2021 7th International Conference on Signal Processing and Intelligent Systems (ICSPIS), Tehran, Iran

Wind Energy Potential Approximation with Various Metaheuristic Optimization Techniques Deployment

Mohammed Wadi
Electrical & Electronics Engineering Department
Istanbul Sabahattin Zaim University
Istanbul, Turkey
mohammed.wadi@izu.edu.tr

Wisam Elmasry
Electrical & Electronics Engineering Department
Istanbul Sabahattin Zaim University
Istanbul, Turkey
wisam.elmasry@izu.edu.tr

Abdulfetah Shobole
Electrical & Electronics Engineering Department
Istanbul Sabahattin Zaim University
Istanbul, Turkey
Abdulfetah.shobole@izu.edu.tr

Mehmet Rida Tur
Electrical & Energy Department
Batman University
Batman, Turkey
mrida.tur@batman.edu.tr

Ramazan Bayindir
Electrical & Electronics Engineering Department
Gazi University
Ankara, Turkey
bayindir@gazi.edu.tr

Hossein Shahinzadeh
Department of Electrical Engineering
Amirkabir University of Technology
Tehran, Iran
h.s.shahinzadeh@ieee.org

2021 7th International Conference on Signal Processing and Intelligent Systems (ICSPIS) | 978-1-6654-0938-4/21/$31.00 ©2021 IEEE | DOI: 10.1109/ICSPIS54653.2021.9729389

***Abstract*—This paper presents a comprehensive empirical study of five different distribution functions to analysis the wind energy potential, namely, Rayleigh, Gamma, Extreme Value, Logistic, and T Location-Scale. In addition, three metaheuristics optimization methods, Grey Wolf Optimization, Marine Predators Algorithm, and Multi-Verse Optimizer are utilized to determine the optimal parameter values of each distribution. To test the accuracy of the introduced distributions and optimization methods, five error measures are investigated and compared such as mean absolute error, root mean square error, regression coefficient, correlation coefficient, and net fitness. To conduct this analysis, the Catalca site in the Marmara region in Istanbul, Republic of Turkey is selected to be the case study. The experimental results confirm that all introduced distributions based on optimization methods are efficient to model wind speed distribution in the selected site. Rayleigh distribution achieved the best matching while Extreme Value distribution provided the worst matching. Finally, many valuable observations drawn from this study are also discussed. MATLAB 2020b and Excel 365 were used to perform this study.**

Keywords— ***Wind Energy Approximation, Probability Distribution Function (PDF), Cumulative Distribution Function (CDF), Inverse CDF (ICDF), GWO, MPA, MVO.***

I. INTRODUCTION

Wind potential approximation is crucial for many causes like planning wind farms, feasibility analyses, turbine design, and long-term investment decisions. Approximation wind potential primarily relies on the wind speed distribution. Wind speed distribution for a specific location shows the available wind potential. Once the wind pattern is created, the wind potential can easily be determined. Thus, wind regime description via distribution functions is a significant step. During the two last decades, many Probability Density Functions (PDFs) were employed to describe wind speed patterns like Weibull [1,2], Rayleigh [3], Gamma [4], Normal [5], Lognormal [6], Logistical [7], Beta [8], Nakagami [9], Burr [10] distribution functions, and others. However, Rayleigh, Gamma, and Weibull distributions are the most widely used among these functions [11,12,13]. The Weibull distribution was introduced to analyze the features of wind data for three datasets at Catalca, Turkey [12]. Three assessment methods for Weibull parameters: approximation, graphical, and Energy Pattern Factor (EPF) methods, were examined and compared. Wind speed data for two-year in Pakistan at four different hub heights were utilized to assess the wind potential based on Weibull distribution [13]. The parameters were modeled based on three optimization algorithms; Grey Wolf Optimization (GWO), Particle Swarm Optimization (PSO), and Cuckoo Search Optimization (CSO). Besides, four numerical methods, like EPF, Method of Moments (MOM), Empirical Method of Justus (EMJ), and Modified Maximum Likelihood (MML) estimation methods, were employed. Six estimation methods, namely Mean Standard Deviation (MSD), least-squares (LS), Method of Moment (MOM), EPF, Power Density (PD), and Genetic Algorithm (GA), to model the wind speed distribution [14]. Five error criteria were employed to estimate these distributions' Goodness-Of-Fitting (GOF). The obtained results revealed that GA exceeded the other assessment methods while EPF provided the worst matching.

Four assessment methods to evaluate Weibull distribution parameters, like graphical, empirical, EPF, and MML, then to assess the capacity factor of wind turbines were introduced in [15]. MML technique achieved the best matching while the graphical method provided the most insufficient matching. The airport site's wind speed in Dolny Hricov was approximated in Lognormal, Gamma, and Weibull [16]. ML assessment approach was applied to select the parameters of these distributions. The 3-parameter Weibull and the 2-parameter Weibull achieved the best first and second fitting, respectively.

