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Modeling of wind speed using differential evolution: Istanbul case

Emre KOÇAK[1,*], Volkan Soner ÖZSOY[2], H. Hasan ÖRKCÜ[1]

ABSTRACT

Over the years, increasing energy demands with the growth of the population and the development of technology have caused more fossil fuel consumption. Besides, environmental pollution and climate change, which are vital importance for humanity, are encountered. In order to avoid these dangerous situations, people have started to turn to clean and renewable energy sources such as wind energy. Due to the rapid development of such situations, it is very important to obtain information on the determination of the regions where wind energy facility will be installed and the characteristics of the wind speed. Wind power estimation can be made through various statistical distributions used to explain the characteristics of wind speed data. Rayleigh, Weibull, Nakagami, Gamma, Logistic, Loglogistic, Lognormal and Burr Type XII distributions, which are frequently used in the wind energy literature, are discussed in this study and the performances of the specified distributions are compared through the data sets obtained from the stations in Istanbul from Marmara region. One of the most preferred methods in estimation problems is the maximum likelihood method, and a differential evolution algorithm is proposed for ML estimation of the parameters of the distributions examined in the study. In addition, various model selection criteria are also utilized to determine the distribution that best fits the wind speed data.

Keywords: *Wind Energy; Maximum Likelihood; Differential Evolution*

INTRODUCTION

Wind energy, one of the most substantial renewable energy sources, is developing rapidly. According to preliminary wind power statistics published by the World Wind Energy Association (WWEA), the total capacity of all wind farms worldwide reached 744 gigawatts, which is sufficient to generate 7% of the world's electricity demand [1]. To increase this percentage, it is very important to have information such as determining the regions where wind energy will be used maximum and estimating wind speeds and characteristics. The accurate modeling of the wind regime based on its statistical properties such as humidity, temperature, solar radiation, pressure, and wind speed is very important for exploiting the existing potential in the region [2].

Statistical distributions are used to reveal the characteristics of the wind speed data used to determine the wind energy potential of a region. Wind power estimation can be made with the parameters of these distributions. Therefore, it is very important to choose an appropriate distribution and to make an accurate parameter estimation in order to accurately determine the wind energy potential of a region [3]. There are different distributions that are frequently used in the wind energy literature; thus, it is not possible to cite all of them here. The most important of these is undoubtedly the Weibull Distribution, due to its flexible and easily computable mathematical form [4–7]. Rayleigh Distribution, a special case of the Weibull distribution, is also widely used in this literature [8–14]. Furthermore, the wind speed data are modelled by using other different statistical distributions to find the characteristics of the data. In the related literature, the most popular distributions to model the wind speed data are Nakagami, Gamma, Logistic, Loglogistic, Lognormal, and Burr Type XII distributions [8,12,14–20].

Although there are many studies in the literature that make wind speed modeling using these distributions, this study focuses on Turkey's wind energy potential. There are several studies that have been conducted with this aim in Turkey. Dursun and Alboyaci [21] analyzed wind energy characteristics and potential of four different locations in

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[1] Department of Statistics, Faculty of Science, Gazi University, Ankara, Turkey
[2] Department of Management Information Systems, Faculty of Economics and Administrative Sciences, Aksaray University, Aksaray, Turkey
**E-mail address: emrekocak@gazi.edu.tr*
Orcid id: https://orcid.org/0000-0001-6686-9671 Emre Koçak, 0000-0002-6417-8946 Volkan Soner Özsoy, 0000-0002-2888-9580 H. Hasan Örkcü
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Bandırma, Gonen, Ayvalık, and Dursunbey from Balıkesir region. Ucar and Balo [22] explored the potential for wind energy of 12 locations in the south regions of Turkey. Ozerdem and Turkeli [23] investigated the wind speed characteristics of Izmir located on Turkey's Aegean coast. Ilkilic and Nursoy [24] examined the potential of wind energy in Turkey and its development in wind energy systems. To do this, they investigated the wind speed characteristics of several locations in Turkey. Arslanet al. [25] analyzed wind speed data collected from the Bilecik, Bursa, Eskişehir and Sakarya provinces of Turkey located in the Marmara and central Anatolia regions of Turkey. According to the data by the Turkish National Committee of the World Energy Council, the highest mean wind speed is 3.29 (m/s) in the Marmara region while the lowest mean wind speed is 2.12 (m/s) in the East Anatolian region [26]. In addition, there is a major potential of Marmara regions because the wind speed is above 7 (m/s) based on Turkish Wind Potential Atlas in Turkey [27]. However, in none of the previous studies, data from the Marmara region, one of Turkey's most energy-consuming and wind energy potential regions, was used for the whole of Istanbul. In this study, data were obtained from stations positioned to cover all regions of Istanbul. Therefore, this study will contribute to the literature as the first study using such a comprehensive data set. In addition, another purpose of this research is to contribute to the existing literature by performing an in-depth analysis of a wind resource by investigating different statistical distributions using the differential evolution algorithm.

