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Estimation of Weibull Probability Distribution Parameters with Optimization Algorithms and Foça Wind Data Application

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Highlights

- This paper focuses on estimating WEP and determining wind characteristics.
- The Weibull parameters are obtained using PSO, SCA, SGO, and BA.
- Actual measurements in Foça are used to estimate the wind energy.
- The performance of the algorithms used is evaluated using the RMSE and χ^2 criteria.

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Abstract

In this study, the scale and shape parameters of the Weibull probability distribution function (W.pdf) used in determining the profitability of wind energy projects are estimated using optimization algorithms and the moment method. These parameters are then used to estimate the wind energy potential (WEP) in Foça region of İzmir in Turkey. The values of Weibull parameters obtained using Particle Swarm Optimization (PSO), Sine Cosine Algorithm (SCA), Social Group Optimization (SGO), and Bat Algorithm (BA) were compared with the estimation results of the Moment Method (MM) as reference. Root mean square error (RMSE) and chi-square (χ^2) tests were used to compare the parameter estimation methods. The wind speed measurement values of the observation station in Foça were used. As a result of Foça speed data analysis, the annual average wind speed was determined as 6.15 m/s, and the dominant wind direction was found as northeast. Wind speed frequency distributions were compared with the measurement results and calculated with the estimated parameters. When RMSE and χ^2 criteria are evaluated together; it can be concluded that each used method behaves similarly for the given parameter estimation problem, with minor variations. As a result, it has been found that the optimization parameters produce very good results in wind speed distribution and potential calculations.

1. INTRODUCTION

A significant part of the growing energy demand caused by population growth, technological progress and rising living standards is met by electrical energy. According to an estimate published in 2018, the increase in electrical energy consumption will be able to supply 70% of the required energy in the next 25 years [1]. Therefore, it is expected that future investments in the energy sector will be focused on electrical energy. With the economic and environmental concerns increasing day by day, the demand for sustainable, safe, reliable, and efficient energy sources is also increasing. For this reason, low-cost, environmentally friendly energy sources that have a positive impact on the environment are becoming more popular for electricity generation [2].

Energy sources can be categorized based on whether they are renewable or consumable. The classification depends on whether the resources will be depleted at the end of their use. Renewable energy sources do not degrade after use and remain the same throughout the natural cycle. On the other hand, nonrenewable energy sources are depleted and cannot be replenished. The two categories of nonrenewable energy sources can be divided into fossil (natural gas, petroleum, and coal) and nuclear (thorium and uranium). Renewable energy sources include wave, tidal, hydro, geothermal, solar, wind, and biomass-type sources [3].

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Using environmentally friendly and sustainable energy sources is vital to meet the world's growing energy needs. For this reason, renewable energy sources should be preferred over fossil fuels. Renewable energy sources are always available and their use does not pollute the environment. Consequently, humanity can meet its energy needs in a safe, durable, and affordable way [4].

Wind energy is becoming one of the most important forms of renewable energy for electricity generation. The economic potential of wind energy in Turkey is estimated at 66 GW. This is according to the study "Turkey Wind Energy Potential Atlas" conducted by Electricity Works Survey Administration and General Directorate of Meteorology in 2006 [5]. Exploiting this potential is crucial for improving energy reliability and diversity by reducing dependence on foreign energy supplies.

A commonly used renewable energy source for generating electrical energy is wind energy. However, using wind as an energy source to generate electricity can present some challenges due to its unpredictable and fluctuating nature. In addition, modern technology may not be able to generate electricity at all wind speeds, which may affect the financial feasibility of wind energy projects. Therefore, to realize investments in wind energy, forecasts based on a statistical analysis of wind speed are required [6].

The proposed investment region's wind parameters and energy potential should be evaluated before investing in wind power plants. The policies introduced and the market trends support this. However, drawbacks such as the fluctuation of wind, its unpredictability, and its volatility in time and location lead to uncertainties in wind power generation. Studies on statistical modeling of probability distributions of wind speed random variables aim to reduce these uncertainties and avoid potential problems [7].

Studies on modeling and analyzing the frequency distribution of wind speed have been published in the literature. Several studies have been conducted to estimate the probability distributions of wind speeds. These studies use distribution functions such as Pearson type V and Burr [8], and probability density functions derived from Gamma, Rayleigh [9], Weibull [10, 11] , Lognormal [12], normal [13-15], half-normal [16, 17], Nakagami [18], Inverse Gaussian [16], Logistic [17, 18], Log-Logistic [19], Generalized extreme value [20, 21], and Generalized Pareto [22]. In general, the relevant studies agree that the two-parameter Weibull probability distribution is appropriate for the frequency distribution of wind speed. Heuristic techniques from artificial intelligence algorithms have also been used to estimate the Weibull parameters [23-27].

Wind energy assessment is significantly affected by the distribution of wind speed, and even modest modeling errors in wind speed data can lead to incorrect energy computations [28]. The Weibull distribution, one of the most popular and advantageous distribution functions, has various advantages and offers the greatest fit to wind data [29]. The key characteristics that make this distribution so popular are the ease with which its two parameters may be estimated, its flexibility, and its correctness at different places [30].

According to the literature, the W.pdf is best suited for statistical analysis and characterization of wind data for a region [31, 32]. It is possible to calculate the Weibull probability distribution variables using mathematical techniques and the appropriate data [33]. The defined probability distribution functions can be justified using the determined variables and the accuracy of these models can be evaluated. The Weibull probability distribution is a single-peaked probability distribution with two different variables, shape (k) and scale (c). There are also multivariate Weibull probability distributions [34].

Heuristic algorithms are those that draw their inspiration from natural processes to solve problems and complete tasks. In the solution space, heuristic algorithms converge to the best solution, but they do not ensure the absolute answer [35]. These algorithms are easier to understand for the decision maker. These algorithms are required since, unlike other types of issues, optimization problems lack a framework that would allow for the discovery of an absolute solution, which is used to teach us how to solve difficulties.

In this work, the two-parameter W.pdf is utilized to simulate the frequency distribution of wind speed. To obtain the correct parameters of the probability distribution function, the MM, SCA, PSA, SGO and BA are all utilized. To calculate the wind speed distribution model, an estimating approach was employed. The Weibull probability distribution model's fit efficiency was then assessed using the goodness of fitting. Figure 1 illustrates the steps of the approach taken in the study in further detail.