In some cases, due to the variability of wind speed patterns, some distributions fail to achieve a satisfactory matching. In other cases, the computations complexity of parameters of some distributions forces to employ others. Thus, considerable researchers suggested different distributions, such as Birnbaum Saunders [17,18]. Mohammadi et al. [18] introduced the Birnbaum Saunders distribution to approximate the wind shape at ten different locations over Ontario, Canada. The GOF of the 2-parameter Birnbaum Saunders distribution was compared with other nine one-component distributions, and the Birnbaum Saunders distribution surpassed all the other distributions.

Many studies using Burr and inverse Burr distributions have appeared in the literature [10,19,20,21]. Burr distribution to represent wind frequency data in Antakya, Turkey, was introduced [10]. From the GOF view, the Burr distribution accomplished fitting more than the Weibull and Gamma distributions. The inverse Burr distribution with two-parameter to estimate the wind speed extreme values was introduced in [20]. Three estimation techniques: moment, ML, and quantile, were used. The inverse Burr distribution accomplished the most proper matching.

Due to the unsteady and stochastic nature of wind speed, different distribution functions must be used on the location. Thus, this paper suggests a comprehensive study to compare the performance of five distributions, namely, Rayleigh, Gamma, Extreme Value, Logistic, and T Location-Scale. Three optimization estimation methods: Grey Wolf Optimization (GWO), Marine Predators Algorithm (MPA), and Multi-Verse Optimizer (MVO), were employed to assess the most suitable parameter values of each distribution. To test these methods, five error measures like Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Regression Coefficient (R^2), Correlation Coefficient (R), and net fitness were employed. Wind data for two years (2019 and 2020) belonging to the Marmara area (Catalca) were used to carry out this analysis.

The remainder of this study is organized into six sections: Section II presents the methodology of selecting the optimal parameters of the distributions using GWO, MPA, and MVO. Section III illustrates the accuracy criteria employed to examine each distribution's performance. Besides, Section IV gives the results. Finally, Section V illustrates the conclusion.

II. Materials and Methodology

Evolutionary Algorithms (EAs) are prevalent in considerable research areas. This is owed to their simplicity, flexibility, and capability to bypass local optima. On the other hand, EAs may suffer from weaknesses like long computation time, no guarantee to converge, and several operating parameters to be adjusted before starting [21]. In order to overcome the limitations described above, three intelligence algorithms, namely, GWO, MPA, and MVO, are employed. In this section, these algorithms are presented shortly. Then, how the metaheuristics mentioned above are exploited to determine the optimal parameters of the presented distributions is justified.

A. Grey Wolf Optimization

GWO algorithm emulates the trapping mechanism of grey wolves in reality. The trapping mechanism consists of three primary stages: seeking prey, surrounding prey, and attacking prey [22]. The GWO method consists of three primary stages: firstly, all grey wolves (search agents) in the pack (population) are initialized randomly in [LB, UB], where LB and UB are the lower and upper limits of the problem variables, respectively. Later, the fitness score for each search agent is assessed utilizing the objective function. So far, the fittest solution is supposed to be alpha accompanied by beta and delta, respectively. Meanwhile, the rest of the wolves is arranged under the omega. The GWO optimization is carried out by alpha, beta, and delta, whereas omega follows them. Then, search agents renew their positions relying on the prey position.

B. Marine Predators Algorithm

MPA simulates the food foraging tactics of marine predators [23]. Mainly, marine predators rely on Levy and Brownian movement and the effects of vortex generation or Fish Aggregating Devices (FADs) [24] when searching for prey in the deep ocean. In other words, MPA balances both the optimal foraging strategy and encounters rate policy between prey and predator in marine ecosystems.

The optimization by MPA can be summarized as follows. Firstly, all marine predators (search agents) in the Prey matrix (population) are initialized randomly in [LB, UB]. The size of the Prey matrix is NxM, where N is the population size, and M is the dimension of the problem variables, respectively. Later, the fitness score for each search agent is estimated employing the objective function, and the top predator is determined. The best predator vector is reproduced N times to construct the Elite matrix. Then, the optimization method of MPA consists of three main stages: the first stage occurs when the prey is moving quicker than the predator in which the most suitable plan for the predator to stay without moving. This stage happens in the first iterations, where the exploration process matters.

The second stage occurs when both predator and prey move at nearly the same speed. This stage happens when the exploration process begins to convert to exploitation. That is, the predator is responsible for exploration, whereas the prey for exploitation. Accordingly, the predator moves in Brownian while prey moves in Levy motion.

The third stage occurs when the predator moves faster than the prey. This stage happens when only the exploitation process matters. Thus, the best maneuvering for a predator is the Levy motion.

