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Estimation of Wind Speed Probability Distribution Parameters by Using Four Different Metaheuristic Algorithms

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Abstract: The inclusion of energy produced from renewable energy sources (RES) such as solar and wind energy into existing energy systems is important to reduce carbon emissions, air pollution and climate change, and to ensure sustainable development. However, the integration of RES into the energy system is quite difficult due to their highly uncertain and intermittent nature. In this study, considering three different probability density functions (PDFs) in total, the scale and shape parameters of the Weibull PDF, the scale parameter of the Rayleigh PDF, and the scale and shape parameters of the Gamma PDF were estimated for the wind speed data obtained from urban stations located in Istanbul by using the four different metaheuristic algorithms, namely Genetic Algorithm (GA), Differential Evolution (DE), Particle Swarm Optimization (PSO) and Grey Wolf Optimization (GWO) algorithms. Calculating the mean absolute error (MAE), root mean squared error (RMSE), and R^2 values for each PDF at each station, the PDF that characterizes the wind speed probability distribution the best was identified.

Keywords: Wind speed, renewable energy, probability density function, parameter estimation, metaheuristic algorithm

Dört Farklı Metasezgisel Algoritma Kullanılarak Rüzgâr Hızı Olasılık Dağılımı Parametrelerinin Tahmini

Öz: Güneş ve rüzgâr enerjisi gibi yenilenebilir enerji kaynaklarından (YEK) üretilen enerjinin mevcut enerji sistemlerine dahil edilmesi, karbon salınımlarını, hava kirliliğini ve iklim değişikliğini azaltmak ve sürdürülebilir bir kalkınmayı sağlamak için önemlidir. Ancak YEK'lerin enerji sistemine entegrasyonu, oldukça belirsiz ve kesintili yapıları nedeniyle hayli zordur. Bu çalışmada, İstanbul'da bulunan kentsel istasyonlardan elde edilen rüzgâr hızı verileri için, toplamda üç farklı olasılık yoğunluk fonksiyonu dikkate alınarak, Weibull olasılık yoğunluk fonksiyonunun ölçek ve şekil parametreleri, Rayleigh olasılık yoğunluk fonksiyonunun ölçek parametresi ve Gamma olasılık yoğunluk fonksiyonunun ölçek ve şekil parametreleri, Genetik Algoritma (GA), Diferansiyel Evrim (DE), Parçacık Sürü Optimizasyonu (PSO) ve Gri Kurt Optimizasyonu (GWO) algoritmaları olmak üzere dört farklı metasezgisel algoritma kullanılarak tahmin edilmiştir. Her istasyonda her bir olasılık yoğunluk fonksiyonu için ortalama mutlak hata (MAE), kök ortalama kare hata (RMSE) ve R^2 değerleri hesaplanarak, rüzgâr hızı olasılık dağılımını en iyi karakterize eden olasılık yoğunluk fonksiyonu belirlenmiştir.

Anahtar Kelimeler: Rüzgâr hızı, yenilenebilir enerji, olasılık yoğunluk fonksiyonu, parametre tahmini, metasezgisel algoritma

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1. Introduction

Energy consumption in the world is increasing rapidly and most of this energy is provided from fossil resources. However, the use of fossil resources causes environmental problems such as acid rain, air pollution and climate change. Since this situation is not sustainable, the importance of sustainable renewable energy sources is increasing day-by-day [1]. Clean and limitless wind energy, as one of the most important sources of renewable energy with a long history, has made significant development in recent years, and worldwide installed wind power is rising fast [2, 3]. Wind speed distribution is one of the characteristics of the wind. The distribution of wind speed is important for structural and environmental analysis, as well as for determining the wind energy potential and evaluating wind energy conversion performance. As mentioned above, with the increasing importance of wind energy, various statistical models are used to describe the wind speed distribution in a particular place [4]. Large-scale maps provide information about the behavior of the wind at high altitudes around the world, but in the urban areas less information is available about the wind speed at low altitudes [5].

Wind speed is a random variable that may be represented using a PDF, which is a mathematical function that expresses the probability of a random variable occurring at a particular position [6]. The major goal of this research is to estimate the parameters of the PDF most appropriate to the wind speed data obtained from 30 stations located in various places in Istanbul by using GA, DE, PSO and GWO algorithms for each PDF. A wide variety of PDFs are used in the literature to describe the wind speed distribution. Three different PDFs considered in this study are the two-parameter Weibull PDF, the Rayleigh PDF, and the two-parameter Gamma PDF.

The remainder of the research is organized as follows. The wind speed probability distribution models utilized in the study are introduced in the second part. A literature review is included in the third section. In the fourth section, the methods used in the study are explained and in the fifth section, the application is reported. The study will end with the conclusions in the sixth section.

2. Wind Speed Probability Distribution Models

In this section, the wind speed PDFs used in this study is explained. These are the two-parameter Weibull PDF, the Rayleigh PDF the two-parameter Gamma PDF.

2.1. Two-parameter Weibull PDF

The Weibull distribution is commonly applied to express the wind speed frequency distribution. The Weibull PDF is given by

$$f(v) = \frac{k}{c}\left(\frac{v}{c}\right)^{k-1} \exp\left[-\left(\frac{v}{c}\right)^{k}\right] \tag{1}$$

where, v, c and k are the wind speed (m/s), the scale parameter (m/s) and the dimensionless shape parameter, respectively [7].

2.2. Rayleigh PDF

The Rayleigh distribution is a special case of the Weibull distribution with $k = 2$ and the Rayleigh PDF is given by

$$f(v) = \frac{v}{c^2} \exp\left(-\frac{v^2}{2c^2}\right) \tag{2}$$

where, v and c are the wind speed (m/s) and the scale parameter (m/s), respectively. The Rayleigh distribution has found wide application as there is only one parameter to calculate [7]

2.3. Two-parameter Gamma PDF

The Gamma distribution has also been employed to fit the wind speed frequency distribution and the Gamma PDF is expressed as follows:

$$f(v) = \frac{1}{c^k \Gamma(k)} v^{k-1} \exp\left(-\frac{v}{c}\right) \tag{3}$$

where, v, c and k are the wind speed (m/s), the scale parameter (m/s) and the dimensionless shape parameter, respectively [8].

3. Literature Review

Researchers evaluated and compared four potential probability distributions for wind energy, namely Weibull, Rayleigh, Gamma, and lognormal probability distributions. In addition, three diverse kinds of numerical methods including method of moment, maximum likelihood estimation, and least squares method are deployed with these probability distributions to obtain parameter estimation. Furthermore, optimal parameters were tuned by three distinct types of metaheuristic optimization algorithms, such as cuckoo search algorithm, bat algorithm and PSO. According to their evaluation outcomes, metaheuristics optimization algorithms gave better performances as compared to numerical methods. Moreover, combinations of Weibull probability distribution with the three considered metaheuristics optimization algorithms provided slightly superior results in comparison with other three probability distributions. In addition, comparative analysis between possible combinations of Weibull probability distribution with different metaheuristics optimization algorithms revealed that bat algorithm-Weibull and PSO-Weibull are even finer than cuckoo search-Weibull. They claimed that parameters of Weibull model considerably influence the key factors, which estimate the wind energy potential in low-speed regions [7].

As Weibull probability distribution is most commonly deployed for wind speed modelling in energy applications, mainly because of its simplicity and flexibility, some researchers proposed a novel "Power Density (PD) method" for estimation of scale parameters and shape parameters for Weibull distribution. They claimed that this newly developed method has easier implementation and simpler formulation. In addition, it requires minimal computations as there are no linear least square problems, iterative procedures, and binning to be solved. However, it requires information like power density and mean wind speed to estimate Weibull parameters. The authors have also evaluated this PD method by comparing it with other state-of-the-art methods including maximum likelihood, graphic, and moment methods. Also, earlier studies were being consulted and their power density and mean wind estimation results were being compared to estimate the accuracy of PD method. Their comparative analysis revealed the adequacy of PD method in extracting Weibull parameters. Moreover, PD method tends to outperform other methods [9].

Pobočíková et al. [10] experimented with four types of probability distributions, namely the 2-parameter Weibull, the 3-parameter Weibull, the 2-parameter Gamma, and the 2-parameter lognormal. For parameter estimation, they opted for the maximum likelihood method. Their research work proved that the 3-parameter Weibull is the optimal alternative, while the 2-parameter is found to be second best [10].