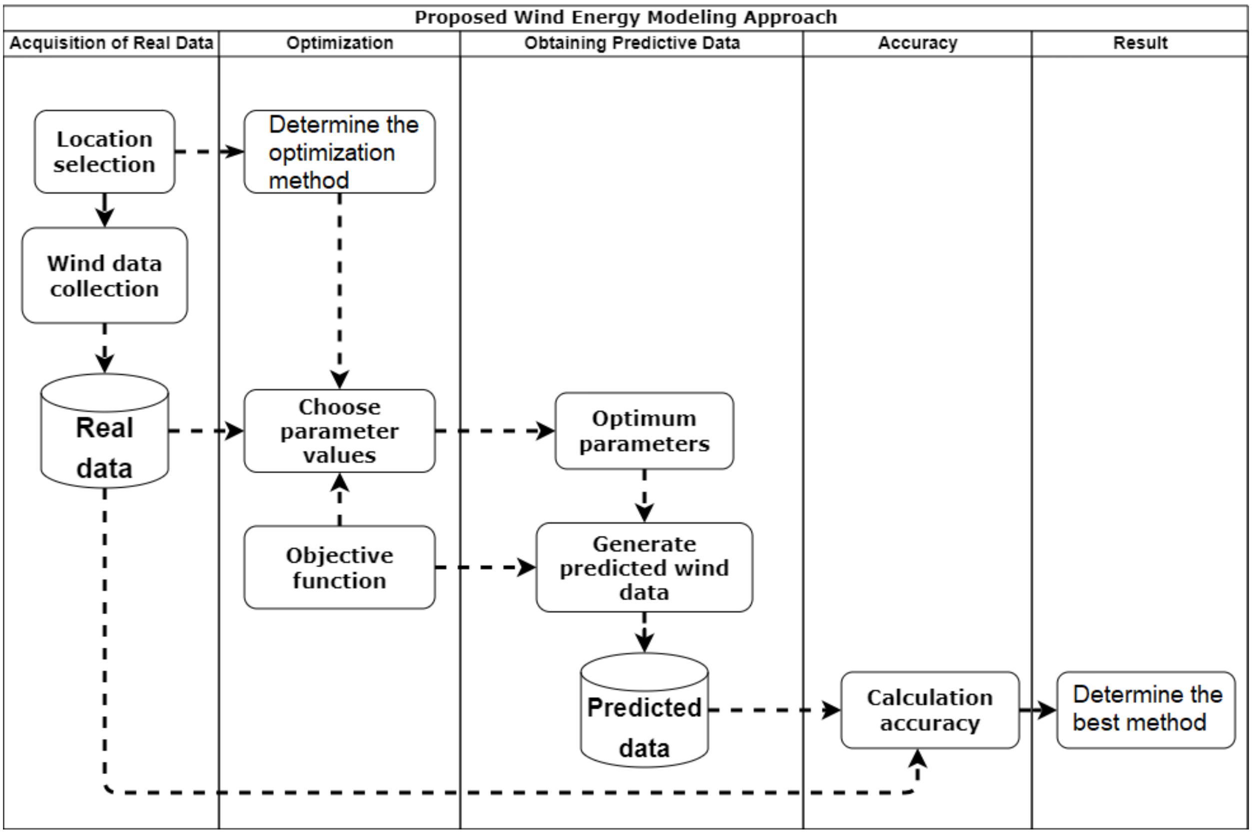

Figure 1. *Approach of the model*

2. MATERIAL METHOD

2.1. Data

The wind speed measurement results from the İzmir Foça meteorological observation station were utilized for computations in this study. The average wind speed at Foça town was discovered to be 6.15 m/s, with the prevalent wind directions being 0 degrees north, 45 degrees northeast (NE), and 330 degrees north northwest (NNW). In addition, Figure 2 shows a wind rose graph depicting the prevalent wind direction based on sixteen wind sectors. Table 1 depicts the blow intensities of wind speed observations. To calculate wind potential, hourly wind speed data over the course of a year was observed. A total of 8594 hours of wind speed data were analyzed from the required 8760 hours of wind speed data per year, which included 166 hours that were missing.

During wind potential computation and feasibility studies, wind data is analyzed to evaluate its suitability for investment reasons. Currently, the prevailing wind direction and wind properties hold significant importance. When estimating the prevailing wind direction in this context, it is important to further analyze wind characteristics using the Weibull distribution function.

Table 1. *Blow intensities of wind speed measurements*

Speed	# of Blows	Cumulative Frequency	Blowing Frequency		Speed	# of Blows	Cumulative Frequency	Blowing Frequency
0	8	8	0.000931		12	215	8264	0.025017
1	337	345	0.039213		13	143	8407	0.016640

2	799	1144	0.092972	14	79	8486	0.009192
3	939	2083	0.109262	15	58	8544	0.006749
4	900	2983	0.104724	16	25	8569	0.002909
5	947	3930	0.110193	17	10	8579	0.001164
6	1032	4962	0.120084	18	8	8587	0.000931
7	973	5935	0.113219	19	3	8590	0.000349
8	871	6806	0.101350	20	2	8592	0.000233
9	565	7371	0.065744	21	1	8593	0.000116
10	401	7772	0.046660	22	1	8594	0.000116
11	277	8049	0.032232				

One of the essential requirements for evaluating wind resources is to provide descriptive statistics of wind power plant measurement data. Descriptive statistics can be found in Table 2. As can be seen from the descriptive statistics data, the wind speed data are skewed toward the point where the values are less than the average wind speed, and they are slightly sharper than the normal distribution with a kurtosis coefficient of 0.27. The standard deviation is 3.18 m/s, and the greatest wind speed was measured at 21.9 m/s.

Table 2. *The descriptive statistics data*

Foça Descriptive Statistics Data	
Average	6.15459623
Standard Error	0.034367716
Median	5.9
Standard Deviation	3.186018848
Sample Variance	10.1507161
Kurtosis	0.276911107
Skewness	0.638000799
Range	21.5
Biggest	21.9
Smallest	0.4
Number of measurements	8594

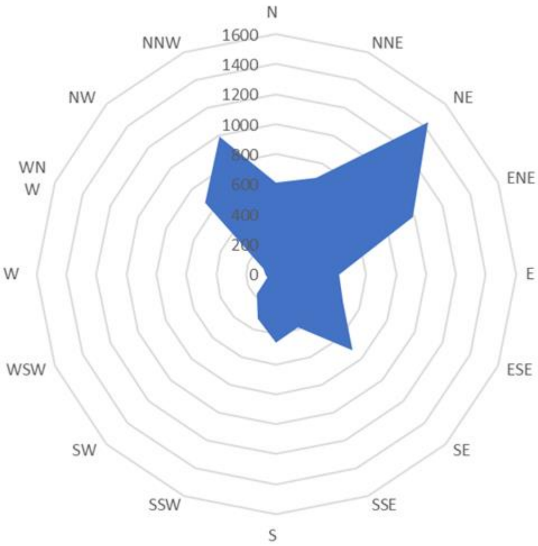

Figure 2. *Wind Rose Chart in Foça*

2.2. Weibull Probability Distribution Function

The formula of the Weibull probability density, which is used in almost every study related to wind energy calculations, is very flexible and continuous, and its parameters can be easily estimated compared to most other probability distribution functions, is given in Equation (1), and the cumulative distribution formula is given in Equation (2). Where, k and c are the shape parameter and the scale parameter, respectively. The wind speed bin is indicated by v [34-36]

$$f(v) = \frac{k}{c}\left(\frac{v}{c}\right)^{k-1} * \exp\left(-\left(\frac{v}{c}\right)^{k}\right), \ \ 0 < v < \infty \tag{1}$$

$$F(v) = 1 - \exp\left(-\left(\frac{v}{c}\right)^{k}\right). \tag{2}$$

Given the suitability of the frequency variation of wind speed for the Weibull distribution, the shape and scale parameters must be estimated using appropriate techniques to construct the function given the measured speed data.