C. Multi-Verse Optimizer

MVO simulates three concepts in cosmology, white, black, and wormholes [25]. Indeed, white holes/black holes and wormholes are modeled to achieve exploration and exploitation operations in the space of the problem. The operation of MVO can be illustrated as follows: firstly, all universes (search agents) in the U matrix (population) are initialized randomly in [LB, UB]. The size of the U matrix is NxM, where N is the population size and M is the dimension of the problem variables, respectively. Later, the fitness score (inflation rate) for per search agent is assessed utilizing the objective function, and the U matrix is sorted in descending order. The best solution is updated if the fitness score of the first universe in the sorted U is better than the fitness score of the current best solution. Then, MVO allows moving objects from one universe with a higher inflation rate to another with a lower inflation rate. In this case, the universe with a high inflation rate indicates a white hole, whereas the universe with less inflation rate describes a black hole. Consequently, a tunnel between the two universes will be designated to exchange objects from white holes to black holes. Mathematically, to model white/black hole tunnels and the motion of objects through them, a roulette wheel is employed to determine one of the universes from the sorted U matrix. The selected universe by the roulette wheel is considered to have a white hole.

Table I outlines all the used distributions, the name, and notation of their parameters.

D. Methodology

The parameter selection of a distribution can be represented as a non-linear optimization problem that minimizes the mean absolute error between the real and predicted wind speed vectors as shown in Equation (1).

$$min\{MAE(V_m, V_d)\} \tag{1}$$

where V_m and V_d are the vectors of measured and predicted wind speed vectors, respectively. Equally important,

V_d can be obtained artificially by using the ICDF of the distribution.

To solve the optimization problem mentioned above, EAs can perform well these problems [25,26,27,28]. In GWO, MPA, and MVO, a population of search agents indicates candidate solutions to the problem. Regarding the parameter selection problem of the distribution, each search agent consists of integer values representing the values of the parameters of a particular distribution. The first population of search agents is generated randomly within defined LB and UB parameters.

Then, the fitness score of each search agent is estimated using Equation (1). Afterward, the population increases by searching for the top solution using the specified operation of the used EA. It continues in the same manner until the condition of the number of maximum iterations is attained.

Table II presents the operation parameter values of GWO, MPA, and MVO.

TABLE I. ALL USED DISTRIBUTIONS AND THEIR PARAMETERS

Distribution	Number, (Name) of parameters
Rayleigh	1, (Defining parameter)
Gamma	2, (Shape, Scale)
Extreme Value	2, (Location, Scale)
Logistic	2, (Mean, Scale)
T Location-Scale	3, (Location, Scale, Shape)

TABLE II. THE OPERATING PARAMETERS OF GWO, MPA, AND MVO

Parameter	Domain	Parameter Value
Population size	[5, 50]	50
Maximum number of iterations	[50, 300]	100 for RD, 200 for GD, 300 for EVD, LD, and TLSD distributions
Stopping threshold	[$1x10^{-4}$, $1x10^{-6}$]	$1x10^{-6}$

Table III presents the resulting parameter values of the used distributions based on the employed optimization algorithms. Notably, GWO, MPA, and MVO selected almost the same parameter values in most cases.

III. ACCURACY TESTS

Many statistical tests were used to discover the method with the best GOF. Five error measures were applied in this paper for each distribution and estimation method presented in this study as given below:

- **MAE** is the mean between the real (x) and the predicted (y) wind speed vectors as follows [29]:

$$MAE = \frac{\sum_{i=1}^{N} |y_i - x_i|}{N} \quad (2)$$

where N is the vector length.

- **RMSE** is the square root of the average of the differences between the predicted and real wind speeds [30]. It is defined as follows:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N} (y_i - x_i)^2}{N}} \quad (3)$$

- **Regression Coefficient** manifests the degree of linearity between the predicted wind speeds from the particular distribution and the real data. It can be defined as follows:

$$R^2 = \frac{\sum_{i=1}^{N} (x_i - z_i)^2 - \sum_{i=1}^{N} (x_i - y_i)^2}{\sum_{i=1}^{N} (x_i - z_i)^2} \quad (4)$$

where z_i is the i^{th} real mean wind speed.

- **Correlation Coefficient** reveals the degree of correlation between two datasets. Its values are between -1 and 1. The correlation coefficient is given below:

$$R = \frac{1}{N-1} \sum_{i}^{N} \frac{(x_i - \overline{x})(y_i - \overline{y})}{\sigma_x \sigma_v} \quad (5)$$

where ($\bar{x}$, $\bar{y}$) and (σ_x, σ_y) express the mean and the standard deviation of the real and the predicted wind speed vectors, respectively.

- **Net Fitness** calculates the average of the measures mentioned above. Furthermore, the main purpose of applying such a test is ranking distributions based on their overall performance. Its formula is as follows [31].

$$Net\ Fitness = \frac{\sum_{i=1}^{N} |MAE_i| + \sum_{i=1}^{N} |RMSE_i| + \sum_{i=1}^{n} 1 - R_i + \sum_{i=1}^{n} 1 - R_i^2}{4n} \quad (6)$$

where n equals 1, if all accuracy measures are balanced.