Maximum likelihood method is being widely used in combination with Weibull probability distribution for parameter estimation. It incorporates iterative techniques such as Newton-Raphson (NR), which randomly selects some initial values. However, this selection of initial values is critical in determining success rate of these iterative methods. Thus, a recent research paper proposes GA to overcome the problem of random initial value selection. For evaluation purposes, it has compared the maximum likelihood estimators obtained through both techniques (namely GA and NR) with the method of moment estimators. As a result, the maximum likelihood estimator with GA technique outperformed the method of moment as well as the maximum likelihood estimator with NR technique [11].

Another piece of research work featured bi-parameter Weibull function for estimation of wind energy potential at Catalca (Marmara region of Istanbul, Turkey). Researchers investigated six different estimation methods, specifically energy pattern factor, graphical method, method of moment, power density methods, mean standard deviation, and GA. Moreover, five different test procedures, namely MAE, RMSE, chi-square error, normalized MAE, and regression coefficient were deployed to evaluate all the considered estimation methods. A new approach "Net Fitness test" was also experimented to determine most suitable estimation method. Their research work figured out that GA showed the best performance, while energy pattern factor demonstrated worst performance as estimation method. All other estimation methods depicted relatively similar performances [12].

A similar research work experimented with three mixture PDFs, namely Weibull-Lognormal, Weibull-Extreme Value Distribution (GEV) and GEV-Lognormal to model wind speed characteristics. They also deployed various judgment criteria such as RMSE, maximum error in the Kolmogorov-Smirnov Test, power density error, chi-square error and coefficient of determination to determine the most suitable PDF. The outcomes of their experiments indicated the suitability of Weibull-GEV PDF for both unimodal and bimodal wind distributions while GEV-lognormal PDF was found to be appropriate for bell-shaped unimodal distribution. In addition, researchers of this study found that mixture PDFs perform better than conventional Weibull, Gamma, lognormal, and two-component mixture Weibull for modeling wind speed characteristics [13]. Mazzeo et al. [14] suggested another technique called the Mixture of Two Truncated Normal Distributions (MTTND). In this technique, two normal distributions exhibiting dissimilar values of variance and mean are being combined to demonstrate PDF for wind speed. They observed greater accuracy by MTTND as compared to other conventional PDFs for wind speed [14].

Similarly, another study proposed "Nonparametric Kernel Density" estimation method as an appropriate option for wind speed probability distribution. For evaluation purposes, they compared their proposed method with other ten state-of-the-art parametric distribution models. According to their experimental results, the presented method demonstrated better accuracy and adaptability as compared to other methods for wind speed [15]. In addition, another innovative non-parametric approach has been proposed for estimating probability distributions. It utilizes differential equations, which are partial and diffuse and provides information to correct boundary and select bandwidth of "Kernel Density" estimation [16].

Subsequently, a group of researchers also developed a novel "Mixture Kernel Density" model. This model contained multiple kernel densities with their own specific coefficients. The authors asserted that their developed model can accurately estimate parameters of probability distributions for wind speed [17]. Some researchers suggested another approach to estimate two important parameters of Weibull distribution function. In this technique, support vector regression (SVR) exhibited radial basis functions (RBF) and polynomial functions as its kernel function. Generally, these RBF and polynomial functions tend to reduce the error bound. The approach demonstrated superior accuracy in prediction and a better tendency to generalize as compared with other soft computing techniques [18].

Further, some researchers conducted a comparative study including seven widely deployed numerical methods for parameter estimation specifically for Weibull distribution. For that purpose, they collected wind speed data for two cities (Camocim and Paracuru) in the northeast region of Brazil within the period of two years (August 2004 to April 2006). The list of considered numerical methods included maximum likelihood method, energy pattern factor method, moment method, empirical method, graphical method, modified maximum likelihood method, and equivalent energy method. These methods were compared by analyzing RMSE, variance and chi-square tests with the aim of determining the most effective solution. The equivalent energy method accurately determines the k and c parameters of Weibull distributions in this comprehensive study. Moreover, the graphical method and energy pattern factor method performed worse in this regard, according to graphical, mean, and standard deviation evaluations. Additionally, those numerical methods that use mathematical iterations possess minimal error for adjusting Weibull distribution curves and are therefore recommended for greater accuracy [19].

Researchers have also proposed a hybrid intelligent learning based numerical method, called Adaptive Neuro-Fuzzy Inference System (ANFIS), for estimating Weibull PDF parameters accurately. They compared their proposed methodology with five other well-known numerical methods in their study. They claimed that the presented methodology, ANFIS, demonstrated best performance as compared to other numerical methods in terms of fitting the Weibull distribution curve. The extracted Weibull parameters were further beneficial for estimating some important parameters and site-based wind energy potential [20].

Similarly, another group of researchers from Egypt investigated the five numerical methods, namely the mean wind speed method, the maximum likelihood method, the modified maximum likelihood method, the graphical method, and the power density method. They conducted this comparative analysis specifically for wind speed data collected at Zafarana Project in Suez Gulf. The accuracies of these considered numerical methods were estimated based on RMSE. As a result, they concluded that the mean wind speed and maximum likelihood methods yield better results for wind speed distribution [21].

In the United Kingdom, a recently conducted research work has also recommended Weibull distribution function as an appropriate manner to model probability distribution for wind speeds. The experimented data was collected at thirty-eight surface observation stations over multiple years (1981-2018). The researchers claimed that parameters of Weibull distribution can be estimated and utilized further for wind power density evaluations locally as well as regionally. Their experimental results indicated that values of Weibull's scale parameters remain within the range of 4.96 m/s and 12.06 m/s, while values of Weibull's shape parameter vary from 1.63 to 2.97. Furthermore, the wind power density estimations remain between 125 W/m^2 to 1407 W/m^2. They have also confirmed that Weibull parameter and wind power density tend to vary seasonally [22].

A comparable case study has also been reported by researchers in Turkey, which highlights the importance of utilizing befitting wind speed distribution. They have contemplated four different numerical methods including least square method, graphical method, standard deviation, and mean wind speed method (SDMWS), maximum likelihood method, and energy pattern factor method. The wind speed data of Izmir, Turkey has been considered for this purpose. To evaluate the robustness of considered numerical methods, three different tests namely the coefficient of determination, the Chi-square goodness-of-fit and RMSE have been deployed. The authors of this study observed that standard deviation and SDMWS method were optimal [23].

The selection of suitable PDF is extremely significant in wind energy applications. To facilitate this selection process, Alrashidi et al. [8] developed a platform, which can effectively compare and evaluate the performances of various PDFs. Moreover, they have proposed a novel metaheuristic optimization algorithm called social spider optimization (SSO) for wind characterization. The authors asserted that combinations of PDFs perform better than individual PDFs for demonstration of wind speed frequencies. However, they found Weibull distribution as most prevailing individual distribution. Additionally, they also claimed that their proposed SSO method is the most effective for parameter estimation of PDFs in Saudi Arabia [8].

Another group of researchers at Antioquia, Colombia also experimented with four types of PDFs, such as Weibull, Rayleigh, Gamma, and lognormal to model the wind speed data histograms. They targeted one rural place and five urban places of the Aburrá Valley to conduct their research work. Wind power density calculated from best fitting PDF for each location was further deployed by several applications in this research work. The best fitting PDF for the variation in wind speed data was also determined by running four goodness of fit tests. Next, the most suitable PDF was utilized in calculation of wind power density and availability. Their measurements concluded that power densities at targeted urban stations vary between 1.38 to 4.54 W/m^2, while rural station exhibited a power density of 911.1 W/m^2 [5].

Furthermore, an analogous research work was conducted in Bitlis, Turkey, where average wind speed data collected for four years (from 2012 to 2016) was analyzed. Researchers experimented with Weibull, Gamma, and lognormal distributions to estimate average wind speed. Moreover, the maximum likelihood method was utilized as underlying numerical method for parameter estimation of all three distributions. To determine the best fitting distribution, three types of tests, namely coefficient of determination, RMSE and Kolmogorov-Smirnov Goodness of Fit test were performed. The authors concluded that all three distributions provided comparable results regarding average wind speed estimations. However, Gamma distribution showed better performance in terms of standard deviation from average wind speed value for the month of August (0.15 m/s). Furthermore, they also observed that Gamma distribution exhibited higher coefficient of determination, lowest Kolmogorov-Smirnov Goodness of Fit test value and smaller RMSE value as compared to other distributions. Consequently, they recommended Gamma distribution as optimal choice for modelling wind speed data in Bitlis [24].