2.3. Parameter Estimation Methods

For modeling wind speed frequency, the parameters of the probability distribution function are estimated using numerical techniques and optimization algorithms. The optimization process usually starts with a random solution set in population-based optimization techniques. This random set is evaluated many times with the fitness function and the predictions are improved with the appropriate optimization technique. Stochastic optimization techniques do not guarantee a solution in a single iteration because they stochastically search for the optimum of the optimization problem. In this case, the probability of finding the global optimum increases with a sufficient number of random solutions and optimization steps.

In this study, using the MM, PSO, SGO, SCA, and BA techniques, parameter estimates for probability distribution functions were obtained that are close to the real results.

2.3.1. Moment method

Moment Method (MM) is based on the determination of scale and shape parameters by solving the W.pdf given in Equation (1) using the mean values and standard deviations obtained from the measured data [37]

$$\bar{v} = \frac{1}{n}\left(\sum_{i=1}^{n} v_i\right). \tag{4}$$

In Equation (4), *n* represents the number of data and v_i is the i^{th} measured wind speed data. The value of scale parameter c is found from Equation (5)

$$\sigma = c\left(\Gamma\left(\frac{2}{k}+1\right) - \Gamma^{2}\left(\frac{1}{k}+1\right)\right)^{0.5}. \tag{5}$$

σ is the value of the standard deviation of the measured wind speeds. Using this value, the value of k can be derived from Equation (6)

$$\sigma = \left[\frac{1}{n-1}\sum_{i=i}^{n}(v_i - \bar{v})^2\right]^{0.5}. \tag{6}$$

Thus, the *k*-shape parameters can be derived from Equation (7) and the *c*-scale parameters from Equation (8)

$$k = \left(\frac{\sigma_v}{\bar{v}}\right)^{-1.086} \tag{7}$$

$$c = \frac{\bar{v}}{\Gamma\left(\frac{1}{k}+1\right)}. \tag{8}$$

Figure 3 shows flowchart of the MM. The detailed pseudocode of the MM algorithm in Figure 3 is given below.

Step 1: Start: Obtain sample data.

Step 2: Calculation of mean and variance: The mean and variance of the sample data are calculated. The mean is calculated as the sum of the sample data divided by the number of data points. The variance is calculated as the sum of the squared differences between each data point and the mean divided by the number of data points minus 1.

Step 3: Estimation of the parameters of the distribution: Using the calculated mean and variance, the parameters of the base distribution are estimated. The particular form of estimation depends on the distribution being modeled. For example, for a normal distribution, the parameters are estimated as the mean and standard deviation and calculated using the mean and variance.

Step 4: Finish: The estimated parameters show the best fit for the base distribution on which the sample data is based and are output.

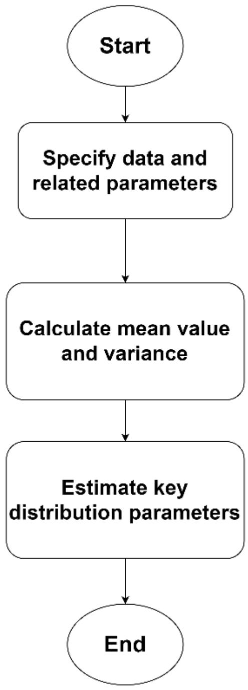

Figure 3. *Flowchart of the MM*

2.3.2. Particle swarm optimization

The PSO is a population-based stochastic optimization approach inspired by birds and fish flocks [38]. The basis of the PSO algorithm is based on the fact that individual solutions called particles have a population called flocks. As each individual in the flock creates a solution path, it benefits from its previous experiences and the previous experiences of the flock. The individuals representing possible solutions to the problem are points that move in the space between the parameters to be optimized. The trajectories of the particles are based on the best-known position in the search space and the best-known position of the entire swarm. As a result, the best solution in the space is expected to be found [38].

The positions of M particles in the D-dimensional solution space are given in Equation (9), and their velocities are given in Equation (10)

$$x_i = (x_{i1}\ x_{i2}\ x_{i3}\ \dots\ x_{iD}), \qquad i = 1,2,3,\dots,M \tag{9}$$

$$v_i = (v_{i1}\ v_{i2}\ v_{i3}\ \dots\ v_{iD}), \qquad i = 1,2,3,\dots,M. \tag{10}$$

The best solution, i.e., the local best position obtained during the search in the *D*-dimensional solution space of M particles, is expressed in Equation (11)

$$p_i = (p_{i1}\ p_{i2}\ p_{i3}\ \dots\ p_{iD}), \quad i = 1,2,3,\dots,M. \tag{11}$$

In Equation (12), it represents the best solution among the local best locations, i.e., the absolute best solution

$$g_i = (g_1\ g_2\ g_3\ \dots\ g_D). \tag{12}$$

The *K*-factor used to guarantee the convergence of the optimization is given in Equation (13)

$$K = \frac{2}{\left|2-\varphi-\sqrt{\varphi^2-4\varphi}\right|},\ \varphi = c_1 + c_2 > 4. \tag{13}$$

Equation (14) determines the particle's current velocity, while Equation (15) defines its present location [38]

$$v_{iD}^{t+1} = K\left[v_{iD}^t + c_1 r_1\left(p_{iD}^t - x_{iD}^t\right) + c_2 r_2\left(g_{iD}^t - x_{iD}^t\right)\right] \tag{14}$$

$$x_{iD}^{t+1} = x_{iD}^t + v_{iD}^{t+1}. \tag{15}$$

For the algorithm to converge to the right answer and for the particles to stay within the solution space, the locations and velocities must be constrained. Equations (16a) and (16b) provide the upper and lower constraints for the particle velocities, respectively.

$$v^{max} = \left(x^{max} - x^{min}\right)/(2) \tag{16a}$$

$$v^{min} = \left(-v^{max}\right) \tag{16b}$$

where the lower and upper bounds of the particle positions in the solution space are given by x^{min} and x^{max}, respectively. Figures 4 depict the PSO flowchart. The PSO algorithm's pseudocode is give as follows.