IV. RESULTS AND DISCUSSION

The half-hourly gathered data from the Catalca site in the Marmara area for two years (2019 and 2020) at 10 m height have been utilized to study the performance of the presented five distributions. Three optimization algorithms, GWO, MPA, and MVO were applied to model the parameters of each distribution. The statistical descriptors such as mean, standard deviation, variance, minimum, maximum, skewness, kurtosis, and average power describe the characteristics of wind data for all datasets are shown in Tables IV and V. It is evident that the mean wind speed values of the real data are 4.31 and 4.47 m/s at wind tower height 10 m for the 2019 and 2020 datasets, respectively.

The mean wind speed value is an essential implication of wind potential at a particular site. Sites with high annual mean wind speed values are appropriate for large-scale generating wind energy. The standard deviation value slightly increases with an increase in the wind tower height. Variance, the square of standard deviation, is a measurement of the spread between wind speed values from their mean value. Also, variance slightly increases with an increase in the wind tower height. The minimum real wind speed was zero, whereas the maximum was 21.50 m/s.

The skewness is the asymmetry from the average value of the dataset. The skewness values of all datasets explain that the real data follow the positive skewness distribution. Kurtosis shows the degree of peakedness of a distribution. There are three types of kurtosis: zero, positive, and negative [32-44]. The real data of all datasets tend to the positive kurtosis (Leptokurtic).

It is evident that the real average power densities at the site are 94.41 and 111.65 W/m^2 at wind tower height 10 m for 2019 and 2020 datasets, respectively. The average power density increases with an increase in the wind tower height. Regarding the statistical descriptor values in Tables VI and VII, it can be noticed that the Rayleigh distribution achieved the best matching, whereas the Extreme Value Distribution presented the worst matching.

The distribution function achieves optimal matching when the difference between the real and the predicted data approximates zero [45-55]. Tables VI and VII summary the GOF of the introduced distribution functions based on GWO, MPA, and MVO. The bold values in these tables point to the best for each optimization method, while the underlined values point to the best among them. In most cases, Rayleigh distribution achieved the best GOF.

TABLE III. THE DISTRIBUTIONS PARAMETER VALUES GENERATED BY GWO, MPA, AND MVO

Distributions	**Parameters**	**Datasets**					
		2019			**2020**		
		GWO	MPA	MVO	GWO	MPA	MVO
Rayleigh	P1	3.250	3.250	3.235	3.460	3.460	3.462
Gamma	P1	3.332	3.335	3.330	2.864	2.872	2.647
	P2	1.234	1.233	1.236	1.512	1.509	1.628
Extreme Value	P1	4.807	4.808	4.763	5.034	5.033	4.945
	P2	1.885	1.879	1.890	2.154	2.154	2.098
Logistic	P1	3.872	3.868	3.844	4.017	4.016	4.130
	P2	1.416	1.419	1.390	1.580	1.579	1.614
T Location-Scale	P1	3.849	3.845	3.929	4.033	4.006	4.032
	P2	2.374	2.276	2.315	2.723	2.642	2.641
	P3	345.387	8.370	14.147	614.771	24.251	33.535

TABLE IV. THE STATISTICAL ANALYSIS OF THE 2019 DATASET

Optimization Methods	**Distributions**	**Mean**	**Standard Deviation**	**Variance**	**Min**	**Max**	**Skewness**	**Kurtosis**	**Average Power (W/m^2)**
-	**Real**	4.307	2.254	5.079	0.000	14.440	0.756	0.505	94.413
GWO	**Rayleigh**	4.323	2.123	4.507	0.367	13.948	0.622	0.276	88.945
	Gamma	4.366	2.283	5.212	0.588	18.024	1.100	1.822	100.793
	Extreme Value	4.038	2.185	4.775	-4.723	8.992	-0.960	1.438	69.638
	Logistic	4.197	2.460	6.054	-3.284	16.917	0.217	1.043	93.960
	T Location-Scale	4.149	2.294	5.261	-2.097	12.774	0.066	0.004	84.356
MPA	**Rayleigh**	4.323	2.123	4.507	0.367	13.948	0.622	0.276	88.934
	Gamma	4.366	2.282	5.209	0.588	18.018	1.100	1.821	100.773
	Extreme Value	4.042	2.178	4.744	-4.691	8.980	-0.960	1.438	69.605
	Logistic	4.194	2.465	6.077	-3.302	16.938	0.217	1.043	93.995
	T Location-Scale	4.175	2.497	6.234	-3.339	18.102	0.230	1.079	94.610
MVO	**Rayleigh**	4.304	2.114	4.467	0.365	13.886	0.622	0.276	87.754
	Gamma	4.370	2.286	5.225	0.588	18.047	1.100	1.823	101.115
	Extreme Value	3.993	2.190	4.798	-4.789	8.958	-0.960	1.438	67.999
	Logistic	4.163	2.415	5.833	-3.181	16.649	0.217	1.043	90.686
	T Location-Scale	4.245	2.399	5.757	-2.672	15.432	0.142	0.490	92.962

