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Estimation of Wind Power Probability Density Distribution Functions Parameters By Using Meta-Heuristic Algorithms

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ABSTRACT

Wind energy is a very popular renewable energy resource and is used as an energy source global because of its benefits of being environmentally friendly, renewable and having great reserves. The probability density distribution of wind speed can be used to estimate wind power density. In this study, Weibull and Rayleigh density distributions were employed to analytically eliminate the presumption that the total wind power is described by a single random variant and to calculate the wind power probability density distribution. In the modeling of complex high-dimensional stochastic wind power, although it can be solved with various mathematical approaches, since there are generally large-scale power systems containing many generators, buses, planning periods and non-linear stochastic variables, it is quite leisurely in searching for the optimum point and most of the time the solutions are far from reality. Consequently, heuristic methods have now substituted classical mathematical methods in obtaining wind parameters. Therefore, the advantage of heuristic methods compared to classical methods is that they can produce efficient solutions in a shorter time and with greater precision. Therefore, in this study, the main metaheuristic algorithms Symbiosis Organisms Search (SOS) and Artificial Bee Colony (ABC) algorithms and the classical statistical methods Energy Pattern Factor and Maximum Likelihood Method were employed to investigate the accuracy of wind power parameter calculations.

Keywords: Power Systems, Wind Energy, Optimization, Metaheuristic Search Algorithms

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Rüzgar Enerjisi Olasılık Yoğunluk Dağılımı Fonksiyonları Parametrelerinin Meta-Sezgisel Algoritmalar Kullanılarak Tahmini

ÖZ

Rüzgar enerjisi oldukça popüler bir yenilenebilir enerji kaynağıdır ve çevre dostu olması, yenilenebilir olması ve büyük rezervlere sahip olması gibi faydaları nedeniyle dünya çapında bir enerji kaynağı olarak kullanılmaktadır. Rüzgar hızının olasılık yoğunluk dağılımı, rüzgar gücü yoğunluğunu tahmin etmek için kullanılabilmektedir. Bu çalışmada, toplam rüzgar gücünün tek bir rastgele değişkenle tanımlandığı varsayımını analitik olarak ortadan kaldırmak ve rüzgar gücü olasılık yoğunluk dağılımını hesaplamak için Weibull ve Rayleigh yoğunluk dağılımları kullanılmıştır. Karmaşık yüksek boyutlu stokastik rüzgar enerjisinin modellenmesinde, çeşitli matematiksel yaklaşımlarla çözülebilmesine rağmen genellikle çok sayıda jeneratör, bara, planlama periyodu ve doğrusal olmayan stokastik değişkenler içeren büyük ölçekli güç sistemleri bulunduğundan oldukça yavaştır. Optimum noktayı ararken çoğu zaman çözümler gerçeklikten uzak olmaktadır. Sonuç olarak, rüzgar parametrelerinin elde edilmesinde günümüzde klasik matematiksel yöntemlerin yerini sezgisel yöntemler almıştır. Dolayısıyla sezgisel yöntemlerin klasik yöntemlere göre avantajı, daha kısa sürede ve daha yüksek hassasiyetle etkin çözümler üretebilmesidir. Bu nedenle, bu çalışmada rüzgar gücü parametre hesaplamalarının doğruluğunu araştırmak için bilinen başarılı metasezgisel algoritmalardan Symbiosis Organisms Search (SOS) ve Yapay Arı Kolonisi (ABC) algoritmaları ile klasik istatistiksel yöntemlerden Enerji Eğilim Faktörü ve Maksimum Olabilirlik yöntemleri kullanılmıştır.

Anahtar Kelimeler: Güç Sistemleri, Rüzgar enerjisi, Optimizasyon, Meta Sezgisel Algortimalar

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1. Introduction

With the increasing consumption of non-renewable conventional energy such as coal, natural gas and oil, the use of renewable energy has become a very important strategy issue all over the world to solve the current and future energy crisis. Wind energy has received great attention as a promising renewable energy source. It has potential benefits in reducing emissions and consumption of thermal fuel reserves. Wind energy is a very popular renewable energy resource and is used as an energy source global because of its benefits of being environmentally friendly, renewable and having great reserves. With growing concerns about global climate change, renewable energy resources, particularly wind power generation, are being promoted as a way to meet emissions reduction targets.