Step 1: Define parameters such as the number of iterations and particles

Step 2: Define the velocities and positions of the particles

Step 3: Define the velocity and position values of the particles randomly

Step 4: for $t = 1$: number of iterations

Step 5: for $i = 1$: number of particles

Step 6: if $\left(F_{xi}^{t+1} < F_{pi}^t\right)$

$p_i^{t+1} = x_i^{t+1}; F_{pi}^{t+1} = F_{xi}^{t+1}$

Step 7: else

$p_i^{t+1} = p_i^t; F_{pi}^{t+1} = F_{pi}^t;$

Step 8: endif

Step 9: if $\left(F_{pi}^{t+1}(en \text{ iyi }) < F_g^t\right)$

$$g^{t+1} = p_i^{t+1}(\text{ en iyi }); F_g^{t+1} = F_{pi}^{t+1}(\text{ en iyi })$$

Step 10: Else

$$g^{t+1} = g^t; F_g^{t+1} = F_g^t;$$

Step 11: endif

Step 12: Update velocity and position sequentially

Step 13: end for(particles)

Step 14: end for(iterations)

Step 15: Optimized parameters $= g^{t+1}$

The objective function in this study is to minimize the sum of square errors given by Equation (17). The error in the objective function is represented by the difference between the wind speed probability values observed in the histogram and the speed distribution probability produced by the Weibull distribution

$$E = \sum_{v_i=1}^{n} \left[f_{observed}(v_i) - f_{predited}(v_i)\right]^2. \tag{17}$$

where n is the number of the histogram velocity intervals, $f_{observed}(v_i)$. $f_{observed}(v_i)$ represents the frequencies determined by the calculated parameters, and $f_{predited}(v_i)$ represents the frequencies derived from the histogram observations.

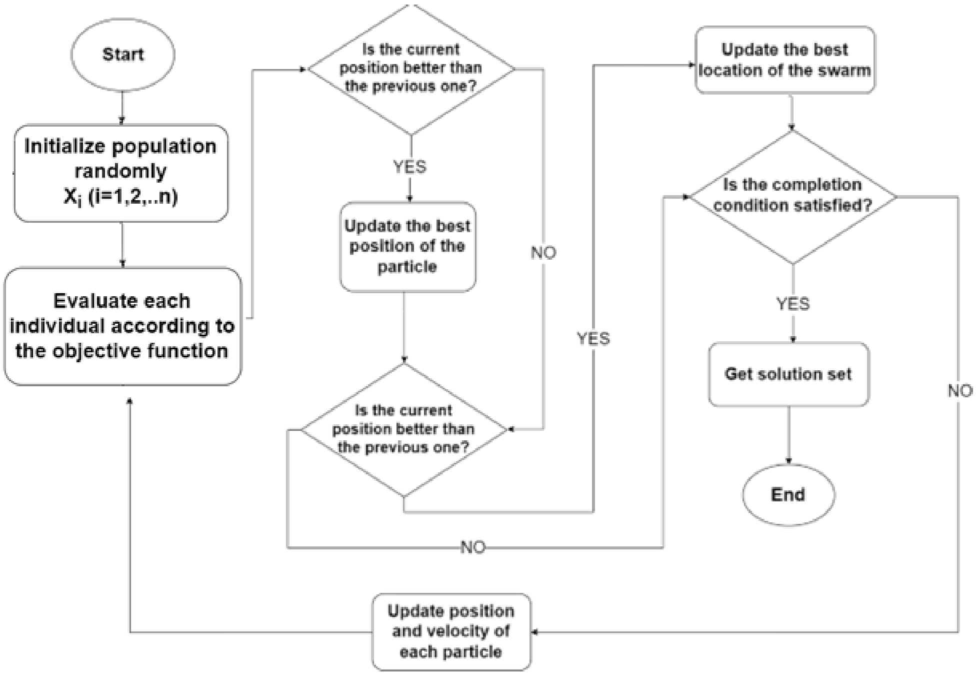

Figure 4. *Flowchart of the PSO algorithm*

At the end of the iterations evaluated according to the objective function, the absolute best position value is determined, which contains the optimized position and shape parameters.

In the pseudocode in Figure 4, F_x denotes the fitness value of the particle positions, F_p denotes the fitness value of the local best position of the particles, and F_g denotes the fitness value of the absolute best position.

2.3.3. Sine cosine algorithm

The SCA is a population-based heuristic algorithm. The SCA initially generates a number of random solutions, making sure that these solutions move either toward or away from the ideal solution. The program also includes several random and adaptive variables to enhance the exploration and use of the research space. Two frequent phases of the stochastic population-based optimization process are discovery and exploitation. The algorithm must strike a balance between exploration and exploitation to identify interesting regions of the search space and arrive at the global optimum [39].

The produced random solutions are modified gradually throughout the algorithm's exploitation phase when the random fluctuations are significantly less than during the exploration phase. In Equations (18) and (19), the position update equations for the SCA are given

$$X_i^{t+1} = x_i^t + r_1 \times \sin(r_2) \times \left| r_3 P_i^t - X_i^t \right| \tag{18}$$

$$X_i^{t+1} = x_i^t + r_1 \times \cos(r_2) \times \left| r_3 P_i^t - X_i^t \right| \tag{19}$$

where x_i^t is the current position of the i^{th} candidate solution, t^{th} iteration. r_1, r_2 and r_3 are random numbers. Here r_4 is a random number in the range [0, 1]. P_i is the location of the target point in the i^{th} dimension. Figure 5 illustrates the effect of sine and cosine functions in Equations (18) and (19) [39].

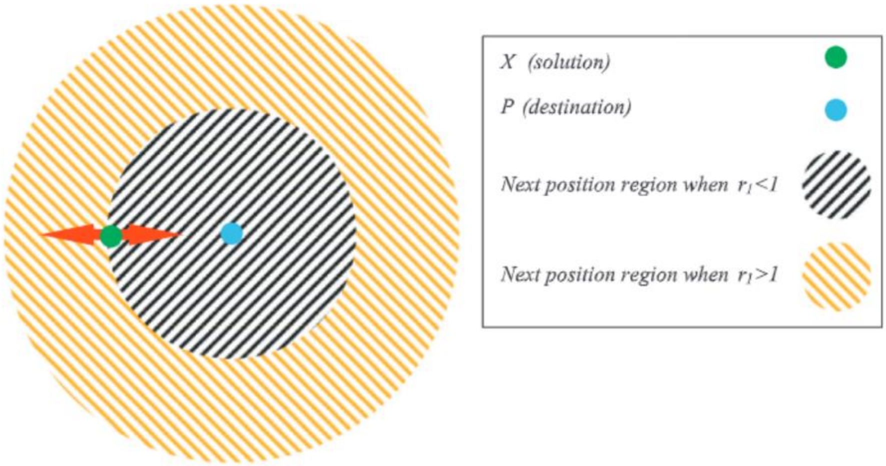

Figure 5. *Effects of sine and cosine on the next position*

Figure 5 demonstrates how to determine the region in the search space of Equations (18) and (19) that lies between two solutions. Equation (20) is also derived from these two equations [19]

$$X_i^{t+1} = \begin{cases} x_i^t + r_1 \times \sin(r_2) \times \left| r_3 P_i^t - X_i^t \right|, & r_4 < 0.5 \\ x_i^t + r_1 \times \cos(r_2) \times \left| r_3 P_i^t - X_i^t \right|, & r_4 \geq 0.5. \end{cases} \tag{20}$$