The remainder of the paper is organized as follows. Section 2 includes a brief description of the estimation method and evaluation criteria. In Section 3, descriptions of some distributions are briefly provided. Section 4 consists of the results of the analysis and discussion are presented. The paper is ended with some concluding remarks.

MODELING METHODOLOGY

Modeling of wind data consists of four steps. The first step is the determination of appropriate statistical distributions. The second step is the selection of the appropriate estimation method to make an accurate parameter estimation to accurately determine the wind energy potential of a region. The third step is to determine the best optimization algorithm to accurately obtain parameter estimates. The last step is the evaluation of the obtained parameters with objective evaluation criteria.

THE SUITABLE DISTRIBUTIONS FOR WIND SPEED

Statistical distributions play a significant part in modeling wind speed appropriately; therefore, many distributions have been used in the literature. However, wind speed may show different distributions according to location and time. Considering the distributions used in the literature, summary about the distributions used in this study is given Table 1. In this table, f(v) represents the probability of wind speed v (m/s). Moreover, σ, μ, c and k are scale, location, 1st shape and 2nd shape parameters, respectively. And exp(·) is the exponential function.

MAXIMUM LIKELIHOOD ESTIMATION METHOD

There are many estimation methods such as the maximum likelihood estimation (MLE), the maximum product spacing (MPS), and the least-squares (LS) methods in the literature. There are many studies in the literature on their comparison [28,29]. Considering the related literature, ML, which is one of the most important estimation methods, was preferred in this study. Therefore, other estimation methods were ignored. In this subsection, a brief description of ML for estimating unknown parameters of the distributions is given.

Let $x_1, x_2, \ldots, x_n$ be a random sample of size n drawn at random, from a probability density function *(pdf)*, $f_X(x;\theta)$, of unknown parameters, the likelihood function is as follows $L = \prod_{i=1}^{n} f_{X_i}(x_i;\theta)$, where θ is a vector of size m representing the unknown parameters, i.e. $\theta = (\theta_1, \ldots, \theta_m)$. In this study, the aim was to find a vector, say θ, that maximizes the so-called likelihood function. To maximize L, we may equivalently use its logarithm, say *ln L*. This maximization problem can be difficult for some distributions. Therefore, heuristic methods are needed to solve such problems.

Table 1. The names, parameter numbers and probability density functions of the distributions

Name of Distribution	Number of Parameters	The probability density function (pdf)
Rayleigh	1	$f(v\|\sigma) = \frac{v}{\sigma^2} e^{\left(-\frac{x^2}{2\sigma^2}\right)}$
Weibull	2	$f(v\|\sigma, c) = \frac{c}{\sigma}\left(\frac{v}{\sigma}\right)^{c-1} e^{-\left(\frac{v}{\sigma}\right)^c}$
Nakagami	2	$f(v\|\sigma, c) = 2\left(\frac{c}{\sigma}\right)^c \frac{1}{\Gamma(c)} v^{(2c-1)} e^{-\frac{c}{\sigma}v^2}$
Gamma	2	$f(v\|\sigma, c) = \frac{1}{\sigma^c \Gamma(c)} v^{c-1} e^{-\frac{v}{\sigma}}$
Logistic	2	$f(v\|\sigma, \mu) = \frac{e^{\left(\frac{v-\mu}{\sigma}\right)}}{\sigma\left(1+e^{\left(\frac{v-\mu}{\sigma}\right)}\right)^2}$
Loglogistic	2	$f(v\|\sigma, \mu) = \frac{1}{\sigma}\frac{1}{v}\frac{e^{\left(\frac{log(v)-\mu}{\sigma}\right)}}{\left(1+e^{\left(\frac{log(v)-\mu}{\sigma}\right)}\right)^2}$
Lognormal	2	$f(v\|\sigma, \mu) = \frac{1}{v\sigma\sqrt{2\pi}} e^{\left(-\frac{(log(v)-\mu)^2}{2\sigma^2}\right)}$
Burr Type XII	3	$f(v\|\sigma, c, k) = \frac{kc}{\sigma}\left(\frac{v}{\sigma}\right)^{c-1}\left(1+\left(\frac{v}{\sigma}\right)^c\right)^{-(k+1)}$

DIFFERENTIAL EVOLUTION ALGORITHM

There are many studies in the literature comparing heuristic methods [30–32]. However, there are limited studies on the comparison of different heuristics in the parameter estimation problem. A study compared 4 different heuristic optimization methods, Genetic Algorithms (GA), Differential Evolution (DE), Particle Swarm Optimization (PSO), and Simulated Annealing (SA) to estimate the parameters of seven different distributions [33]. DE algorithm was preferred in this study since DE has a better performance than other heuristics in terms of bias values of parameter estimations.