In traditional power system problems, deterministic models are used in the integration of wind energy, which cannot reflect the uncertain situations of wind energy. Since wind power plants integrated to power systems have dynamic and stochastic performance characteristics, stochastic power system models are more appropriate. There are various studies aiming to research the impact of wind energy on generation resource management because of its stochastic and non-dispersible properties for the integration of wind energy into conventional power systems. Wind energy is produced thanks to wind turbines. Therefore, wind direction and wind speed characteristics are very important for accurate calculation of wind power and effective plan and modeling of wind turbines. Wind speed probability density distribution can be used to forecast wind power density and determine the most probable wind direction [1-5]. The collective probability distribution of wind direction and wind speed is of great interest as it can be utilized to optimize the layout of the wind farm, that is, to acquire wind speed properties under different wind directions. Wind speed properties under different wind directions play an important part in the design of wind turbines. It should be given that the wind speed with the highest frequency and the wind speed that can catch the maximum wind energy are different. To acquire maximum wind energy, the two wind speeds must be as close as likely. Additionally, probability distribution is important in determining the prediction method and calculating the wind load [6 and 7]. This stochastic approach avoids local solution traps in solving power systems optimization problems by adding probabilistic features to traditional power system models. This strategy eliminates the probabilistic feasibility inherent in traditional models. Additionally, the solutions prevent the occurrence of reserve costs due to overestimation of available wind power and penalty costs due to underestimation of available wind power.

In a region, researchers utilize probability density functions (PDFs) to define the frequency distribution of wind speed. In addition to wind speed, parameters such as air density, altitude, and surface roughness also affect the calculation of wind power of wind power plants (WPPs) [8]. Data-based statistical distribution methods such as gamma distribution, two-parameter gamma distribution, lognormal distribution, gaussian distribution, rayleigh distribution, weibull distribution and hybrid distribution are commonly used to obtain probability density functions [9–13]. These distribution methods are based on probability density functions associated with wind speed data in modeling wind conditions. The two-parameter Weibull distribution appears to be the most frequently used and accepted statistical model [14,15].

In the literature, studies are carried out on topics such as technical and economic evaluation of regional wind energy potential, energy characteristics, wind turbine location and sizing, levelized unit energy costs, environmental impacts, using wind speed data from previous years using different distribution methods. In [16], M. K. Mridul et al. examined wind energy potential and characteristics for Faridpur, Bangladesh. To make this happen, monthly resolution wind speed data for the region at a vertical height of 50 m for 2019 was used. Weibull probability density function (PDF) and Weibull cumulative distribution function (CDF) were calculated for the region using the Weibull distribution method. Using Weibull PDF and Weibull CDF, the most probable wind speed, maximum energy carrying wind speed, energy and power densities were calculated. In [17], J. C. Lam et al. used long-term average wind speed data from three different regions in Hong Kong to calculate Weibull PDF for three regions. Numerical wind speed estimates were obtained for each region using the calculated functions. In [18], A. S. S. Dorvlo used Weibull distribution in wind speed modeling of four regions in Oman. In [19], A. Keyhani et al. tried to analyze the wind speed data of the Firouzkooh region of Iran. For this purpose, wind speed and wind power production potentials of the region were analyzed using 3-hour wind speed data from the past 10 years. In [20], A.H. Shahirinia et al. proposed Monte Carlo simulation algorithm to find PDFs of solutions in the optimum power flow problem. In [21], G.J. Osorio and others have used the Monte Carlo simulation approach to find PDFs of solutions to the economic dispatch problem. In [22], M. Eladany et al. used a Weibull PDF to represent their stochastic nature, since wind speed and solar irradiance are random variables. For this purpose, the stochastic wind power probability based on Weibull PDF was included as a constraint in their proposed model. They examined the effects of Weibull pdf factors on total cost values. In [23], S. Nasser Keshmiri and others applied the Weibull distribution function and Normal distribution function to calculate the short-term and long-term characterization functions of wind speed in solving the multi-objective economic dispatch optimization problem. In [24], J. Hetzer et al. used Weibull PDF to calculate the parameters of stochastic wind power in solving the wind power integrated economic dispatch problem. In [25], A. Albani et al. examined the wind energy potential and characteristics of different locations in Malaysia according to Weibull and Rayleigh types. In [26], C. Peng et al. analyzed the stochastic structure of wind power output, obtained the Weibull distribution parameters of zonal wind speed for different time intervals respectively, and then obtained the probability density functions of wind power output for different time intervals. In [27], H.T. Jadhav and R. Roy modeled the random nature of wind power using Weibull PDF in solving the environmental economic power dispatch problem. Also, the uncertainty in wind power is taken into account in the cost model by including power imbalance terms such as overestimation and underestimation costs of available wind power. In [28], S. Velamuri et al. used the Weibull distribution function to solve the stochastic structure of wind in the static economic dispatch problem, since the integration of wind power into the existing system is complicated due to its stochastic structure. They discussed the scenarios with and without wind power penetration in detail. In [29], E. Arriagada et al. considered the demand and generation randomness to model and solve the stochastic economic dispatch problem involving renewable energies. They modeled the demand, wind speed, solar distribution through Normal, Weibull, Beta and Uniform distributions, respectively. In [30], Z. Zhang et al. formulated the versatile distribution probability distribution model and developed it with its applications since wind power forecast errors are one of the most challenging issues for power system operation in economic dispatch applications.