In the SCA, there are four main parameters used as follows:

r_1 : Determines the region (or route) of the next location.
r_2 : Determines how far to move inward or outward to reach the destination.
r_3 : Determines the stochastic weight randomly. If r_3 is more than 1, the stochasticity is significant, and if r_3 is less than 1, the stochasticity is ineffective.
r_4 : Determines the transition between the sine and cosine components in Equation (20).

To determine the search space, one must look for solutions other than the space between the fields that correspond to the various goals. Figure 6 illustrates this by showing the effects of sine and cosine functions with a range of variation [-2, 2].

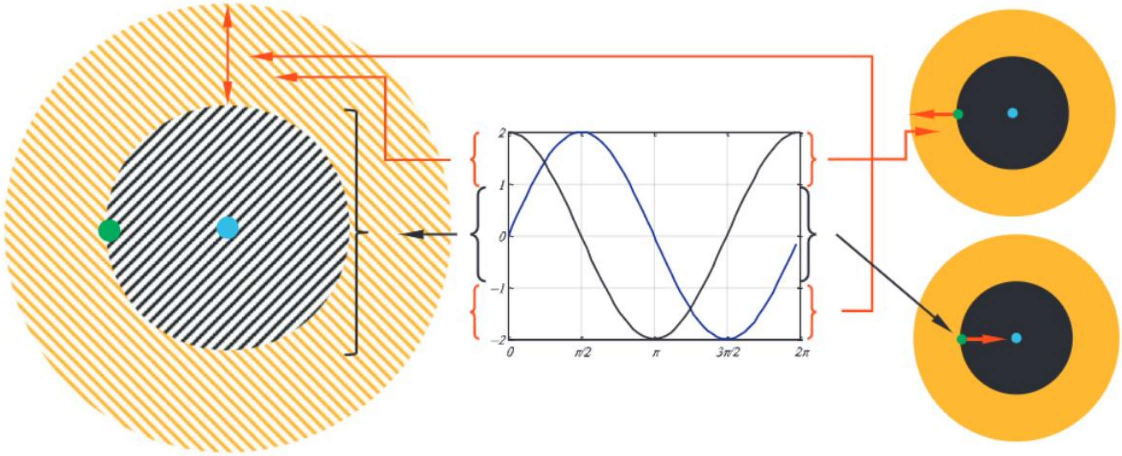

Figure 6. *Moving Around or Beyond a Solution Using Sine and Cosine in [-2, 2]*

Figure 6 depicts how the sine and cosine function ranges vary along with a method for updating the location of one solution to another. By supplying a random number r_2 in the range [0, 2], as in Equation 18, the random location is determined. Since of this, the search space will be explored and utilized [39].

Equations (18), (19), and (20) are used to adaptively change the sine and cosine distances to balance exploration and exploitation. Equation (21) illustrates how the range of the sine and cosine functions decreased during the iterations.

$$r_1 = a - t\frac{a}{T} \tag{21}$$

where t is the current iteration. T is the maximum number of the iteration and a is a constant.

The flowchart of the SCA is illustrated in Figure 7. As explained in Figure 7, the flow of the algorithm starts with a random solution set. The optimization stores the best solution and assigns it as the goal point. The other solutions are updated based on the target point. The range of sine and cosine functions is updated as the number of iterations increases to ensure utilization. When the iteration counter reaches the maximum number of iterations, the algorithm ends the optimization process by default.

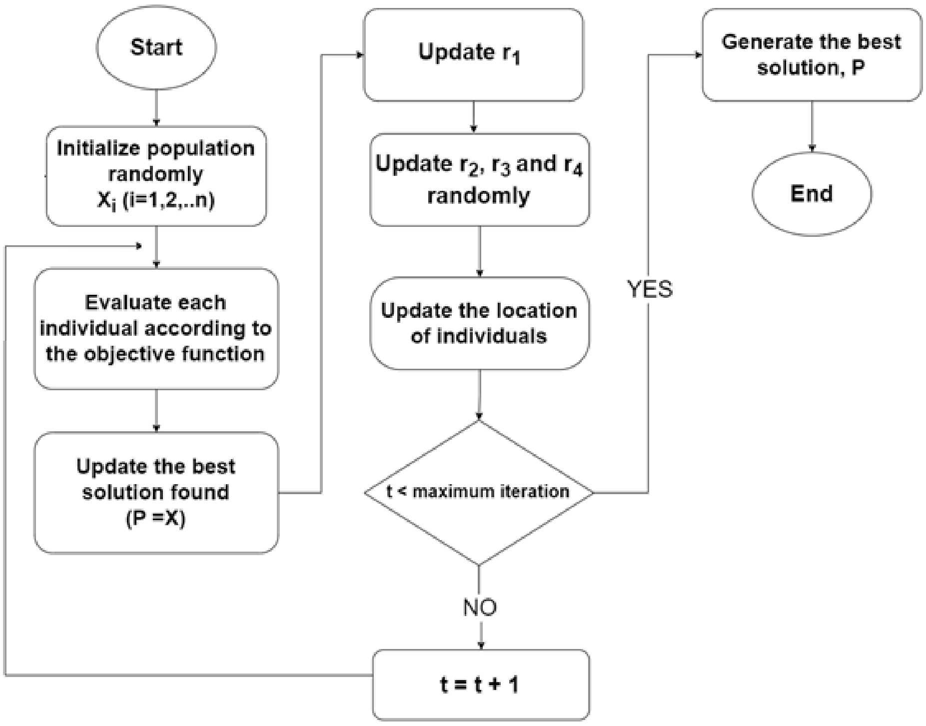

Figure 7. *The flowchart of the SCA*

2.3.4. Social group optimization

Humans are known to be excellent imitators or followers when accomplishing a task. It has been found that the problem-solving abilities of groups are superior to the skills of individuals when it comes to utilizing and exploring the various attributes of individual group members to solve a particular problem. As a result of this idea, a novel optimization method known as social group optimization (SGO) was introduced [40].