TABLE V. STATISTICAL ANALYSIS AND AVERAGE POWER OF 2020 DATASET FOR ALL DISTRIBUTIONS GENERATED BY GWO, MPA AND MVO

Optimization Methods	**Distributions**	**Mean**	**Standard Deviation**	**Variance**	**Min**	**Max**	**Skewness**	**Kurtosis**	**Average Power (W/m^2)**
-	**Real**	4.470	2.491	6.205	0.000	15.560	0.632	0.218	111.653
GWO	**Rayleigh**	4.576	2.271	5.158	0.610	14.850	0.632	0.239	106.577
	Gamma	4.589	2.611	6.820	0.699	20.639	1.178	2.002	129.567
	Extreme Value	4.125	2.489	6.193	-3.938	9.816	-0.828	0.777	82.118
	Logistic	4.350	2.745	7.534	-2.552	18.567	0.275	0.832	114.092
	T Location-Scale	4.344	2.637	6.952	-1.861	14.223	0.103	-0.107	106.878
MPA	**Rayleigh**	4.576	2.271	5.158	0.610	14.850	0.632	0.239	106.570
	Gamma	4.591	2.609	6.807	0.701	20.617	1.177	1.997	129.483
	Extreme Value	4.125	2.489	6.193	-3.938	9.815	-0.828	0.777	82.098
	Logistic	4.349	2.743	7.524	-2.548	18.557	0.275	0.832	113.975
	T Location-Scale	4.322	2.659	7.070	-2.052	15.560	0.147	0.114	107.294
MVO	**Rayleigh**	4.578	2.273	5.165	0.610	14.859	0.632	0.239	106.775
	Gamma	4.575	2.707	7.330	0.626	21.473	1.222	2.155	135.097
	Extreme Value	4.059	2.425	5.880	-3.797	9.604	-0.828	0.777	77.590
	Logistic	4.470	2.804	7.863	-2.581	18.993	0.275	0.832	122.967
	T Location-Scale	4.344	2.628	6.907	-1.923	15.057	0.133	0.043	106.836

I. CONCLUSION

Determining suitable distributions for wind speed frequency is influential for feasibility studies, wind turbine design, and long-term investment decisions. Furthermore, deciding the appropriate assessment method is also essential since one method can achieve the best GOF with specific distribution but may fail with others. This paper suggests five different distributions to assess the wind potential. The optimal parameter values for each distribution were selected based on GWO, MPA, and MVO methods. The statistical features of the analyzed location and the GOF of each distribution function were examined and compared via many statistical descriptors and various error measures. The data collected from Catalca location in the Marmara region in Istanbul, Republic of Turkey is employed to carry out this study. The Rayleigh distribution exceeded the other distributions for all datasets in most cases. Besides, it was the best in respect of computation complexity. Contrarily, the Extreme Value distribution was the most inadequate in matching. Finally, the used distribution function, optimization method, and error measure are paramount factors in determining the best GOF for wind pattern at any site.

TABLE VI. ACCURACY MEASURES OF GWO, MPA, AND MVO FOR THE 2019 DATASET

Optimization methods	Distributions	Accuracy measures				Net Fitness	Rank
		MAE	RMSE	R^2	R		
GWO	Rayleigh	0.1411	0.1795	0.9937	0.9984	0.0821	1
	Gamma	0.1240	0.2107	0.9913	0.9961	0.0868	2
	Extreme Value	0.5686	0.9481	0.8230	0.9165	0.4443	5
	Logistic	0.2343	0.4981	0.9512	0.9826	0.1997	4
	T Location-Scale	0.2510	0.4457	0.9609	0.9833	0.1881	3
MPA	Rayleigh	0.1411	0.1795	0.9937	0.9984	0.0821	1
	Gamma	0.1239	0.2105	0.9913	0.9961	0.0868	2
	Extreme Value	0.5686	0.9462	0.8237	0.9165	0.4436	5
	Logistic	0.2342	0.5012	0.9505	0.9826	0.2006	3
	T Location-Scale	0.2337	0.5178	0.9472	0.9830	0.2053	4
MVO	Rayleigh	0.1439	0.1856	0.9932	0.9984	0.0845	1
	Gamma	0.1243	0.2125	0.9911	0.9961	0.0874	2
	Extreme Value	0.5727	0.9627	0.8175	0.9165	0.4504	5
	Logistic	0.2439	0.4863	0.9534	0.9826	0.1985	4
	T Location-Scale	0.2516	0.4458	0.9609	0.9839	0.1882	3