DE algorithm, first introduced by Storn and Price [34], is a population-based algorithm. DE algorithm has become one of the most popular heuristic methods thanks to its strong global search capability and fast convergence speed. While The DE algorithm uses three operators, crossover, mutation, and selection, it also has important parameters, population size (P), crossover rate (C_r), and mutation factor (F). With the help of these parameters, it exhibits a remarkable performance in terms of accuracy, computation speed and robustness while optimizing different objective functions [35]. The pseudocode of the DE algorithm by Özsoy et al. [33] is given in Table 2.

Table 2. Pseudocode of DE algorithm

```
Initialize the DE parameters F (Mutation factor), C_r (Crossover rate), P (Population size)
Initialize the population, x̄_0
Calculate cost of initial population, f(x̄_0)
do
  for i=1:P
    Select random individuals r_1, r_2, r_3, r_1 ≠ r_2 ≠ r_3 ≠ i ∈ [0, P]
    Generate random parameter index, j_rand ∈ [0, D]
    for j=1:D
      if (rand[0,1] ≤ C_r ∨ j = j_rand)
        Calculate u_{j,i} = x_{j,r_0} + F(x_{j,r_1} − x_{j,r_2})
        Bring u_{j,i} into parameter bound x_{i,min} < u_{j,i} < x_{i,max}
      else
        Set u_{j,i} = x_{j,i}
      end
    end
  end
  for i=1:P
    Calculate cost of trial vector, f(ū_i)
    Calculate cost of rival vector, f(x̄_i)
    if f(ū_i) ≥ f(x̄_i)
      Replace x̄_i with ū_i
      Update cost vector
    end
  end
while (the termination criteria are met)
```

MODEL EVALUATION CRITERIA

There are some comparison criteria, such as root mean square error (RMSE), coefficient of determination (R^2), Akaike Information Criterion (AIC), Bayesian information criterion (BIC) and Kolmogorov–Smirnov (KS) test to determine the probability distribution that best fits the wind speed data. The formulas for the criteria discussed in this study are given in Table 3.

In Table 3, $\hat{F}_i$, is the estimated cdf for the ith ordered observation, $\bar{\hat{F}} = (1/n)\sum_{i=1}^{n}\hat{F}_i$, n is the sample size, and p is the number of estimated parameters. High R^2 values and, low values of RMSE, AIC, BIC and KS indicate that the distribution or model performs better.

ANALYSIS AND RESULTS

WIND SPEED DATA

In this study, the city of Istanbul is chosen as the location because it has a very rough terrain and is a city built on the two extremes that serve as a bridge between the continents of Europe and Asia, and at the point where they are closest to each other. Istanbul is one of the highest potential wind energy locations in Turkey. Figure 1 shows the relief map of the city of Istanbul [36]. Wind speed data are collected seasonally and annually from the 2020 open data portal of the Istanbul metropolitan municipality, which consists of 79 different observation stations. Wind speed data were collected between January 2020 and January 2021.

Table 3. The formulas of criteria for model evaluation

Name of Criteria	Formulas
Root mean square error	$RMSE = \sqrt{\left[\frac{1}{n}\sum_{i=1}^{n}\left(\hat{F}_i - \frac{i}{n+1}\right)\right]}$
Coefficient of determination	$R^2 = \frac{\sum_{i=1}^{n}\left(\hat{F}_i - \overline{\hat{F}}\right)^2}{\sum_{i=1}^{n}\left(\hat{F}_i - \overline{\hat{F}}\right)^2 + \sum_{i=1}^{n}\left(\hat{F}_i - \frac{i}{n+1}\right)^2}$
Akaike Information Criterion	$AIC = -2\ln L + 2p$
Bayesian information criterion	$BIC = -2\ln L + p\ln n$
Kolmogorov–Smirnov	$KS = \max_{1\le i\le n}\left\lvert\hat{F}_i - \frac{i}{n+1}\right\rvert$