SGO is an optimization technique that focuses on the ability of a group to solve a problem. This algorithm assembles a group of people with different abilities, and the group works together to solve a given problem. The method is divided into two phases: the development phase, also called the exploration phase, and the extraction phase, also called the exploitation phase [41].

The algorithm development phase focuses on the transfer of knowledge by the most knowledgeable member of the group to others. Equation (22) expresses this phase mathematically, which helps the other group members rank themselves in comparison to the best person:

$$X_{\text{new}} = c * X_{\text{old}} + r * (X_{\text{best}} - X_{\text{old}}) \tag{22}$$

where r is a random integer in [0,1]; c is the self-observation or self-introspection parameter for each individual, and its value varies from 0 to 1; X_{new}, X_{old}, and X_{best} represent the individual's new position, the individual's old position of in the initialization phase, and the position of the group's best individual, respectively.

The social interaction of the people with one another is the focus of the acquiring phase. During this phase, the individual's social behavior is mathematically modeled to interact with the group's top performer (X_{best}) and the other randomly chosen group members. By this procedure, the interacting person (X_i) learns any new information from the random individual (X_r), if any, and develops. The following is a presentation of the mathematical model:

$$X_{\text{new}} = X_{\text{old}} + r_1 * (X_i - X_r) + r_2 * (X_{\text{best}} - X_i), \text{ if } X_i, \text{ better than } X_r, \left(f(X_i) < f(X_r)\right) \tag{23}$$

$$X_{\text{new}} = X_{\text{old}} + r_1 * (X_r - X_i) + r_2 * (X_{\text{best}} - X_i), \text{ if } X_r, \text{better than } X_i, \left(f(X_i) > f(X_r)\right) \quad (24)$$

where r_1 and r_2 are random numbers between 0 and 1, promoting algorithmic randomness and improving interpersonal behavior. In this case, X_{old} refers to a person's status during development. They are allowed if X_{new} values provide a higher fitness value for the desired function.

The flowchart for social group optimization is shown in Figure 8. Its pseudocode is given below [20].

Step 1: Problem enumeration and parameter initialization
Set initial values for population size (*N*), number of design variables (*D*) and generations (*g*), and variable constraints (U_L, L_L).

Step 2: Determine the optimization problem: maximize or reduce *f*(*x*).

Step 3: Initialize the population
Based on the user-selected characteristics (number of parameters) and population size, a random population is created.

Step 4: Improving Phase
Next, decide which iteration's best answer is $gbest_g$. Each individual receives knowledge from the best member of its group, or gbest, just as in evolution.

Step 5: The self-monitoring factor is represented by the parameter *c*. The value of *c* can be determined empirically for a given problem. For this study, it was set at 0.2.

Step 6: Acquiring phase
Each member of a social group socializes with the best people in the group throughout the acquisition period. It also sporadically converses with other group members to learn more.

Step 7: Termination criterion
If the maximum generation number is reached, end the simulation; otherwise, repeat Steps 3 and 4.

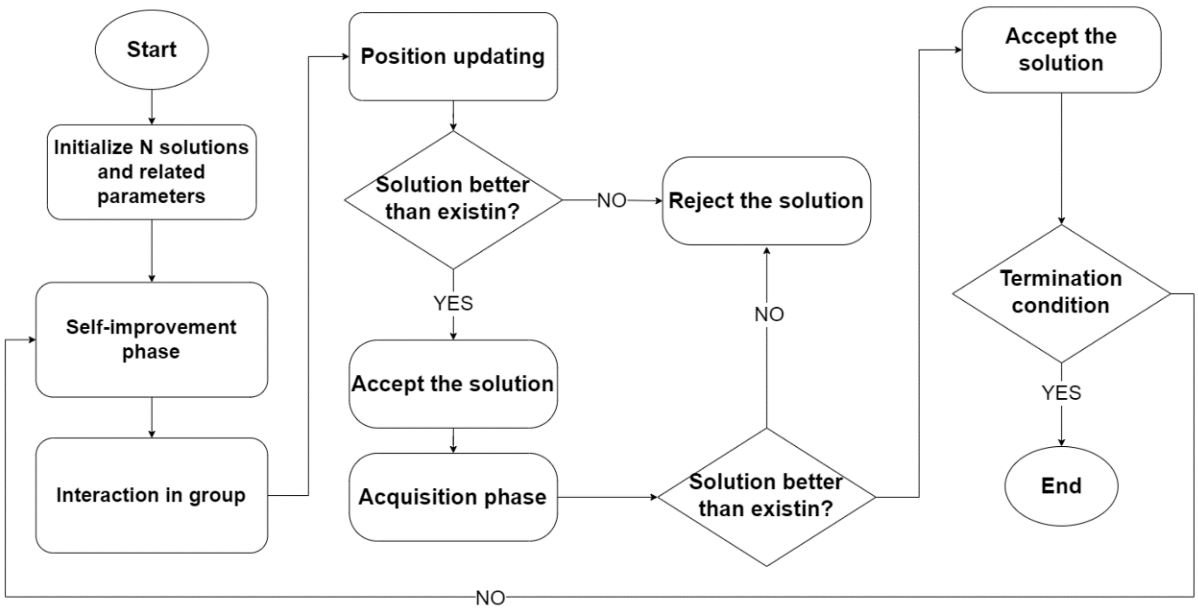

Figure 8. *Flowchart of the SGO*

2.3.5. Bat Algorithm

The Baat Algorithm (BA) is a natural metaheuristic optimization algorithm presented by Xin-She Yang in 2010. This algorithm focuses on solving global optimization problems by mimicking the echolocation method used by bat species in nature [42]. In the wild, bats use a method such as sonar to detect their prey, avoid obstacles, and stay in the dark. BA was designed to mimic this natural process and find the best solutions to specific optimization problems. The principle of the algorithm is based on the fact that it scans the problem domain like a bat and then moves to the point it has determined to be the best solution.

Bats move randomly to locate their prey. To determine the position of their prey, they emit sound signals of different wavelength r with loudness L_0, position x_i, a fixed frequency f_{min}, and velocity v_i. Bats adjust the frequency of sound waves to determine the distance to their targets and regulate their signal propagation rate between 0 and 1. Each bat can have a different frequency, loudness, and signal propagation rate [43].