4. Method

In this section, the four metaheuristic algorithms used in the study are explained. These are genetic algorithm, particle swarm optimization, differential evolution algorithm and grey wolf optimizer algorithm.

4.1. Genetic Algorithm (GA)

In computer science, a genetic algorithm (GA) is a form of search algorithm that is used to obtain an exact or approximate response to optimization and search processes [25]. GA is an optimization algorithm that is inspired from the natural selection. It is a population-based search method that employs the concept of survival of the fittest. In the early 1970s, John Holland proposed genetic algorithms [26]. Inversion, a novel element that is often used in GA implementations, was also introduced by Holland [26].

The first set of solutions in GA is population. A chromosome is a representation of a solution. From generation to generation, the population size is maintained [27]. Each chromosome's fitness is evaluated for each generation, and chromosomes for the next generation are probabilistically chosen depending on their fitness scores. At random, some of the selected chromosomes mate and produce children. Crossover and mutation occur at random when producing progeny [28]. The offspring produced from crossover of parent chromosomes is probable to abolish the admirable genetic schemas parent chromosomes and crossover formula is defined as [29].

$$R = (G + 2\sqrt{g}) \big/ (3G) \tag{4}$$

where, G is the total number of evolutionary generations set by the population, and g is the number of generations. It is observed from Eq. (4) that R is dynamically changed and increases with increase in number of evolutionary generations. The binary string format is commonly used for chromosomes. Each locus on chromosomes has two potential alleles (gene variants)- 0 and 1. In the solution space, chromosomes are treated as points. These are processed by iteratively replacing its population with genetic operators. The fitness function is used to assign a value to each of the population's chromosomes [29].

The next generation's chromosomes may have a greater average fitness value than the previous generation's because chromosomes with high fitness values are more likely to be selected. The process of evolution is repeated until the ultimate condition is satisfied [28]. Figure 1 depicts the GA's fundamental steps. Firstly, the population is initialized with random chromosomes. The fitness function is then used to evaluate each individual chromosome. The chromosomes that best fit the new population are chosen. By crossing over, certain chromosomes are reproduced and altered [30]. Thereafter, the new population is exposed to the new iteration. If the maximum number of generation counts or termination conditions are met, the GA is terminated [30]. The GA is used for many optimizations, search, and selection problems.

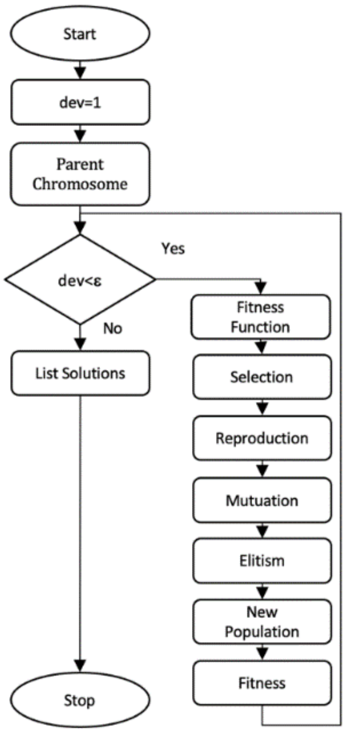

Figure 1. Flow Chart of GA.

4.2. Particle Swarm Optimization (PSO)

Kennedy and Eberhart [31] developed the PSO, a general-purpose optimization approach that operates by maintaining a swarm of particles that move around in the search space, impacted by the improvements identified by the other particles [32,33]. The PSO is a relatively new metaheuristic search method whose mechanics are based on biological populations' swarming behavior [34]. Like other evolutionary computation techniques, PSO is a population-based search method that begins with a population of randomly generated solutions, also known as particles. In contrast to other evolutionary computation algorithms, each particle in the PSO is also associated with a velocity. Particles move around the search space with velocities that are dynamically changed based on their previous actions. A form of the PSO can be expressed as [35].

$$v_{i,j}^{(k+1)} = \eta v_{i,j}^{(k)} + c_1 r_1^{(k)} \left(p_{i,j}^{(k)} - \mathcal{X}_{i,j}^{(k)}\right) + c_2 r_2^{(k)} \left(g_j^{(k)} - \mathcal{X}_{i,j}^{(k)}\right) \tag{5}$$

$$\mathcal{X}_{i,j}^{(k+1)} = \mathcal{X}_{i,j}^{(k)} + v_{i,j}^{(k+1)} \tag{6}$$

where,
$v_{i,j}$ is the velocity of each particle i with dimension j, and k is the iteration index,
$\mathcal{X}_{i,j}$ represents each particle’s position,
η is the inertia weight that can balance a global or local search,
$p_{i,j}$ is the previous best position of each particle,
g_j indicates the global best during all particles,
c_1 and c_2 are two positive constants, being set as constant 2,
r_1 and r_2 are two random values set between [0,1] in each iteration.

4.3. Differential Evolution (DE) Algorithm

The differential evolution (DE) algorithm introduced by Storn [36] is a fast and simple technique that performs well on a wide variety of problems that has been widely employed in many scientific and engineering domains. DE is an intrinsically parallel population-based stochastic search approach [37]. The DE algorithm tries to evolve a population of NP D-dimensional parameter vectors, known as individuals that encode possible solutions, i.e., $X_{i,G} = \left\{X_{i,G}^1, \dots, X_{i,G}^D\right\}$, $i = 1, \dots, NP$ towards the global optimum. By uniformly randomizing individuals within the search space constrained by the prescribed minimum and maximum parameter bounds, the initial population should better cover the entire search space as much as possible such that $X_{min} = \{X_{min}^1, \dots, X_{min}^D\}$ and $X_{max} = \{X_{max}^1, \dots, X_{max}^D\}$. For example, the initial value of the jth parameter in the ith individual at the generation $G = 0$ is generated by

$$\mathcal{X}_{i,0}^j = \mathcal{X}_{min}^j + rand(0,1).\left(\mathcal{X}_{max}^j - \mathcal{X}_{min}^j\right),\ j = 1, 2, \dots, D. \tag{7}$$

where, rand (0,1) represents a uniformly distributed random variable within the range [0,1] [38].

The traditional DE algorithm begins with initializing a population of NP target individuals. $P_G = \left\{X_{1,G,} X_{2,G,} \dots, X_{NP,G}\right\}$, where individual $X_{\mathrm{i},G} = \left\{X_{i,G}^1, X_{i,G}^2, \dots, X_{i,G}^n\right\}$, $i = 1,2, \dots, NP$, is an. n-dimensional vector with parameter values determined randomly and uniformly between predefined search ranges $[X_{min}, X_{max}]$, where $X_{min} = (X_{min}^1, X_{min}^2, \dots, X_{min}^n)$, and $X_{max} = (X_{max}^1, X_{max}^2, \dots, X_{max}^n)$. Then, using mutation and crossover operators, new candidate vectors are generated, and a selection procedure is used to determine whether the child or the parent will survive to the next generation. The process is repeated until a criterion for termination is met [39].