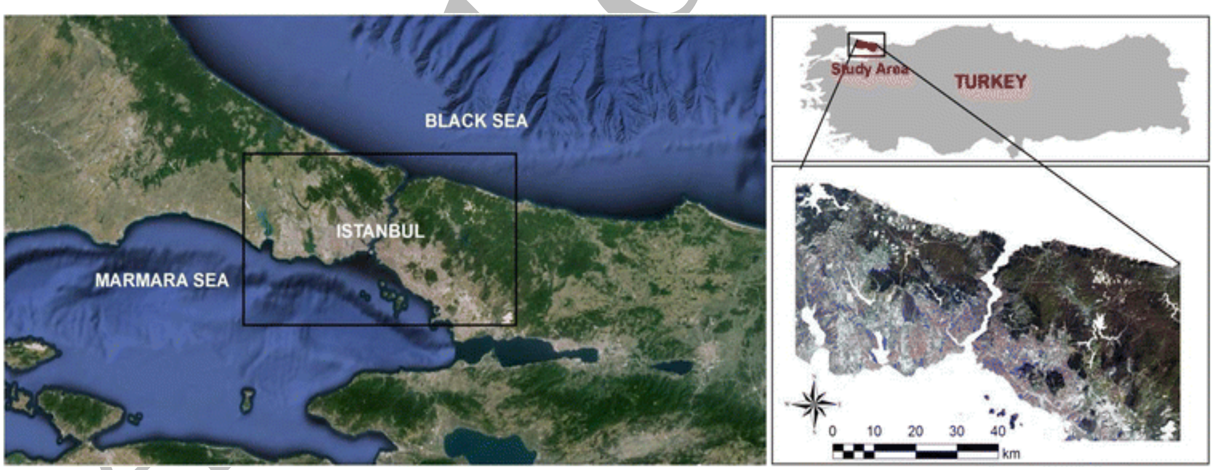

Figure 1. The relief map of the city of Istanbul

Table 4 demonstrates descriptive statistics of the wind speed data for Istanbul including number of observations, mean, variance, skewness, kurtosis, minimum and maximum in terms of seasonally and annually. According to descriptive statistics, it is seen that while spring has the highest average wind speed, autumn has the lowest speed. The wind speeds for summer are more homogeneous; therefore, it has the smallest variance in terms of the dispersion of the wind speeds. Table 4 also shows that wind speeds for spring has the biggest skewness value while for winter it has the biggest kurtosis value among other seasons.

Table 4. Descriptive statistics of wind speed data (m/s)

	n	Mean	Variance	Skewness	Kurtosis	Maximum
Autumn	147954	2.6371	4.1896	1.6937	7.2321	22.3340
Winter	134119	3.0606	5.5372	1.8369	8.3250	23.7450
Spring	110927	3.0748	5.8304	1.8774	8.2572	24.5000
Summer	132235	2.7689	3.5978	1.4686	6.3359	16.1567
Annual	525235	2.8709	4.7672	1.8024	8.1957	24.5000

RESULTS

First and foremost, the ML estimates of the interest parameters for the recorded wind speed datasets in İstanbul were obtained by the differential evolution algorithm, and the modeling performances of the Rayleigh, Weibull, Nakagami, Gamma, Logistic, Loglogistic, Lognormal and Burr Type XII distributions were compared. Estimated values of parameters obtained by DE algorithm are presented seasonally and annually in Table 5.

Table 5. Parameter estimates of wind speed distributions

Distributions	Parameters	Autumn	Winter	Spring	Summer	Annual
Rayleigh	σ	2.3605	2.7299	2.7645	2.3732	2.5504
Weibull	σ	2.8656	3.3556	3.3590	3.0723	3.1453
	c	1.3255	1.3736	1.3459	1.5142	1.3764
Nakagami	σ	11.1441	14.9044	15.2850	11.2644	13.0091
	c	0.5384	0.5731	0.5550	0.6621	0.5727
Gamma	σ	1.6638	1.7408	1.8135	1.3714	1.6543
	c	1.5850	1.7582	1.6955	2.0191	1.7354
Logistic	σ	1.0545	1.1974	1.2153	1.0044	1.1154
	μ	2.3639	2.7399	2.7389	2.5468	2.5818
Loglogistic	σ	0.5032	0.4697	0.4790	0.4359	0.4740
	μ	0.7131	0.8711	0.8682	0.8183	0.8130
Lognormal	σ	1.0175	0.9135	0.9349	0.8590	0.9386
	μ	0.6222	0.8080	0.8003	0.7508	0.7396
Burr Type XII	σ	11.3089	6.8551	6.9065	8.0512	7.6553
	c	1.4371	1.6165	1.5878	1.6896	1.5750
	k	7.9197	3.8872	3.8542	5.8163	4.7781

