML	6.966558	0	1121.0000000	0	7.022868	
MM	7.298058	0.2	339.8550865	0.25	7.008441	1.543045
Jefferys	6.991268	0.4	109.4701356	0.5	6.994242	
Laplace	7.00261	0.6	38.4250388	1	6.966558	
SG	6.966626	0.8	15.1850272	2	6.914045	
Minimax	6.96924	1	6.9665583	4	6.818394	
CS	8.971675	1.2	3.7560562	8	6.648995	
Shrink	7.022868	1.4	2.3445998	16	6.421101	
		1.6	1.6406739	32	6.257288	
		1.8	1.2450889	64	6.167304	
		2	0.9990063	∞	6.071981	

Table 10. Different entropy measures of wind energy of Tokat

Shannon		Tsallis		Renyi		Approximate entropy
Method		α		β		
ML	6.98351	0	1121.000000	0	7.022868	
MM	7.289477	0,2	340.876730	0,25	7.013088	
Jefferys	6.999707	0,4	109.958582	0.5	7.003271	1.582739
Laplace	7.007598	0,6	38.600650	1	6.983510	
SG	6.983553	0.8	15.241301	2	6.943399	
Minimax	6.985279	1	6.983510	4	6.860746	
CS	8.669994	1.2	3.760972	8	6.697245	
Shrink	7.022868	1.4	2.345990	16	6.479793	
		1.6	1.641060	32	6.326607	
		1.8	1.245195	64	6.244278	
		2	0.999035	∞	6.152132	

Table 11. Different measures of wind energy of Van

Shannon		Tsallis		Renyi		Approximate entropy
Method		α		β		
ML	6.913045	0	1120.0000000	0	7.021976	
MM	7.086855	0.2	336.7635467	0.25	6.994455	1.323248
Jefferys	6.943257	0.4	108.0262519	0.5	6.967231	
Laplace	6.962255	0.6	37.9005605	1	6.913045	
SG	6.913116	0.8	15.0129616	2	6.804623	
Minimax	6.916888	1	6.9130449	4	6.599782	
CS	7.493113	1.2	3.7399328	8	6.322431	
Shrink	7.022868	1.4	2.3398390	16	6.095550	
		1.6	1.6392869	32	5.950578	
		1.8	1.2446885	64	5.865924	
		2	0.9988914	∞	5.775141	

Table 12. Different measures of wind Energy of Zonguldak

Shannon		Tsallis		Renyi		Approximate entropy
Method		α		β		
ML	6.980583	0	1121.0000000	0	7.022868	
MM	7.305888	0.2	340.7512071	0.25	7.012506	1.549878
Jefferys	6.998585	0.4	109.8933998	0.5	7.002017	
Laplace	7.007087	0.6	38.5751537	1	6.980583	
SG	6.980631	0.8	15.2323977	2	6.935311	
Minimax	6.982524	1	6.9805829	4	6.830564	
CS	8.8486	1.2	3.7600442	8	6.585156	
Shrink	7.022868	1.4	2.3457025	16	6.309732	
		1.6	1.6409726	32	6.154293	
		1.8	1.2451685	64	6.075327	
		2	0.9990272	∞	5.993207	

Conclusion

In this article we have considered fitting to each of marginal distributions for the wind energy variables and the entropy approach to explain volatility of wind energy. The wind is a clean, free, and readily available RES, around the world. Wind turbines are capturing the wind energy and converting it to electricity and so wind energy is a rising star in the world. In our study shows that the wind energy time series of Bursa, Tokat, Van, and Zonguldak are best represented by Gamma distribution. The wind energy time series of Elazıg, Istanbul, and Rize are best represented by Lognormal and the wind energy time series of Mugla is best represented by Burr distribution. Later, we have employed the entropy approximation evaluate the volatility of the wind energy. We employed the Tsallis, Shannon, Renyi, and the approximate entropy. Our results demonstrate that Tokat for the period 2015-2018 is more volatile than other stations in daily data series.

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