4.4. Grey Wolf Optimizer (GWO)

The GWO algorithm is based on the natural leadership structure and hunting mechanism of grey wolves. For simulating the leadership structure, four sorts of grey wolves are used alpha, beta, delta, and omega. Furthermore, the three basic processes of hunting, namely seeking for prey, encircling prey, and attacking prey are implemented. Other wolves update their positions randomly around the prey, while alpha, beta, and delta estimate the position of the prey. When the target stops moving, the grey wolves conclude the hunt by attacking it. We reduce the value of $\vec{a}$ to mathematically model approaching the prey. Note that the fluctuation range of $\vec{A}$ is also decreased by $\vec{a}$. In other words, $\vec{A}$ is a random value in the interval $[-2a, 2a]$ where a is decreased from 2 to 0 over the course of iterations. When random values of $\vec{A}$ are in $[-1,1]$, the next position of a search agent can be in any position between its current position and the position of the prey [40]. A wolf (i) calculates its distance from the three optimal solutions by Eqs. (8)-(11) and then uses Eq. (12) to update its position.

$$\overrightarrow{A} = 2\overrightarrow{a}.\overrightarrow{r_1} - \overrightarrow{a} \tag{8}$$

$$\overrightarrow{B} = 2\overrightarrow{r_2} \tag{9}$$

$$\overrightarrow{D_\propto} = \left|\overrightarrow{B}.\overrightarrow{X_\propto} - \overrightarrow{X_\iota}\right|, \overrightarrow{D_\beta} = \left|\overrightarrow{B}.\overrightarrow{X_\beta} - \overrightarrow{X_\iota}\right|, \overrightarrow{D_\delta} = \left|\overrightarrow{B}.\overrightarrow{X_\delta} - \overrightarrow{X_\iota}\right| \tag{10}$$

$$\overrightarrow{X_1} = \overrightarrow{X_\propto} - \overrightarrow{A}.\overrightarrow{D_\propto}, \overrightarrow{X_2} = \overrightarrow{X_\beta} - \overrightarrow{A}.\overrightarrow{D_\beta}, \overrightarrow{X_3} = \overrightarrow{X_\delta} - \overrightarrow{A}.\overrightarrow{D_\delta} \tag{11}$$

$$\overrightarrow{X_\iota}(nt) = \frac{\overrightarrow{X_1}+\overrightarrow{X_2}+\overrightarrow{X_3}}{3} \tag{12}$$

Where, $\overrightarrow{X_\iota}, \overrightarrow{X_\propto}, \overrightarrow{X_\beta}$ and $\overrightarrow{X_\delta}$ represent the position vectors of i, $\propto$, β and δ; nt denotes the next iteration; $\overrightarrow{D_\propto}$, $\overrightarrow{D_\beta}$ and $\overrightarrow{D_\delta}$, respectively mean the distance vectors between $\propto$, β , δ and i. Both $\overrightarrow{r_1}$ and $\overrightarrow{r_2}$ are random vectors between [0,1]; $\overrightarrow{A}$ and $\overrightarrow{B}$ are two coefficient vectors. a is calculated as follows

$$a = 2 - 2 * it/MAX\_IT \tag{13}$$

where, it is the present number of iteration and MAX_IT indicates the maximum number of iteration [41].

5. Application and Evaluation

The application side of the suggested optimization algorithms is discussed in this section. To fully comprehend the performance of such a method, it is required to apply it to a real-world use case and run the relevant evaluation parameters.

5.1. Implementation Details

In this study, hourly mean wind speed data for the year 2020 from 30 stations in Istanbul were used. These data were derived from Istanbul Metropolitan Municipality Open Data Portal [42]. For this reason, no ethics committee approval is required (Although it varies from station to station, no data recordings were made for some days and no data are available for a few hours on some days. For some stations, there are no data available after 07.12.2020. 0 is entered for the hourly mean wind speed at some stations, but not exceeding a maximum of 4 hours, which can be neglected). After the dataset was created, GA, DE, PSO and GWO algorithms were run for each PDF on the same dataset and same conditions. On the application side of this study, Python was used for all optimization algorithms. A computer system running an Intel Xeon e5-2620 6c/12t 2.00 GHz CPU with 24 GB RAM was employed for all algorithms. The parameters of each algorithm were optimized for GA. The maximum number of iterations was determined as 200, the population number was 50, the mutation rate was 0.15, and the elitism rate was 0.1. In addition, roulette wheel was used for the selection process and a single point crossover was used. For DE, the crossover factor was 0.7 and the scaling factor was 0.5. For PSO, the inertia weight was 0.1, the lower bound was 1, the upper bound was 2, attraction terms c_1 and c_2 were both equal to 2. Finally, for GWO, the population number was determined as 40 and the maximum number of iterations as 100.

5.2. Testing and Evaluation of Optimization Algorithms on PDFs

The scale and shape parameters of the Weibull PDF, the scale parameter of the Rayleigh PDF, and the scale and shape parameters of the Gamma PDF were estimated for the wind speed data obtained from different stations located in Istanbul by using GA, DE, PSO and GWO algorithms. $[0.1, 10]$ was taken when estimating the scale parameter for all PDFs, and $[1, 10]$ was taken when estimating the shape parameter for the Weibull PDF and Gamma PDF. Estimated parameters were given for each station in Tables 1-3 (4 decimal places were used). The MAE, RMSE and R^2 values obtained for each distribution according to these algorithms are shown in the Tables 4-12 below where green cells indicate the maximum value in a row and the blue cells show the minimum value (5 decimal places were used).

Table 1. Estimated Weibull scale and shape parameters for each station by using GA, DE, PSO and GWO algorithms

	GA		DE		PSO		GWO	
STATION	*c*	*k*	*c*	*k*	*c*	*k*	*c*	*k*
ARNAVUTKOY_MGM	5.4854	2.3342	5.5483	2.3987	5.5476	2.3982	5.8589	2.1928
ATASEHIR	3.8376	2.4573	3.8068	2.4160	3.8067	2.4157	3.9145	2.3576
B_CEKMECE_SVIRAJLARI	3.7323	2.7164	3.7452	2.6667	3.6660	3.5958	3.9145	2.3576
BASAKSEHIR	4.2886	2.2354	4.2851	2.2201	4.2853	2.2205	3.9145	2.3576
BAYRAMOGLU_TUZLA	2.9999	2.6580	3.0147	2.7300	3.0145	2.7297	3.1609	2.4796
BEYKOZ_MGM	3.0477	1.8296	3.0503	1.8499	3.0502	1.8499	3.0595	1.7910
BUYUKADA	6.7456	2.5147	6.7616	2.4834	6.7607	2.4821	6.4472	2.3392
BUYUKCEKMECE_MGM	3.6774	1.8404	3.7536	1.8776	3.7523	1.8774	3.9145	2.3576
CANTA	5.0509	2.0649	5.1061	2.1034	5.1062	2.1036	5.8589	2.1928
CATALCA	8.1536	2.5433	8.2465	2.5286	8.2454	2.5289	8.4445	2.9149
DURUSU	5.3352	2.2147	5.3676	2.2298	5.3671	2.2299	5.8589	2.1928
EMINONU	3.5229	2.2187	3.5344	2.1939	3.5337	2.1945	3.9145	2.3576
EYUP_MGM	4.2353	1.8246	4.2293	1.8352	4.2293	1.8349	4.9956	1.4663
FLORYA	3.0551	2.2651	3.1313	2.2565	3.1314	2.2562	3.1609	2.4796
GOZTEPE	4.1860	2.1976	4.1726	2.1765	4.1724	2.1765	3.9145	2.3576
HADIMKOY	5.9744	2.2983	5.9866	2.2793	5.9867	2.2794	5.9334	2.1870
KARTAL	1.8068	2.7027	1.8189	2.7132	1.8349	2.5690	1.7517	2.5514
KILYOS	3.0845	2.0405	3.1276	2.0157	3.0686	2.0618	3.1244	1.9285
ODAYERI	2.0565	1.9900	2.0330	2.0085	2.0334	2.0106	2.0166	2.1777
PASAKOY	2.5516	1.9514	2.5750	1.9311	2.5775	1.9303	2.8330	1.8342
SABIHAGOKCEN	1.4166	1.7113	1.4137	1.8225	1.4135	1.8229	1.4713	1.7847
SARIYER_YSS_KOPRU_MGM	5.4147	2.2068	5.4705	2.1962	5.4704	2.1960	5.8589	2.1928
SILE_2	3.0290	2.2514	2.9736	2.1860	2.9734	2.1859	3.1244	1.9285
SILIVRI_MGM	5.2289	2.2435	5.2231	2.3004	5.2232	2.3003	5.8589	2.1928
SILIVRI_ORMAN_SAHASI	3.9404	1.8806	3.9715	1.8648	3.9704	1.8639	3.9145	2.3576
SISLI_MGM	2.4297	2.7926	2.4306	2.7451	2.4306	2.7483	2.3136	2.7026
SUREYYAPASA	1.7194	2.1787	1.7412	2.2246	1.7410	2.2243	1.7517	2.5514
TUZLA_MGM	2.4186	2.7424	2.4304	2.7445	2.4304	2.7447	2.3136	2.7026
USKUDAR_MGM	4.5065	2.0647	4.5165	2.1384	4.5165	2.1385	4.5774	2.7056
ZINCIRLIKUYU	2.8663	2.5599	2.9085	2.6235	2.9085	2.6239	3.1609	2.4796