TABLE VII. ACCURACY MEASURES OF GWO, MPA AND MVO FOR 2020 DATASET

Optimization methods	Distributions	Accuracy measures				Net Fitness	Rank
		MAE	RMSE	R^2	R		
GWO	Rayleigh	0.2226	0.2707	0.9882	0.9988	0.1266	1
	Gamma	0.2211	0.3812	0.9766	0.9910	0.1587	2
	Extreme Value	0.5942	0.9779	0.8459	0.9325	0.4484	5
	Logistic	0.2604	0.5052	0.9589	0.9871	0.2049	4
	T Location-Scale	0.2334	0.4334	0.9697	0.9885	0.1771	3
MPA	Rayleigh	0.2226	0.2707	0.9882	0.9988	0.1266	1
	Gamma	0.2210	0.3801	0.9767	0.9911	0.1583	2
	Extreme Value	0.5941	0.9781	0.8458	0.9325	0.4485	5
	Logistic	0.2602	0.5044	0.9590	0.9871	0.2046	4
	T Location-Scale	0.2285	0.4444	0.9682	0.9889	0.1790	3
MVO	Rayleigh	0.2227	0.2707	0.9882	0.9988	0.1266	1
	Gamma	0.2276	0.4414	0.9686	0.9898	0.1776	3
	Extreme Value	0.6094	0.9945	0.8406	0.9325	0.4577	5
	Logistic	0.3000	0.5273	0.9552	0.9871	0.2212	4
	T Location-Scale	0.2307	0.4255	0.9708	0.9888	0.1741	2

REFERENCES

[1] Wadi, M., & Elmasry, W. (2021, March). Modeling of Wind Energy Potential in Marmara Region Using Different Statistical Distributions and Genetic Algorithms. In *2021 International Conference on Electric Power Engineering–Palestine (ICEPE-P)* (pp. 1-7). IEEE.

[2] Chang, T. P. (2011). Estimation of wind energy potential using different probability density functions. *Applied Energy*, *88*(5), 1848-1856.

[3] Pishgar-Komleh, S. H., Keyhani, A., & Sefeedpari, P. (2015). Wind speed and power density analysis based on Weibull and Rayleigh distributions (a case study: Firouzkooh county of Iran). *Renewable and sustainable energy reviews*, *42*, 313-322.

[4] Morgan, E. C., Lackner, M., Vogel, R. M., & Baise, L. G. (2011). Probability distributions for offshore wind speeds. *Energy Conversion and Management*, *52*(1), 15-26.

[5] Crutcher, H. L., & Baer, L. (1962). Computations from elliptical wind distribution statistics. *Journal of Applied Meteorology and Climatology*, *1*(4), 522-530.

[6] Garcia, A., Torres, J. L., Prieto, E., & De Francisco, A. (1998). Fitting wind speed distributions: a case study. *Solar energy*, *62*(2), 139-144.

[7] Scerri, E., & Farrugia, R. (1996). Wind data evaluation in the Maltese Islands. *Renewable energy*, *7*(1), 109-114.

[8] Yilmaz, V., & Çelik, H. E. (2011). A statistical approach to estimate the wind speed distribution: the case of Gelibolu region. *Doğuş Üniversitesi Dergisi*, *9*(1), 122-132.

[9] Alavi, O., Mohammadi, K., & Mostafaeipour, A. (2016). Evaluating the suitability of wind speed probability distribution models: A case of study of east and southeast parts of Iran. *Energy Conversion and Management*, *119*, 101-108.

[10] Mert, I., & Karakuş, C. (2015). A statistical analysis of wind speed data using Burr, generalized gamma, and Weibull distributions in Antakya, Turkey. *Turkish Journal of Electrical Engineering & Computer Sciences*, *23*(6), 1571-1586.

[11] Sohoni, V., Gupta, S., & Nema, R. (2016). A comparative analysis of wind speed probability distributions for wind power assessment of four sites. *Turkish Journal of Electrical Engineering & Computer Sciences*, *24*(6), 4724-4735.

[12] Wadi, M., Kekezoglu, B., Baysal, M., Tur, M. R., & Shobole, A. (2019, November). Feasibility study of wind energy potential in turkey: Case study of Catalca district in Istanbul. In *2019 2nd International Conference on Smart Grid and Renewable Energy (SGRE)* (pp. 1-6). IEEE.

[13] Gul, M., Tai, N., Huang, W., Nadeem, M. H., & Yu, M. (2020). Evaluation of wind energy potential using an optimum approach based on maximum distance metric. *Sustainability*, *12*(5), 1999.

[14] Wadi, M., & Elmasry, W. (2021). Statistical analysis of wind energy potential using different estimation methods for Weibull parameters: a case study. *Electrical Engineering*, 1-22.