For each bat, position (x_i) and velocity (v_i) values can be specified and updated throughout the process. Sound intensity (L_m^{iter}) can vary from a fixed large value (L_0) to the smallest constant value (L_{min}). The current velocities (v_i^t) and positions (x_i^t) are calculated using Equations (25), (26) and (27) in a given time interval (t) [44]

$$f_i = f_{min} + (f_{max} - f_{min})a \tag{25}$$

$$v_i^t = v_i^{t-1} + \left(x_i^t - x_{best}^t\right)f_i \tag{26}$$

$$x_i^t = x_i^{t-1} + v_i^t. \tag{27}$$

where f_i is the frequency value of the sound produced by the bat; while f_{max} and f_{min} express the minimum and maximum values of this frequency, the variable a is a random variable and ranges from 0 to 1. After selecting the best solution value among the calculated values, a new solution value is found as a result of local random operations

$$x_{\text{new}} = x_{\text{old}} + \varepsilon L^t. \tag{28}$$

In Equation (28), the average sound intensity produced by the bats in the time interval t is expressed as L^t. ε is a random variable between 1 and -1. The signal propagation rate and loudness should be updated during the iterations performed. When the bat detects its prey, the loudness generally decreases (L) while the signal propagation rate (r) increases

$$A_i^{t+1} = \beta A_i^t, r_i^{t+1} = r_i^0[1 - \exp(-\gamma t)]. \tag{29}$$

In Equation (28), when t approaches infinity, $r_i^t \to r_i^0$ and $L_i^t \to 0$. In Equation (29), γ is a positive constant and β is a constant between 0 and 1. The flowchart of the BA is depicted in Figure 9.

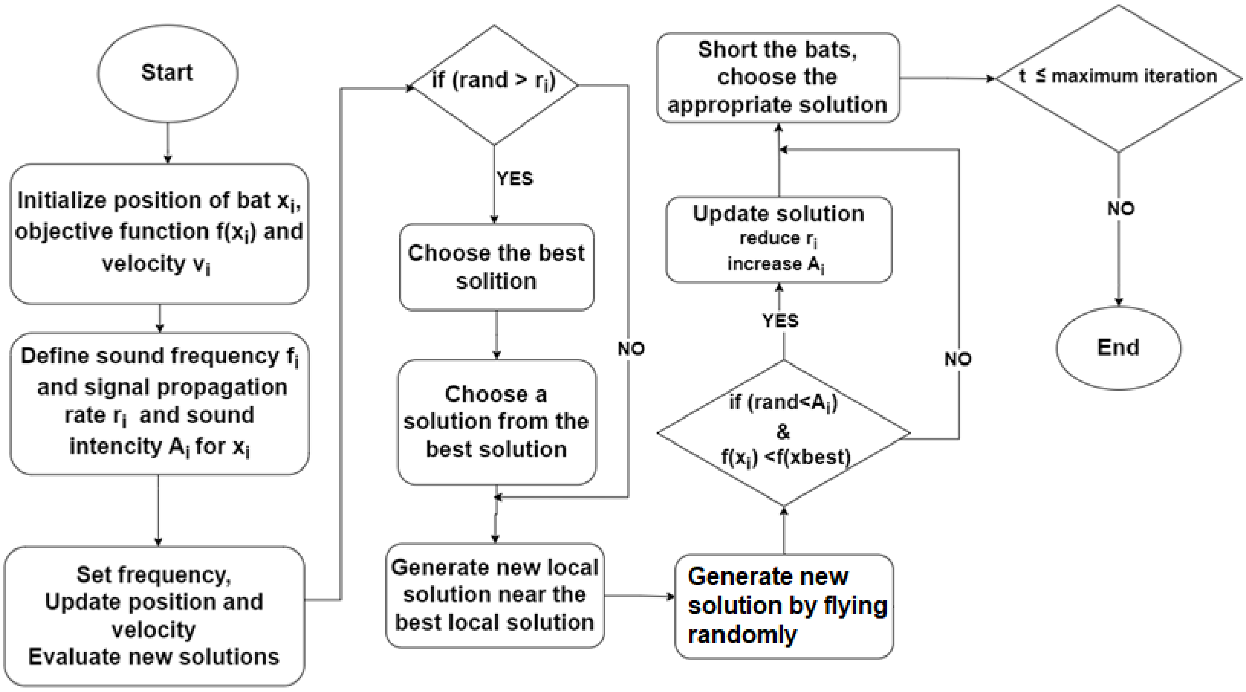

Figure 9. *The flowchart of the BA*

3. EVALUATION CRITERIA

The shape and scale parameters of the W.pdf were estimated using the above methods, and the frequency of the wind speed distribution was modeled. To evaluate the integration between the frequency values obtained by the methods and the actual frequency values, the RMSE and the chi-square test were used as performance criteria. These criteria are given in Equations (30) and (31)

$$MSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(V_{ci} - V_{oi})^2} \tag{30}$$

$$\chi^2 = \sum_{k=0}^{n}\left(\frac{(V_{ci}-V_{oi})^2}{V_{oi}}\right). \tag{31}$$

In Equation (28) and Equation (29) V_i, is represented the i^{th} value, and $\bar{V}_o$ is the average of measured wind speed. Representing with V_{ci} estimated i^{th} wind data of W.odf and n is the number of the measured data. The fact that RMSE and the chi-square performance criteria are as close to zero as possible shows the success of the model.

4. RESULTS AND DISCUSSION

In the Foça area in Izmir province, wind speed data are first divided into wind speed bin. The wind frequencies were determined for these velocity bins, and the distribution of the wind probabilities of the velocity classes was determined using their frequencies. The determined values for the mean velocity and standard deviation are based on the measurements of the wind speed bin and the probabilistic blowing density. The moment approach and metaheuristic optimization techniques were used to estimate the scale and shape parameters of the W.pdf based on the blow percentages of the wind speed frequencies. Four different swarm intelligence-based optimization algorithms, PSO, SCA, SGO, and BA, were used in this work. Table 3 lists the Weibull distribution parameters obtained.

As seen Table 3, the largest value of the shape parameter was determined in MM, while the smallest value was determined in BA. The largest value was calculated with PSO and the smallest value was estimated with BA when we considered the scale parameter.

Table 3. *Weibull distribution parameters*

Model Name	Shape parameter k	Scale parameter c
Moment Method (MM)	2.0166	6.8901
Particle Swarm Optimization Algorithm (PSO)	1.9483	6.9418
Sine Cosine Algorithm (SCA)	1.9611	6.9401
Social Group Optimization Algorithm (SGO)	1.9618	6.9359
Bat Algorithm (BA)	1.9788	6.8591

The swarm intelligence heuristic optimization algorithms PSO, SCA, SGO, and BA were run with 50, 100, 500, and 1000 iterations, and it was observed that the best answers were usually very close. The convergence graphs of these algorithms are shown in Figures 10 for iterations of 50. The outcomes of the other iterations were extremely similar to those of iterations 50. The charts show how rapidly the algorithms get the desired outcome. The figures show that the algorithms converge to the result very quickly.