Table 2. Estimated Rayleigh scale parameter for each station by using GA, DE, PSO and GWO algorithms

STATION	GA *c*	DE *c*	PSO *c*	GWO *c*
ARNAVUTKOY_MGM	3.9718	3.9716	3.8524	3.9583
ATASEHIR	2.7118	2.7118	2.6305	2.7409
B_CEKMECE_SVIRAJLARI	2.6472	2.6471	2.5677	2.6314
BASAKSEHIR	3.0516	3.0512	2.9597	3.0595
BAYRAMOGLU_TUZLA	2.1126	2.1124	2.0490	2.1028
BEYKOZ_MGM	2.1226	2.1232	2.0595	2.1324
BUYUKADA	4.7899	4.7902	4.6465	4.7894
BUYUKCEKMECE_MGM	2.6270	2.6272	2.5484	2.6314
CANTA	3.6231	3.6228	3.5141	3.7033
CATALCA	5.8413	5.8414	5.6662	5.8517
DURUSU	3.8173	3.8187	3.7041	3.8389
EMINONU	2.5165	2.5170	2.4415	2.4845
EYUP_MGM	2.9175	2.9170	2.8294	2.8887
FLORYA	2.2332	2.2333	2.1663	2.2093
GOZTEPE	2.9795	2.9792	2.8898	3.0177
HADIMKOY	4.2756	4.2756	4.1473	4.2537
KARTAL	1.2905	1.2909	1.2522	1.2750
KILYOS	2.2117	2.2118	2.1454	2.2093
ODAYERI	1.4393	1.4379	1.3947	1.4105
PASAKOY	1.8092	1.8097	1.7554	1.8131
SABIHAGOKCEN	0.9855	0.9842	0.9700	1.0136
SARIYER_YSS_KOPRU_MGM	3.8951	3.8953	3.7785	3.9138
SILE_2	2.1022	2.1024	2.0393	2.1028
SILIVRI_MGM	3.7147	3.7149	3.6035	3.7033
SILIVRI_ORMAN_SAHASI	2.7780	2.7768	2.6935	2.7963
SISLI_MGM	1.7066	1.7064	1.6552	1.6968
SUREYYAPASA	1.2455	1.2411	1.2038	1.2673
TUZLA_MGM	1.7103	1.7065	1.6553	1.6968
USKUDAR_MGM	3.2127	3.2108	3.1145	3.2092
ZINCIRLIKUYU	2.0648	2.0639	2.0020	2.0685

Table 3. Estimated Gamma scale and shape parameters for each station by using GA, DE, PSO and GWO algorithms

	GA		DE		PSO		GWO	
STATION	*c*	*k*	*c*	*k*	*c*	*k*	*c*	*k*
ARNAVUTKOY_MGM	1.1994	4.4015	1.2018	4.4315	1.2005	4.4272	1.1276	4.5703
ATASEHIR	0.8300	4.4590	0.8122	4.4989	0.8114	4.4944	1.0778	3.7458
B_CEKMECE_SVIRAJLARI	0.6672	5.3838	0.6497	5.5421	0.6491	5.5366	1.0778	3.7458
BASAKSEHIR	1.0846	3.8084	1.0852	3.7935	1.0841	3.7897	1.0778	3.7458
BAYRAMOGLU_TUZLA	0.5180	5.6641	0.4979	5.8325	0.4974	5.8267	1.3636	2.1580
BEYKOZ_MGM	1.1032	2.6778	1.0766	2.7177	1.0755	2.7149	1.3636	2.1580
BUYUKADA	1.4147	4.6122	1.3648	4.7593	1.3634	4.7545	1.6039	3.9304
BUYUKCEKMECE_MGM	1.3844	2.6327	1.3503	2.6747	1.3490	2.6720	1.4105	2.8310
CANTA	1.4952	3.2984	1.4445	3.3960	1.4430	3.3926	1.6968	2.9226
CATALCA	1.6428	4.8358	1.6000	4.9582	1.5984	4.9533	1.6373	4.9113
DURUSU	1.3506	3.8720	1.3517	3.8134	1.3503	3.8096	1.6400	3.2655
EMINONU	0.9023	3.7722	0.9156	3.7058	0.9147	3.7021	1.1787	3.2723
EYUP_MGM	1.5148	2.6696	1.5782	2.5751	1.5766	2.5725	1.4105	2.8310
FLORYA	0.7972	3.8119	0.7783	3.8620	0.7775	3.8583	1.5102	2.2421
GOZTEPE	1.0924	3.6078	1.1079	3.6136	1.1068	3.6100	1.0778	3.7458
HADIMKOY	1.4677	3.8932	1.4425	3.9847	1.4411	3.9807	1.3715	4.1147
KARTAL	0.2997	5.8164	0.3046	5.7411	0.3043	5.7354	1.1105	2.0116
KILYOS	0.8854	3.3768	0.9535	3.1556	0.9526	3.1524	1.3636	2.1580
ODAYERI	0.5496	3.4533	0.6253	3.1174	0.6247	3.1143	1.1105	2.0116
PASAKOY	0.9027	2.8215	0.8628	2.8753	0.8619	2.8725	1.1481	2.1860
SABIHAGOKCEN	0.5119	2.6664	0.5294	2.5751	0.5289	2.5726	1.2260	1.4430

SARIYER_YSS_KOPRU_MGM	1.3546	3.8923	1.4273	3.6826	1.4259	3.6789	1.6400	3.2655
SILE_2	0.7337	3.8734	0.7663	3.7415	0.7655	3.7377	1.3636	2.1580
SILIVRI_MGM	1.1925	4.1578	1.2287	4.0800	1.2275	4.0759	1.1276	4.5703
SILIVRI_ORMAN_SAHASI	1.4545	2.6385	1.4473	2.6455	1.4458	2.6429	1.4105	2.8310
SISLI_MGM	0.3934	6.0083	0.3943	5.9503	0.3939	5.9444	1.1481	2.1860
SUREYYAPASA	0.4088	4.0085	0.4367	3.8277	0.4363	3.8239	1.1105	2.0116
TUZLA_MGM	0.3510	6.7422	0.3944	5.9474	0.3940	5.9414	1.1481	2.1860
USKUDAR_MGM	1.2641	3.4398	1.2484	3.4767	1.2471	3.4732	1.2954	3.5113
ZINCIRLIKUYU	0.4958	5.6607	0.5176	5.4000	0.5171	5.3946	1.3636	2.1580

Table 4. MAE values for the estimation of Weibull shape and scale parameters by stations

	MAE			
STATION	**GA**	**DE**	**PSO**	**GWO**
ARNAVUTKOY_MGM	0.00547	0.00395	0.00396	0.01074
ATASEHIR	0.00599	0.00602	0.00602	0.00897
B_CEKMECE_SVIRAJLARI	0.00597	0.00441	0.04845	0.02090
BASAKSEHIR	0.00598	0.00614	0.00613	0.02017
BAYRAMOGLU_TUZLA	0.00771	0.00512	0.00513	0.02362
BEYKOZ_MGM	0.00805	0.00741	0.00741	0.00955
BUYUKADA	0.00346	0.00323	0.00324	0.00838
BUYUKCEKMECE_MGM	0.01096	0.00921	0.00923	0.03300
CANTA	0.00657	0.00557	0.00556	0.02345
CATALCA	0.00293	0.00248	0.00248	0.00998
DURUSU	0.00532	0.00497	0.00497	0.01485
EMINONU	0.00825	0.00844	0.00844	0.02777
EYUP_MGM	0.00752	0.00744	0.00744	0.02196
FLORYA	0.01039	0.00789	0.00789	0.01732
GOZTEPE	0.00603	0.00623	0.00624	0.01540
HADIMKOY	0.00418	0.00419	0.00419	0.00602
KARTAL	0.00970	0.00847	0.01945	0.03057
KILYOS	0.01009	0.00910	0.01121	0.01222
ODAYERI	0.01287	0.01252	0.01244	0.02423
PASAKOY	0.01153	0.01078	0.01072	0.02823
SABIHAGOKCEN	0.03050	0.02075	0.02075	0.02525
SARIYER_YSS_KOPRU_MGM	0.00521	0.00481	0.00481	0.01192
SILE_2	0.00809	0.00682	0.00682	0.02163
SILIVRI_MGM	0.00515	0.00423	0.00423	0.02023
SILIVRI_ORMAN_SAHASI	0.00932	0.00927	0.00929	0.02879
SISLI_MGM	0.00906	0.00739	0.00735	0.02399
SUREYYAPASA	0.01745	0.01354	0.01356	0.04306
TUZLA_MGM	0.00774	0.00740	0.00740	0.02396
USKUDAR_MGM	0.00806	0.00657	0.00657	0.02654
ZINCIRLIKUYU	0.00961	0.00623	0.00622	0.03156
FREQUENCY OF MAX	**1**	**-**	**1**	**28**
FREQUENCY OF MIN	**5**	**18**	**7**	**-**