[15] Saxena, B. K., & Rao, K. V. S. (2015). Comparison of Weibull parameters computation methods and analytical estimation of wind turbine capacity factor using polynomial power curve model: case study of a wind farm. *Renewables: Wind, Water, and Solar*, *2*(1), 1-11.

[16] Wadi, M., Shobole, A., Tur, M. R., & Baysal, M. (2018, April). Smart hybrid wind-solar street lighting system fuzzy based approach: Case study Istanbul-Turkey. In *2018 6th International Istanbul Smart Grids and Cities Congress and Fair (ICSG)* (pp. 71-75). IEEE.

[17] Leiva, V., Barros, M., Paula, G. A., & Galea, M. (2007). Influence diagnostics in log-Birnbaum–Saunders regression models with censored data. *Computational Statistics & Data Analysis*, *51*(12), 5694-5707.

[18] Wadi, M., Baysal, M., & Shobole, A. (2017, April). Comparison between open-ring and closed-ring grids reliability. In *2017 4th*

International Conference on Electrical and Electronic Engineering (ICEEE) (pp. 290-294). IEEE.
[19] Chiodo, E. (2013). A Bayes Inference Method for Probabilistic Transient Stability Assessment of Power Systems. *International Review on Modelling and Simulations (IREMOS)*, *6*(4), 1133-1149.
[20] Chiodo, E., & De Falco, P. (2016). Inverse Burr distribution for extreme wind speed prediction: Genesis, identification and estimation. *Electric Power Systems Research*, *141*, 549-561.
[21] Elaydi, H. A., Jaddu, H., & Wadi, M. (2012). An Iterative technique for solving nonlinear optimal control problems using Legendre scaling function. *International Journal of Emerging Technology and Advanced Engineering*, *2*(6).
[22] Hoxha, B., Selimaj, R., & Osmanaj, S. (2018). An experimental study of Weibull and Rayleigh distribution functions of wind speeds in Kosovo. *TELKOMNIKA (Telecommunication, Computing, Electronics and Control)*, *16*(5), 2451-2457.
[23] Y. Arikan, O. P. Arslan, and E. Cam, "The analysis of wind data with rayleigh distribution and optimum turbine and cost analysis in elmadag, turkey,"Istanbul University - Journal of Electrical and Electronics Engineering, 2015.
[24] Bidaoui, H., El Abbassi, I., El Bouardi, A., & Darcherif, A. (2019). Wind speed data analysis using Weibull and Rayleigh distribution functions, case study: five cities northern Morocco. *Procedia Manufacturing*, *32*, 786-793.
[25] Elmasry, W., Akbulut, A., & Zaim, A. H. (2018). Deep learning approaches for predictive masquerade detection. *Security and Communication Networks*, *2018*.
[26] Rajabi, M. R., & Modarres, R. (2008). Extreme value frequency analysis of wind data from Isfahan, Iran. *Journal of wind Engineering and industrial Aerodynamics*, *96*(1), 78-82.
[27] Quan, Y., Wang, F., & Gu, M. (2014). A method for estimation of extreme values of wind pressure on buildings based on the generalized extreme-value theory. *Mathematical Problems in Engineering*, *2014*.
[28] Van Der Heijden, F., Duin, R. P., De Ridder, D., & Tax, D. M. (2005). *Classification, parameter estimation and state estimation: an engineering approach using MATLAB*. John Wiley & Sons.
[29] Moazzami, M., Ghanbari, M., Moradi, J., Shahinzadeh, H., & Gharehpetian, G. B. (2018). Probabilistic SCUC considering implication of compressed air energy storage on redressing intermittent load and stochastic wind generation. *International Journal of Renewable Energy Research (IJRER)*, *8*(2), 767-783.
[30] Shahinzadeh, H., Gheiratmand, A., Moradi, J., & Fathi, S. H. (2016, April). Simultaneous operation of near-to-sea and off-shore wind farms with ocean renewable energy storage. In *2016 Iranian Conference on Renewable Energy & Distributed Generation (ICREDG)* (pp. 38-44). IEEE.
[31] Freimer, M., Kollia, G., Mudholkar, G. S., & Lin, C. T. (1988). A study of the generalized Tukey lambda family. *Communications in Statistics-Theory and Methods*, *17*(10), 3547-3567.
[32] Moradi, J., Shahinzadeh, H., & Khandan, A. (2017). A Cooperative Dispatch Model for the Coordination of the Wind and Pumped-storage Generating Companies in the Day-ahead Electricity Market. *International Journal of Renewable Energy Research (IJRER)*, *7*(4), 2057-2067.
[33] Wadi, M. (2021). Five different distributions and metaheuristics to model wind speed distribution, *J Ther Eng*, 7(14), 1898-1920.