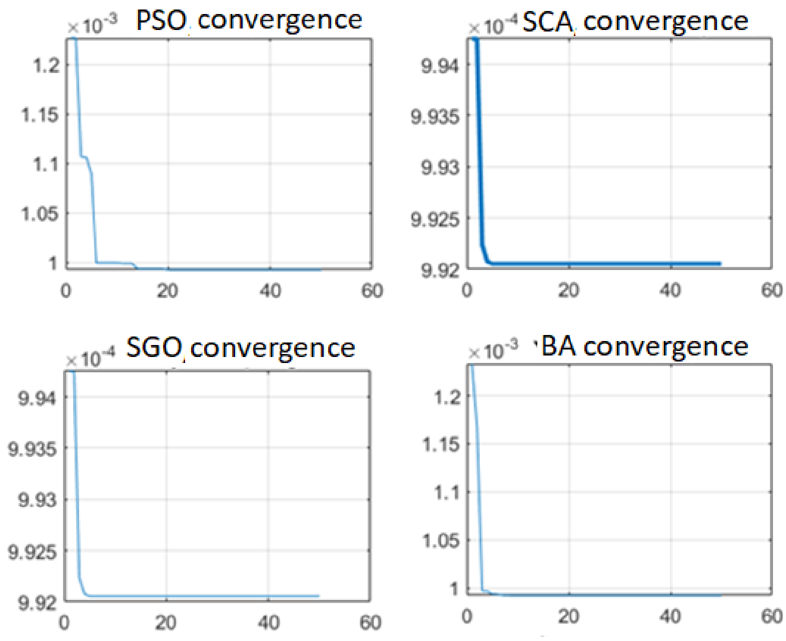

Figure 10. *PSO, SCA, SGO, and BA convergence graphs for 50 iterations*

Using the Weibull distribution parameters determined as a result of applying the methods. The wind speed frequency was computed using RMSE and χ^2 performance criteria and the results obtained according to the performance criteria are illustrated in Table 4. Table 4 shows that the heuristic algorithms give the same result when examining the six digits after the decimal point in the RMSE criterion data. This comparison shows that the metaheuristic algorithms perform better than MM. On the other hand, when the χ^2 criterion is examined, the optimization algorithms give both the best result (BA) and the worst result (PSO). BA is evaluated with an RMSE of 0.006646 and a χ^2 Chisquare of 0.012086. In comparison to other methods, it shows a slightly higher RMSE but a lower χ^2 Chisquare. Overall examination of the Table 4, it can be seen that each method performs similarly for the specific parameter estimation problem, with minor variations. The choice of method should be assessed based on the specific application and problem context.

Table 4. *The performance values of parameter estimation methods*

Methods	Performance Values	
	RMSE	χ^2 Chisquare
Moment Method (MM)	0.006752	0.012475
Particle Swarm Optimization Algorithm (PSO)	0.006578	0.013448
Sine Cosine Algorithm (SCA)	0.006568	0.012934
Social Group Optimization Algorithm (SGO)	0.006567	0.012848
Bat Algorithm (BA)	0.006646	0.012086

Using the parameters of W.pdf obtained by the applied algorithms, percentage values of wind speed are depicted in Figure 11. PSO, SCA, and SGO algorithms have a significant amount of overlap, as seen in the graphs.

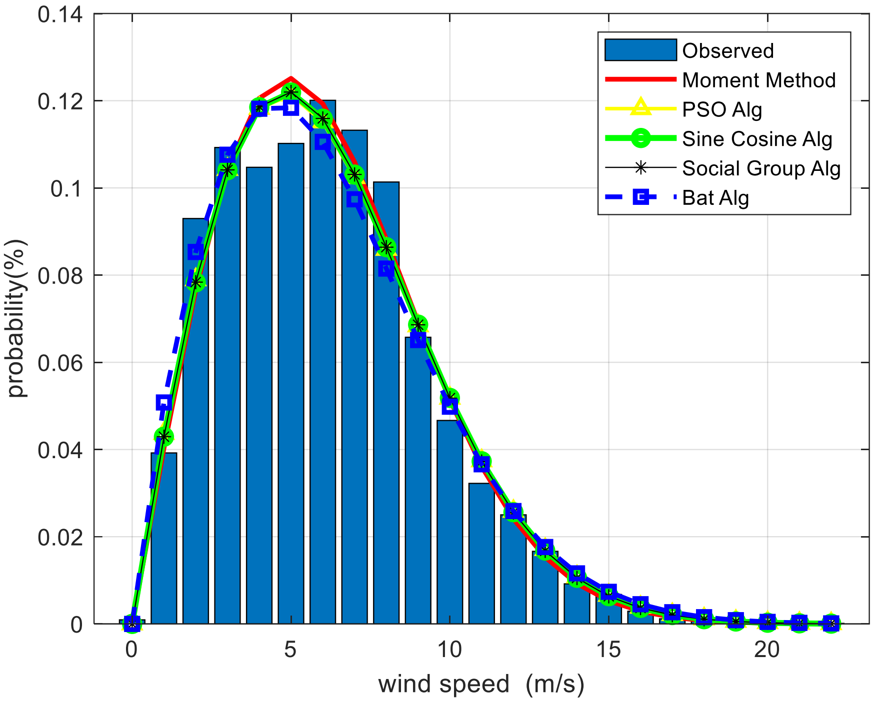

Figure 11. *Using the parameters of the W.pdf obtained by the applied methods*

5. CONCLUSION

In this work, W.pdf is used to characterize the wind essential for wind energy. W.pdf is a widely used method to model the probability distribution of wind speed. The moment method was used for parameter estimation. The moment method aims to estimate the function parameters using the data's mean, variance, and similar properties. The obtained data were tested using PSO, SCA, SGO, and BA. These algorithms are the methods used to find the most appropriate value of the function and test its performance on the data.

Using optimization techniques and the moment method, the shape and scale parameters of the W.pdf were evaluated. The wind energy potential in the Foça district of İzmir was then calculated using these criteria. PSO, SCA, SGO, and BA were used to estimate the values of the dispersion parameters, with the estimation results of MM serving as a reference. The RMSE and chi-square test were used to compare the parameter estimation techniques. As a result, when the performance criteria and graphs were examined, it was found that the proposed Bat algorithm was more successful than the numerical methods in estimating wind speed. This result can help to select methods in wind energy studies and lead to more accurate results in assessing wind speed.

Extending the study to include other relevant parameters and comparing the used algorithms in this work with emerging optimization techniques or hybrid methods could further refine the parameter estimation process. Additionally, a validation study using real-world wind energy data from various locations would validate the algorithm's generalizability, fostering its potential adoption in practical wind energy assessments.

CONFLICTS OF INTEREST

No conflict of interest was declared by the authors.

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