Table 5. RMSE values for the estimation of Weibull shape and scale parameters by stations

	RMSE			
STATION	**GA**	**DE**	**PSO**	**GWO**
ARNAVUTKOY_MGM	0.00622	0.00502	0.00502	0.01327
ATASEHIR	0.00859	0.00785	0.00785	0.01142
B_CEKMECE_SVIRAJLARI	0.00660	0.00567	0.05648	0.02469
BASAKSEHIR	0.00801	0.00795	0.00795	0.02410
BAYRAMOGLU_TUZLA	0.00864	0.00655	0.00655	0.02795
BEYKOZ_MGM	0.01100	0.01083	0.01083	0.01197
BUYUKADA	0.00432	0.00416	0.00416	0.00995
BUYUKCEKMECE_MGM	0.01280	0.01154	0.01154	0.03741
CANTA	0.00776	0.00724	0.00724	0.02502
CATALCA	0.00361	0.00319	0.00319	0.01140

DURUSU	0.00643	0.00629	0.00629	0.01596
EMINONU	0.01115	0.01100	0.01100	0.03070
EYUP_MGM	0.00958	0.00955	0.00955	0.02773
FLORYA	0.01262	0.00983	0.00983	0.01971
GOZTEPE	0.00801	0.00786	0.00786	0.01907
HADIMKOY	0.00540	0.00534	0.00534	0.00675
KARTAL	0.01189	0.01080	0.02228	0.03528
KILYOS	0.01344	0.01273	0.01426	0.01454
ODAYERI	0.01751	0.01675	0.01675	0.02718
PASAKOY	0.01472	0.01440	0.01440	0.03098
SABIHAGOKCEN	0.03507	0.02781	0.02781	0.03452
SARIYER_YSS_KOPRU_MGM	0.00639	0.00613	0.00613	0.01308
SILE_2	0.01262	0.00962	0.00962	0.02632
SILIVRI_MGM	0.00610	0.00551	0.00551	0.02156
SILIVRI_ORMAN_SAHASI	0.01187	0.01176	0.01176	0.03289
SISLI_MGM	0.01053	0.00953	0.00953	0.02817
SUREYYAPASA	0.02020	0.01755	0.01755	0.04868
TUZLA_MGM	0.00989	0.00954	0.00954	0.02815
USKUDAR_MGM	0.00919	0.00820	0.00820	0.03020
ZINCIRLIKUYU	0.01135	0.00820	0.00820	0.03453
FREQUENCY OF MAX	**1**	**-**	**1**	**28**
FREQUENCY OF MIN	**-**	**30**	**-**	**-**

Table 6. R^2 values for the estimation of Weibull shape and scale parameters by stations

		R^2		
STATION	**GA**	**DE**	**PSO**	**GWO**
ARNAVUTKOY_MGM	0.98106	0.98766	0.98766	0.91396
ATASEHIR	0.98459	0.98713	0.98713	0.97275
B_CEKMECE_SVIRAJLARI	0.99246	0.99444	0.44815	0.89457
BASAKSEHIR	0.97978	0.98004	0.98004	0.81672
BAYRAMOGLU_TUZLA	0.99157	0.99515	0.99515	0.91179
BEYKOZ_MGM	0.97136	0.97222	0.97222	0.96609
BUYUKADA	0.98872	0.98955	0.98954	0.94004
BUYUKCEKMECE_MGM	0.94724	0.95711	0.95711	0.54920
CANTA	0.97084	0.97461	0.97461	0.69640
CATALCA	0.98810	0.99069	0.99069	0.88114
DURUSU	0.97989	0.98073	0.98073	0.87607
EMINONU	0.97362	0.97436	0.97436	0.80018
EYUP_MGM	0.95667	0.95688	0.95688	0.63673
FLORYA	0.97355	0.98397	0.98397	0.93550
GOZTEPE	0.97895	0.97973	0.97973	0.88073
HADIMKOY	0.98236	0.98275	0.98275	0.97240
KARTAL	0.99399	0.99505	0.97893	0.94716
KILYOS	0.96506	0.96865	0.96063	0.95906
ODAYERI	0.97364	0.97589	0.97588	0.93649
PASAKOY	0.96686	0.96830	0.96829	0.85324
SABIHAGOKCEN	0.93798	0.96101	0.96101	0.93990
SARIYER_YSS_KOPRU_MGM	0.97793	0.97970	0.97970	0.90767
SILE_2	0.97335	0.98451	0.98451	0.88404
SILIVRI_MGM	0.98332	0.98638	0.98638	0.79140
SILIVRI_ORMAN_SAHASI	0.94949	0.95042	0.95041	0.61213
SISLI_MGM	0.99292	0.99421	0.99420	0.94935
SUREYYAPASA	0.97724	0.98281	0.98281	0.86784
TUZLA_MGM	0.99376	0.99419	0.99419	0.94943
USKUDAR_MGM	0.96877	0.97512	0.97512	0.66236
ZINCIRLIKUYU	0.98652	0.99297	0.99297	0.87530
FREQUENCY OF MAX	**-**	**30**	**-**	**-**
FREQUENCY OF MIN	**1**	**-**	**1**	**28**

Table 7. MAE values for the estimation of Rayleigh scale parameter by stations

	MAE			
STATION	**GA**	**DE**	**PSO**	**GWO**
ARNAVUTKOY_MGM	0.01590	0.01590	0.01674	0.01595
ATASEHIR	0.02471	0.02471	0.02569	0.02465
B_CEKMECE_SVIRAJLARI	0.03966	0.03966	0.04043	0.03973
BASAKSEHIR	0.01323	0.01323	0.01455	0.01319
BAYRAMOGLU_TUZLA	0.04856	0.04856	0.04948	0.04860
BEYKOZ_MGM	0.01442	0.01441	0.01697	0.01430
BUYUKADA	0.01601	0.01601	0.01646	0.01601
BUYUKCEKMECE_MGM	0.01207	0.01207	0.01385	0.01199
CANTA	0.00772	0.00772	0.00898	0.00785
CATALCA	0.01375	0.01375	0.01413	0.01375
DURUSU	0.01105	0.01105	0.01200	0.01100
EMINONU	0.01583	0.01582	0.01713	0.01618
EYUP_MGM	0.01284	0.01284	0.01343	0.01294
FLORYA	0.01957	0.01956	0.02138	0.01998
GOZTEPE	0.01154	0.01155	0.01317	0.01135
HADIMKOY	0.01109	0.01109	0.01196	0.01117
KARTAL	0.08454	0.08453	0.08629	0.08499
KILYOS	0.00948	0.00948	0.01241	0.00953
ODAYERI	0.01271	0.01278	0.01739	0.01522
PASAKOY	0.01285	0.01283	0.01711	0.01263
SABIHAGOKCEN	0.03665	0.03679	0.03900	0.03569
SARIYER_YSS_KOPRU_MGM	0.00948	0.00948	0.01053	0.00943
SILE_2	0.01492	0.01492	0.01751	0.01491
SILIVRI_MGM	0.01345	0.01345	0.01442	0.01350
SILIVRI_ORMAN_SAHASI	0.01211	0.01214	0.01387	0.01184
SISLI_MGM	0.06664	0.06664	0.06752	0.06668
SUREYYAPASA	0.03231	0.03247	0.03594	0.03230
TUZLA_MGM	0.06657	0.06657	0.06746	0.06662
USKUDAR_MGM	0.00989	0.00990	0.01117	0.00991
ZINCIRLIKUYU	0.04862	0.04862	0.04971	0.04859
FREQUENCY OF MAX	**-**	**-**	**30**	**-**
FREQUENCY OF MIN	**10**	**6**	**-**	**14**