In order to determine the modeling performance for the wind speed data of the examined distributions, the model evaluation criteria were used, the formulas of which were given above, and the results of the criteria are given in Table 6. It is obvious from Table 6 that Burr Type XII distribution gives convincing results seasonally and annually in terms of all model evaluation criteria. For the autumn season, the Gamma distribution shows a better performance in terms of RMSE and R^2 criteria, while the Weibull distribution shows a better performance in terms of AIC, BIC, and KS criteria among the distributions other than the Burr distribution. According to RMSE and R^2 criteria, Loglogistic distribution demonstrates a higher performance compared to the distributions outside the Burr distribution for winter and spring seasons. However, the best performance belongs to the Gamma distribution in terms of other comparison criteria. Considering the summer season, the best distribution after Burr distribution is Gamma distribution according to RMSE, R^2 and KS criteria, and Weibull distribution according to AIC and BIC criteria. When the data is investigated annually, Gamma distribution is found to be the best distribution in terms of all the criteria, except the Burr distribution. Except for the AIC and BIC criteria in winter and summer seasons, the Rayleigh distribution has the worst performance in other times and criteria.

Table 6. Model evalaution criteria values for the wind speed distributions

Distributions	Criteria	Autumn	Winter	Spring	Summer	Annual
Rayleigh	RMSE	0.1143^{8}	0.1128^{8}	0.1180^{8}	0.0773^{8}	0.1077^{8}
	R^2	0.8704^{8}	0.8707^{8}	0.8577^{8}	0.9373^{8}	0.8817^{8}
	AIC	620097.1206^{8}	590254.7525^{7}	495506.1477^{8}	523040.9037^{6}	2240516.6111^{8}
	BIC	620107.0252^{8}	590264.5590^{7}	495515.7643^{8}	523050.6960^{6}	2240527.7827^{8}
	KS	0.1690^{8}	0.1681^{8}	0.1725^{8}	0.1186^{8}	0.1598^{8}
Weibull	RMSE	0.0189^{4}	0.0224^{4}	0.0230^{4}	0.0172^{4}	0.0207^{4}
	R^2	0.9953^{4}	0.9934^{4}	0.9929^{4}	0.9962^{4}	0.9943^{4}
	AIC	565535.1117^{2}	548179.7066^{3}	456327.7205^{3}	502131.9300^{2}	2079278.2427^{3}
	BIC	565554.9211^{2}	548199.3196^{3}	456346.9538^{3}	502151.5146^{2}	2079300.5859^{3}
	KS	0.0319^{2}	0.0336^{4}	0.0350^{4}	0.0290^{3}	0.0328^{4}
Nakagami	RMSE	0.0345^{5}	0.0405^{6}	0.0419^{5}	0.0283^{5}	0.0370^{5}
	R^2	0.9839^{5}	0.9778^{5}	0.9759^{5}	0.9895^{5}	0.9814^{5}
	AIC	570901.9180^{4}	555311.5504^{5}	462662.7138^{5}	505439.1739^{4}	2103318.1384^{4}
	BIC	570921.7274^{4}	555331.1633^{5}	462681.9471^{5}	505458.7586^{4}	2103340.4816^{4}
	KS	0.0569^{5}	0.0662^{6}	0.0697^{6}	0.0446^{5}	0.0600^{5}
Gamma	RMSE	0.0170^{2}	0.0138^{3}	0.0154^{3}	0.0122^{2}	0.0146^{2}
	R^2	0.9962^{2}	0.9976^{3}	0.9969^{3}	0.9981^{2}	0.9972^{2}
	AIC	566244.4051^{3}	546620.8311^{2}	455131.8788^{2}	502430.1179^{3}	2076891.1076^{2}
	BIC	566264.2144^{3}	546640.4441^{2}	455151.1121^{2}	502449.7025^{3}	2076913.4508^{2}
	KS	0.0327^{3}	0.0236^{2}	0.0232^{2}	0.0240^{2}	0.0266^{2}
Logistic	RMSE	0.0444^{6}	0.0457^{7}	0.0450^{7}	0.0385^{6}	0.0433^{6}
	R^2	0.9751^{6}	0.9735^{7}	0.9740^{6}	0.9819^{6}	0.9763^{6}
	AIC	613465.2200^{7}	590935.6136^{8}	492957.7223^{7}	532811.1327^{7}	2237954.3066^{7}
	BIC	613485.0293^{7}	590955.2266^{8}	492976.9555^{7}	532830.7174^{7}	2237976.6498^{7}
	KS	0.0961^{7}	0.0921^{7}	0.0950^{7}	0.0742^{7}	0.0899^{7}
Loglogistic	RMSE	0.0178^{3}	0.0124^{2}	0.0144^{2}	0.0154^{3}	0.0150^{3}
	R^2	0.9960^{3}	0.9981^{2}	0.9974^{2}	0.9971^{3}	0.9972^{3}
	AIC	579299.0102^{5}	553524.0001^{4}	460954.1598^{4}	511598.0950^{5}	2110707.4847^{5}
	BIC	579318.8196^{5}	553543.6130^{4}	460973.3930^{4}	511617.6796^{5}	2110729.8279^{5}
	KS	0.0377^{4}	0.0283^{3}	0.0266^{3}	0.0359^{4}	0.0322^{3}
Lognormal	RMSE	0.0545^{7}	0.0402^{5}	0.0432^{6}	0.0452^{7}	0.0467^{7}
	R^2	0.9541^{7}	0.9767^{6}	0.9730^{7}	0.9700^{7}	0.9675^{7}
	AIC	609134.7361^{6}	573097.2954^{6}	477413.5967^{6}	533645.2001^{8}	2200982.0300^{6}
	BIC	609154.5454^{6}	573116.9083^{6}	477432.8299^{6}	533664.7848^{8}	2201004.3732^{6}
	KS	0.0876^{6}	0.0650^{5}	0.0695^{5}	0.0715^{6}	0.0747^{6}
Burr Type XII	RMSE	0.0126^{1}	0.0084^{1}	0.0086^{1}	0.0082^{1}	0.0093^{1}
	R^2	0.9980^{1}	0.9991^{1}	0.9991^{1}	0.9992^{1}	0.9989^{1}
	AIC	564649.1839^{1}	545301.9398^{1}	453897.5780^{1}	500697.9441^{1}	2070949.0133^{1}
	BIC	564678.8979^{1}	545331.3593^{1}	453926.4279^{1}	500727.3211^{1}	2070982.5281^{1}
	KS	0.0242^{1}	0.0160^{1}	0.0151^{1}	0.0167^{1}	0.0182^{1}