[34] Bowling, S. R., Khasawneh, M. T., Kaewkuekool, S., & Cho, B. R. (2009). A logistic approximation to the cumulative normal distribution. *Journal of Industrial Engineering and Management*, *2*(1), 114-127.
[35] Wadi, M., & Baysal, M. (2017). Reliability assessment of radial networks via modified rbd analytical technique. *Sigma Journal of Engineering and Natural Sciences*, *35*, 717-726.
[36] Wadi, M., Baysal, M., Shobole, A., & Tur, M. R. (2018, October). Reliability evaluation in smart grids via modified Monte Carlo simulation method. In *2018 7th International Conference on Renewable Energy Research and Applications (ICRERA)* (pp. 841-845). IEEE.
[37] Moazzami, M., Ghanbari, M., Shahinzadeh, H., Moradi, J., & Gharehpetian, G. B. (2018, March). Application of multi-objective grey wolf algorithm on energy management of microgrids with techno-economic and environmental considerations. In *2018 3rd Conference on Swarm Intelligence and Evolutionary Computation (CSIEC)* (pp. 1-9). IEEE.
[38] Faramarzi, A., Heidarinejad, M., Mirjalili, S., & Gandomi, A. H. (2020). Marine Predators Algorithm: A nature-inspired metaheuristic. *Expert Systems with Applications*, *152*, 113377.
[39] Humphries, N. E., Queiroz, N., Dyer, J. R., Pade, N. G., Musyl, M. K., Schaefer, K. M., ... & Sims, D. W. (2010). Environmental context explains Lévy and Brownian movement patterns of marine predators. *Nature*, *465*(7301), 1066-1069.
[40] Tür Mehmet Rida,Wadi Mohammed,Shobole Abdulfetah Abdela,Hasan Gunduz, Integration Problems of Photovoltaic Systems-Wind Power, Solutions and Effects on Power Quality. European Journal of Technique, 10(2), 340-353.
[41] Mirjalili, S., Mirjalili, S. M., & Hatamlou, A. (2016). Multi-verse optimizer: a nature-inspired algorithm for global optimization. *Neural Computing and Applications*, *27*(2), 495-513.
[42] Shobole, A. A., & Wadi, M. (2021). Multiagent systems application for the smart grid protection. *Renewable and Sustainable Energy Reviews*, *149*, 111352.
[43] Elmasry, W., Akbulut, A., & Zaim, A. H. (2020). Evolving deep learning architectures for network intrusion detection using a double PSO metaheuristic. *Computer Networks*, *168*, 107042.
[44] Wadi, M., & Elmasry, W. (2021, March). An Anomaly-based Technique for Fault Detection in Power System Networks. In *2021 International Conference on Electric Power Engineering–Palestine (ICEPE-P)* (pp. 1-6). IEEE.
[45] Elmasry, W., Akbulut, A., & Zaim, A. H. (2020). Comparative evaluation of different classification techniques for masquerade attack detection. *International Journal of Information and Computer Security*, *13*(2), 187-209.
[46] Willmott, C. J., & Matsuura, K. (2005). Advantages of the mean absolute error (MAE) over the root mean square error (RMSE) in assessing average model performance. *Climate research*, *30*(1), 79-82.
[47] Hyndman, R. J., & Koehler, A. B. (2006). Another look at measures of forecast accuracy. *International journal of forecasting*, *22*(4), 679-688.
[48] A. Papoulis and S. U. Pillai,Probability, random variables, and stochastic processes. Tata McGraw-Hill Education, 2002.
[49] Gul, M., Tai, N., Huang, W., Nadeem, M. H., & Yu, M. (2020). Evaluation of wind energy potential using an optimum approach based on maximum distance metric. *Sustainability*, *12*(5), 1999.
[50] Wadi, M. (2021). Fault detection in power grids based on improved supervised machine learning binary classification. *Journal of Electrical Engineering*, 72(5), 315-322.
[51] DeCarlo, L. T. (1997). On the meaning and use of kurtosis. *Psychological methods*, *2*(3), 292.
[52] Elmasry, W., Akbulut, A., & Zaim, A. H. (2019). Empirical study on multiclass classification-based network intrusion detection. *Computational Intelligence*, *35*(4), 919-954.
[53] Elmasry, W., Akbulut, A., & Zaim, A. H. (2021). A Design of an Integrated Cloud-based Intrusion Detection System with Third Party Cloud Service. *Open Computer Science*, *11*(1), 365-379.
[54] Sahmoud, S., Elmasry, W., & Abudalfa, S. (2013). Enhancement the Security of AES Against Modern Attacks by Using Variable Key Block Cipher. *Int. Arab. J. e Technol.*, *3*(1), 17-26.
[55] Cem Kasapbasi, M., & Elmasry, W. (2018). New LSB-based colour image steganography method to enhance the efficiency in payload capacity, security and integrity check. *Sadhana.*, *43*(5), 1-14.