Table 8. RMSE values for the estimation of Rayleigh scale parameter by stations

	RMSE			
STATION	**GA**	**DE**	**PSO**	**GWO**
ARNAVUTKOY_MGM	0.01805	0.0181	0.0187	0.0181
ATASEHIR	0.02784	0.0278	0.0288	0.0280
B_CEKMECE_SVIRAJLARI	0.04480	0.0448	0.0455	0.0448
BASAKSEHIR	0.01489	0.0149	0.0161	0.0149
BAYRAMOGLU_TUZLA	0.05615	0.0561	0.0570	0.0562
BEYKOZ_MGM	0.01666	0.0167	0.0188	0.0167
BUYUKADA	0.01810	0.0181	0.0186	0.0181
BUYUKCEKMECE_MGM	0.01442	0.0144	0.0158	0.0144
CANTA	0.00885	0.0088	0.0102	0.0096
CATALCA	0.01571	0.0157	0.0161	0.0157
DURUSU	0.01246	0.0125	0.0134	0.0125
EMINONU	0.01789	0.0179	0.0192	0.0181
EYUP_MGM	0.01401	0.0140	0.0152	0.0141
FLORYA	0.02208	0.0221	0.0237	0.0223
GOZTEPE	0.01309	0.0131	0.0146	0.0134
HADIMKOY	0.01254	0.0125	0.0133	0.0126
KARTAL	0.09627	0.0963	0.0976	0.0965
KILYOS	0.01279	0.0128	0.0153	0.0128
ODAYERI	0.01679	0.0168	0.0211	0.0186
PASAKOY	0.01575	0.0158	0.0189	0.0158
SABIHAGOKCEN	0.04247	0.0425	0.0434	0.0459
SARIYER_YSS_KOPRU_MGM	0.01068	0.0107	0.0118	0.0107
SILE_2	0.01703	0.0170	0.0195	0.0170

SILIVRI_MGM	0.01511	0.0151	0.0160	0.0151
SILIVRI_ORMAN_SAHASI	0.01471	0.0147	0.0160	0.0148
SISLI_MGM	0.07616	0.0762	0.0771	0.0762
SUREYYAPASA	0.03680	0.0368	0.0398	0.0382
TUZLA_MGM	0.07610	0.0761	0.0770	0.0761
USKUDAR_MGM	0.01121	0.0112	0.0126	0.0112
ZINCIRLIKUYU	0.05491	0.0549	0.0558	0.0549
FREQUENCY OF MAX	-	-	**29**	**1**
FREQUENCY OF MIN	**1**	**29**	-	-

Table 9. R^2 values for the estimation of Rayleigh scale parameter by stations

	R^2			
STATION	**GA**	**DE**	**PSO**	**GWO**
ARNAVUTKOY_MGM	0.84068	0.84068	0.82844	0.84053
ATASEHIR	0.83804	0.83804	0.82712	0.83673
B_CEKMECE_SVIRAJLARI	0.65289	0.65289	0.64248	0.65250
BASAKSEHIR	0.93008	0.93008	0.91775	0.92999
BAYRAMOGLU_TUZLA	0.64397	0.64397	0.63283	0.64373
BEYKOZ_MGM	0.93430	0.93430	0.91657	0.93396
BUYUKADA	0.80167	0.80167	0.79141	0.80167
BUYUKCEKMECE_MGM	0.93299	0.93299	0.91940	0.93295
CANTA	0.96205	0.96205	0.94944	0.95574
CATALCA	0.77448	0.77448	0.76366	0.77445
DURUSU	0.92449	0.92449	0.91267	0.92415
EMINONU	0.93215	0.93215	0.92143	0.93023
EYUP_MGM	0.90727	0.90727	0.89120	0.90566
FLORYA	0.91909	0.91909	0.90644	0.91753
GOZTEPE	0.94377	0.94377	0.93050	0.94151
HADIMKOY	0.90471	0.90471	0.89236	0.90437
KARTAL	0.60653	0.60653	0.59534	0.60470
KILYOS	0.96834	0.96834	0.95474	0.96833
ODAYERI	0.97578	0.97579	0.96169	0.97021
PASAKOY	0.96205	0.96205	0.94518	0.96199
SABIHAGOKCEN	0.90903	0.90906	0.90519	0.89393
SARIYER_YSS_KOPRU_MGM	0.93846	0.93846	0.92546	0.93816
SILE_2	0.95147	0.95147	0.93606	0.95147
SILIVRI_MGM	0.89759	0.89759	0.88507	0.89746
SILIVRI_ORMAN_SAHASI	0.92245	0.92245	0.90868	0.92175
SISLI_MGM	0.62978	0.62978	0.62071	0.62947
SUREYYAPASA	0.92445	0.92463	0.91144	0.91866
TUZLA_MGM	0.63033	0.63037	0.62130	0.63006
USKUDAR_MGM	0.95350	0.95351	0.94120	0.95350
ZINCIRLIKUYU	0.68473	0.68473	0.67469	0.68468
FREQUENCY OF MAX	-	**30**	-	-
FREQUENCY OF MIN	-	-	**29**	**1**

Table 10. MAE values for the estimation of Gamma shape and scale parameters by stations

	MAE			
STATION	**GA**	**DE**	**PSO**	**GWO**
ARNAVUTKOY_MGM	0.00946	0.00903	0.00910	0.01083
ATASEHIR	0.01369	0.01389	0.01400	0.02900
B_CEKMECE_SVIRAJLARI	0.01364	0.01293	0.01307	0.04030
BASAKSEHIR	0.01219	0.01235	0.01245	0.01369
BAYRAMOGLU_TUZLA	0.01444	0.01445	0.01468	0.08036
BEYKOZ_MGM	0.01225	0.01235	0.01247	0.02475
BUYUKADA	0.00816	0.00794	0.00800	0.01252
BUYUKCEKMECE_MGM	0.01579	0.01574	0.01581	0.02468
CANTA	0.01075	0.01051	0.01058	0.01334
CATALCA	0.00626	0.00610	0.00617	0.00597
DURUSU	0.00990	0.01030	0.01038	0.01313

EMINONU	0.01685	0.01720	0.01729	0.03287
EYUP_MGM	0.01176	0.01176	0.01180	0.01241
FLORYA	0.01633	0.01654	0.01666	0.04556
GOZTEPE	0.01338	0.01258	0.01267	0.01213
HADIMKOY	0.00909	0.00867	0.00874	0.00922
KARTAL	0.02585	0.02567	0.02598	0.15964
KILYOS	0.01579	0.01599	0.01612	0.03611
ODAYERI	0.02674	0.02377	0.02394	0.06100
PASAKOY	0.01706	0.01731	0.01746	0.03191
SABIHAGOKCEN	0.03215	0.03313	0.03341	0.10493
SARIYER_YSS_KOPRU_MGM	0.00914	0.00946	0.00953	0.01111
SILE_2	0.01329	0.01258	0.01278	0.04240
SILIVRI_MGM	0.00961	0.00927	0.00936	0.00970
SILIVRI_ORMAN_SAHASI	0.01508	0.01510	0.01518	0.01544
SISLI_MGM	0.01993	0.02075	0.02100	0.10996
SUREYYAPASA	0.03048	0.02857	0.02883	0.11651
TUZLA_MGM	0.02311	0.02077	0.02102	0.10986
USKUDAR_MGM	0.01268	0.01260	0.01269	0.01387
ZINCIRLIKUYU	0.01671	0.01759	0.01778	0.08437
FREQUENCY OF MAX	**2**	**-**	**-**	**28**
FREQUENCY OF MIN	**14**	**14**	**-**	**2**

Table 11. RMSE values for the estimation of Gamma shape and scale parameters by stations