See the histograms given in Figure 2-6 for the seasonal and annual wind speed data obtained in Istanbul respectively and the corresponding estimated all distribution curves.

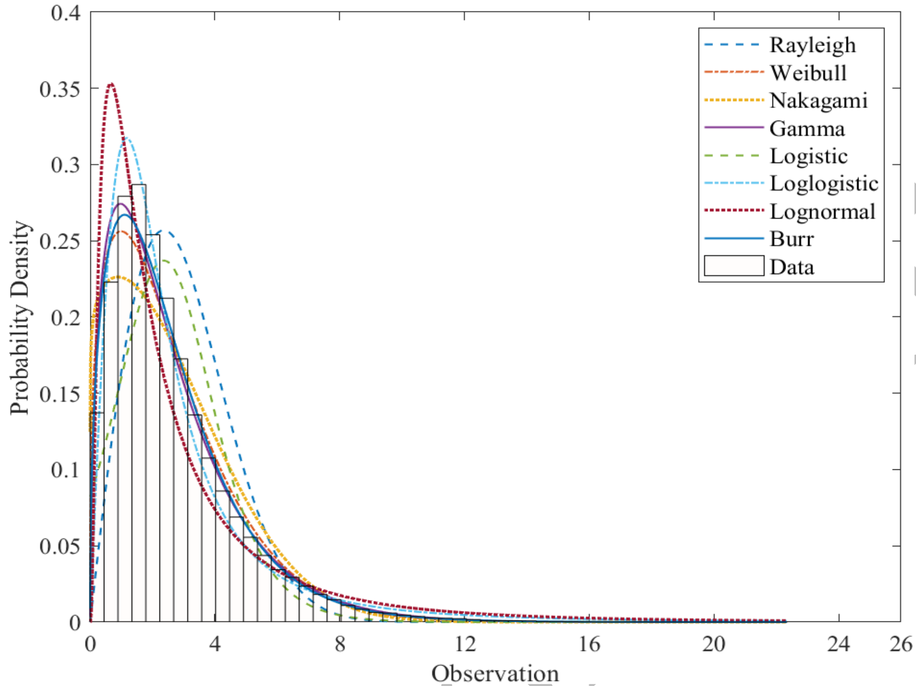

Figure 2. The histograms and fitted densities for the autumn wind speed data

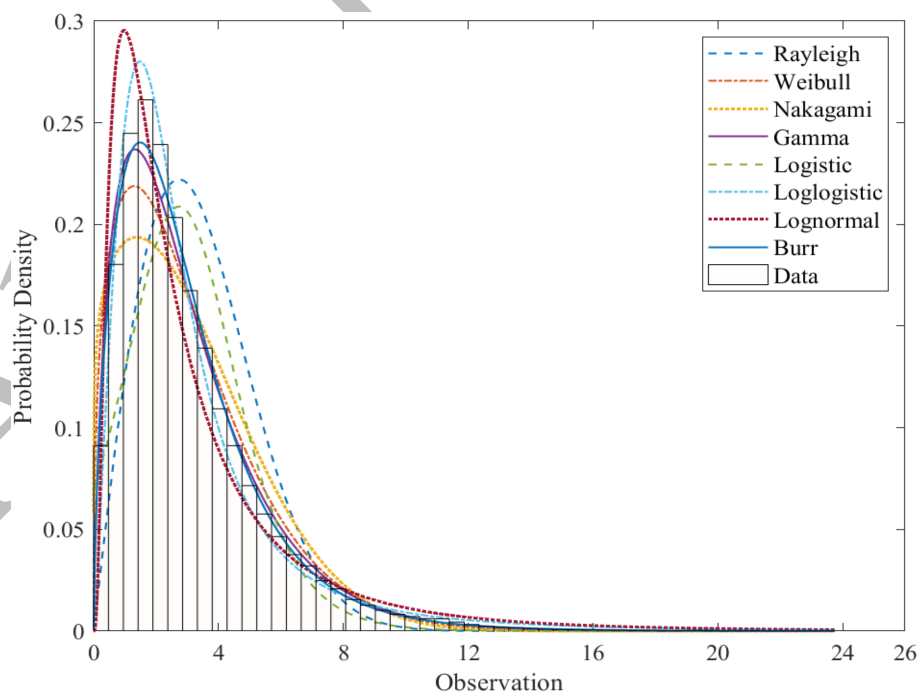

Figure 3. The histograms and fitted densities for the winter wind speed data

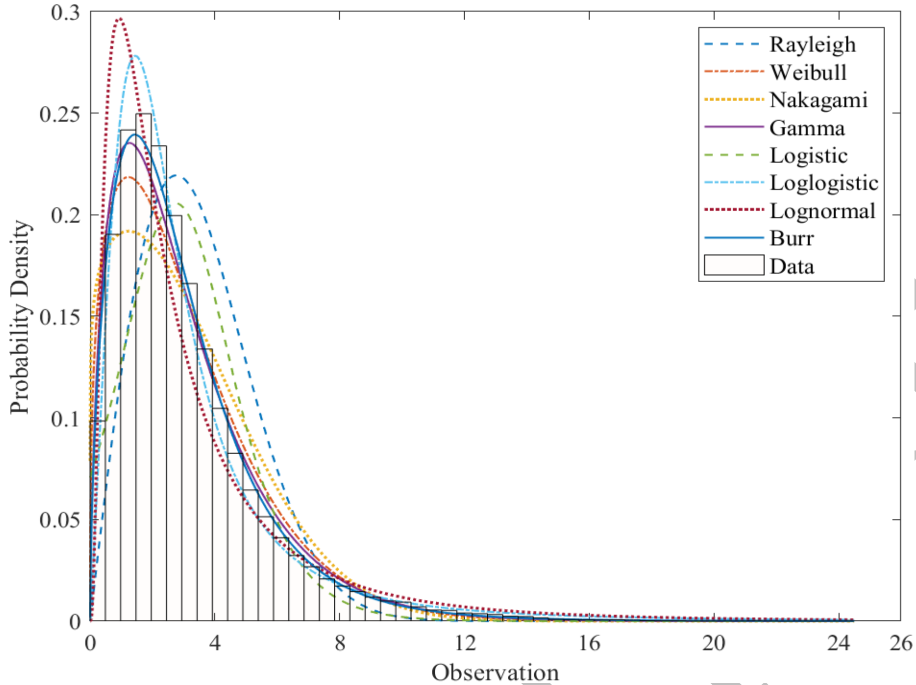

Figure 4. The histograms and fitted densities for the spring wind speed data

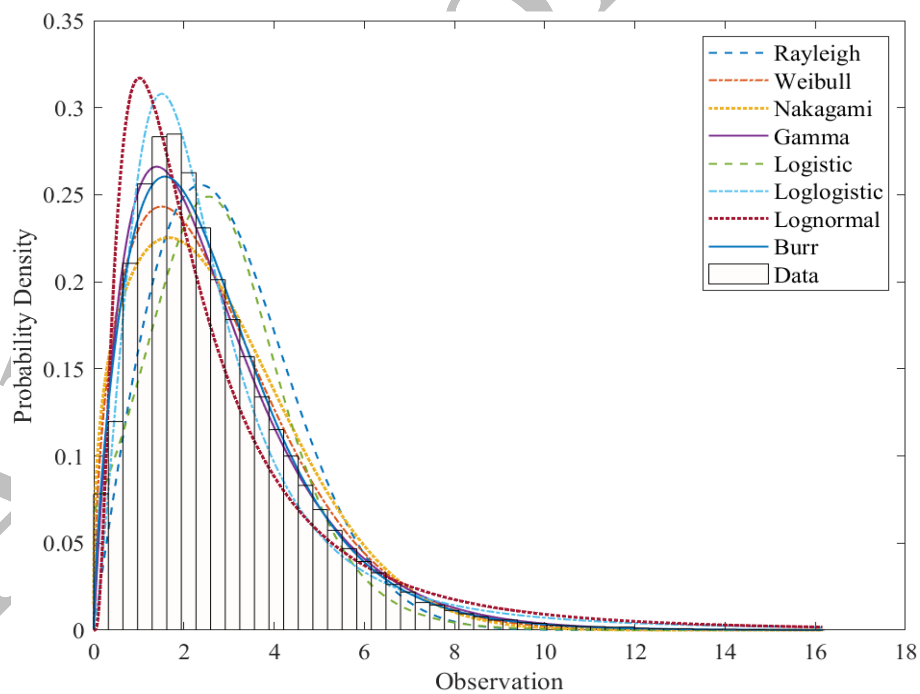

Figure 5. The histograms and fitted densities for the summer wind speed data