	RMSE			
STATION	**GA**	**DE**	**PSO**	**GWO**
ARNAVUTKOY_MGM	0.01114	0.01100	0.01101	0.01266
ATASEHIR	0.01735	0.01701	0.01702	0.03131
B_CEKMECE_SVIRAJLARI	0.01625	0.01600	0.01602	0.04607
BASAKSEHIR	0.01540	0.01537	0.01538	0.01603
BAYRAMOGLU_TUZLA	0.01862	0.01785	0.01787	0.09366
BEYKOZ_MGM	0.01573	0.01556	0.01557	0.02702
BUYUKADA	0.00988	0.00975	0.00975	0.01412
BUYUKCEKMECE_MGM	0.01888	0.01880	0.01880	0.02844
CANTA	0.01321	0.01310	0.01310	0.01562
CATALCA	0.00762	0.00756	0.00757	0.00778
DURUSU	0.01296	0.01267	0.01267	0.01590
EMINONU	0.02128	0.02120	0.02121	0.03516
EYUP_MGM	0.01404	0.01379	0.01380	0.01538
FLORYA	0.01995	0.01968	0.01969	0.05451
GOZTEPE	0.01542	0.01503	0.01503	0.01547
HADIMKOY	0.01080	0.01066	0.01067	0.01111
KARTAL	0.03140	0.03124	0.03127	0.18579
KILYOS	0.02175	0.02081	0.02081	0.04080
ODAYERI	0.03406	0.02918	0.02920	0.07370
PASAKOY	0.02231	0.02090	0.02092	0.03610
SABIHAGOKCEN	0.04189	0.04114	0.04115	0.12624
SARIYER_YSS_KOPRU_MGM	0.01204	0.01160	0.01160	0.01333
SILE_2	0.01660	0.01606	0.01608	0.04994
SILIVRI_MGM	0.01154	0.01132	0.01133	0.01487
SILIVRI_ORMAN_SAHASI	0.01846	0.01845	0.01846	0.02141
SISLI_MGM	0.02649	0.02617	0.02619	0.12555
SUREYYAPASA	0.03741	0.03533	0.03535	0.13621
TUZLA_MGM	0.03183	0.02619	0.02621	0.12545
USKUDAR_MGM	0.01538	0.01536	0.01537	0.01782
ZINCIRLIKUYU	0.02262	0.02182	0.02184	0.09615
FREQUENCY OF MAX	**-**	**30**	**-**	**-**
FREQUENCY OF MIN	**-**	**-**	**-**	**30**

Table 12. R^2 values for the estimation of Gamma shape and scale parameters by stations

	R^2			
STATION	**GA**	**DE**	**PSO**	**GWO**
ARNAVUTKOY_MGM	0.93927	0.94086	0.94079	0.92163
ATASEHIR	0.93711	0.93954	0.93947	0.79521
B_CEKMECE_SVIRAJLARI	0.95431	0.95570	0.95562	0.63294
BASAKSEHIR	0.92522	0.92544	0.92537	0.91891
BAYRAMOGLU_TUZLA	0.96083	0.96402	0.96392	0.00931
BEYKOZ_MGM	0.94139	0.94265	0.94257	0.82718
BUYUKADA	0.94097	0.94249	0.94242	0.87933
BUYUKCEKMECE_MGM	0.88515	0.88616	0.88610	0.73948
CANTA	0.91535	0.91684	0.91678	0.88168
CATALCA	0.94692	0.94776	0.94768	0.94462
DURUSU	0.91823	0.92194	0.92188	0.87699
EMINONU	0.90397	0.90465	0.90460	0.73790
EYUP_MGM	0.90685	0.91015	0.91008	0.88828
FLORYA	0.93393	0.93572	0.93565	0.50689
GOZTEPE	0.92195	0.92593	0.92586	0.92145
HADIMKOY	0.92939	0.93113	0.93106	0.92524
KARTAL	0.95815	0.95857	0.95848	0.46542
KILYOS	0.90843	0.91622	0.91616	0.67788
ODAYERI	0.90029	0.92680	0.92674	0.53319
PASAKOY	0.92386	0.93317	0.93309	0.80069
SABIHAGOKCEN	0.91150	0.91467	0.91460	0.19635
SARIYER_YSS_KOPRU_MGM	0.92170	0.92740	0.92733	0.90407
SILE_2	0.95386	0.95680	0.95672	0.58253
SILIVRI_MGM	0.94020	0.94246	0.94238	0.90071
SILIVRI_ORMAN_SAHASI	0.87785	0.87791	0.87785	0.83568
SISLI_MGM	0.95523	0.95628	0.95621	0.00601
SUREYYAPASA	0.92196	0.93036	0.93029	0.03489
TUZLA_MGM	0.93533	0.95620	0.95613	0.00459
USKUDAR_MGM	0.91249	0.91268	0.91262	0.88242
ZINCIRLIKUYU	0.94651	0.95019	0.95012	0.03335
FREQUENCY OF MAX	**-**	**30**	**-**	**-**
FREQUENCY OF MIN	**-**	**-**	**-**	**30**

As depicted by Tables 4-12, when three PDFs are compared for wind speed data from urban stations in Istanbul, the Weibull PDF has higher R^2 and a lower MAE and RMSE values in parameter estimation than the other two PDFs. This is followed by the Gamma PDF and then the Rayleigh PDF except for a few stations. So, the Weibull PDF fits best to model the wind speed data obtained.

The following Figures 2-4 show the Weibull PDF plotted with the scale and shape parameters obtained by using DE algorithm for the stations with the highest R^2 value.

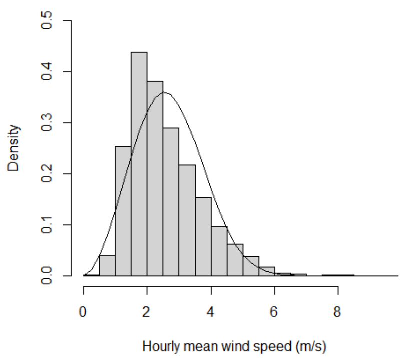

Figure 2. Weibull PDF for the wind speed data from station BAYRAMOGLU_TUZLA

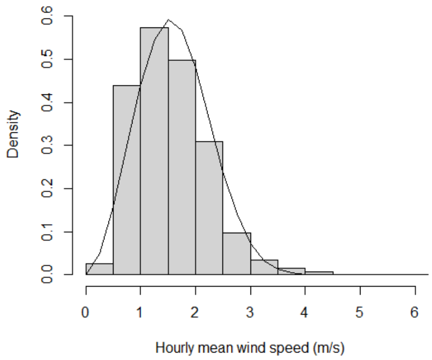

Figure 3. Weibull PDF for the wind speed data from station KARTAL

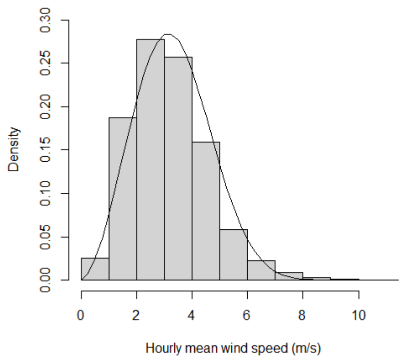

Figure 4. Weibull PDF for the wind speed data from station B_CEKMECE_SVIRAJLARI

It has been observed that when the four metaheuristic algorithms used in the study are compared among themselves, the GWO algorithm, for Weibull PDF and Gamma PDF, generally has the lowest R^2 as well as the highest MAE and RMSE values. For these two PDFs, the DE algorithm outperforms as it yields the highest R^2 values and the lowest RMSE values. As for the Rayleigh PDF, which is less suitable as mentioned before, the DE algorithm yields the highest R^2 values and the lowest RMSE values again except for one station. However, for the Rayleigh PDF, PSO showed the worst performance in terms of MAE, RMSE and R^2 values.

6. Conclusion

As every geographical location exhibit different wind speed profile and characteristics, site-based wind engineering is indispensable for optimal exploitation of available wind energy potential. Researchers all over the world have experimented with different PDFs for modelling available wind speed dataset. They have used different numerical methods and metaheuristic optimization algorithms for the determination of parameters of PDFs. They have also opted for various testing procedures to determine optimal PDFs, optimization algorithms and numerical methods. The conclusions of the research work indicate that the Weibull PDF fits best the wind speed data obtained from urban stations in Istanbul and the DE algorithm outperforms other algorithms used in the study.

Authors' Contributions

MHÖ and BLA were the first to come up with the original idea. BLA and MHÖ reviewed the literature and planned the study by obtaining the data. OO, Mİ and MHÖ conducted the analysis. All authors wrote up the article. All authors read and approved the final manuscript.

Competing Interests

The authors declare that they have no competing interests.

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