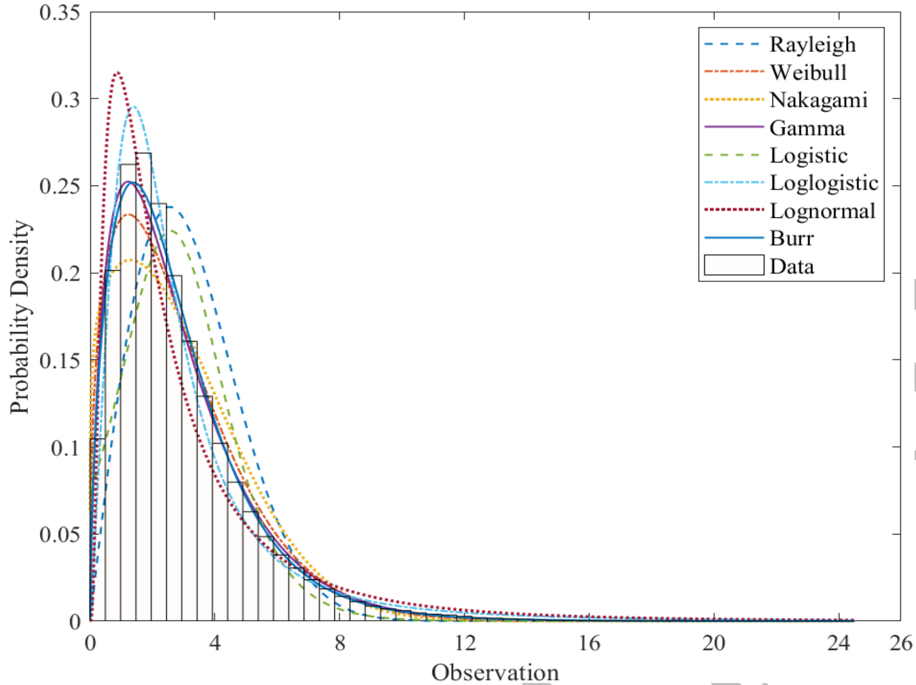

Figure 6. The histograms and fitted densities for the annual wind speed data

CONCLUSION

Determining the appropriate wind speed distribution is extremely important for the assessment of wind energy potential. Although many distributions have been used in the literature to determine the wind distribution, wind speed may show different distributions according to place and time. In this study, eight different distributions, namely Rayleigh, Weibull, Nakagami, Gamma, Logistic, Loglogistic, Lognormal and Burr Type XII were used to determine the distribution of seasonal and annual wind speeds in the province of Istanbul. To the best of our knowledge, a data of this size has been used for the first time in determining the wind speed distribution of Istanbul.
Considering the wind speeds obtained from 79 different observation stations operating in the province of Istanbul in this study, it can be seen that the distribution that best models seasonal and annual wind speed is the Burr Type XII distribution. In contrast, the Rayleigh distribution has the worst performance for modeling wind speed in most cases.

DISCLOSURE STATEMENT

No potential conflict of interest was reported by the authors.

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