In this study, Weibull and Rayleigh density distributions were employed to analytically eliminate the presumption that the total wind power is described by a single random variant and to calculate the wind power probability density distribution. This allows complex and uncertain wind characteristics to be explained more accurately and effectively. To obtain Weibull functions, scale and shape parameters need to be estimated. In order to obtain Weibull parameters, statistical methods such as the Maximum Likelihood Method (MLM), Graphical Method, Empirical Method, Modified-Maximum Likelihood Method, Moment Method, Energy Pattern Factor Method (EPFM) and Equivalent Energy Method Energy are used. In this study, the Root Mean Square Error (RMSE) method was used in error analysis with the objective of identifying which one of the Weibull and Rayleigh parameters computed by the EPFM and the MLM would be appropriate for the real wind speed. What is clear throughout all these studies is that achieving stochastic wind power becomes a composite optimization problem that is hard to resolve by direct mathematical methods. In the modeling of complex high-dimensional stochastic wind power, although it can be solved with various mathematical approaches, since there are generally large-scale power systems containing many generators, buses, planning periods and non-linear stochastic variables, it is quite leisurely in searching for the optimum point and most of the time the solutions are far from reality. Additionally, because of their nonlinear properties, these methods cannot ensure successful results. Consequently, heuristic methods have now substituted classical mathematical methods in obtaining wind parameters. The advantage of heuristic methods compared to classical methods is that they can produce efficient solutions in a shorter time and with greater precision. Heuristics are often stimulated by certain laws of nature, biological characteristics, or mutual behaviors revealed by living things. Therefore, in this study, the main metaheuristic algorithms Symbiosis Organisms Search (SOS) and Artificial Bee Colony (ABC) algorithms were used to investigate the accuracy of wind power parameter calculations. According to the results obtained, error analyzes were calculated and the accuracies of the methods were compared. Thus, the accuracies of the methods were compared according to the results obtained using different parameter estimation methods.

The remaining part of the study is organized as follows. Mathematical formulation of stochastic wind energy, formulation of parameters for calculating wind power, Weibull and Rayleigh probability density functions, stochastic modeling of wind energy are included in Section 2. In Section 3, the analysis studies and methods used to compute the Weibull and Rayleigh parameters are explained in detail. In Section 4, the results obtained using different methods and solutions for stochastic wind power are presented. The study ends with concluding remarks in Section 5.

2. Wind Energy And Its Characteristics

Wind is a climate element that has properties such as speed, direction and frequency and is used in energy generation due to these properties. Factors affecting wind speed can be listed as the geographical location of the region, local surface texture and altitude. Therefore, wind speed is affected by the meteorological and topographic structure of the region. The wind power plant to be established in a region depends on the wind characteristics of the region. To determine the characteristics of wind power, data such as hourly average speed, daily average speed, monthly average speed and seasonal average speed of the wind are needed. However, information on the dominant wind direction of the region is needed in terms of the location of the wind turbine to be installed. Thanks to all these data, parameters such as standard deviation, turbulence, wind speed, most likely speed, cumulative distribution of speeds can be obtained.

More than one statistical approach can be used to evaluate wind data. PDF is employed to define the frequency distribution of wind speed in the area. A variety of techniques are employed in the analysis of wind speeds, with the objective of obtaining a probability density function. It is significant to use suitable statistical models to model the wind modes of a certain region and express their frequency distributions. It is stated in the literature that the two-parameter Weibull and Rayleigh distribution is an appropriate distribution method since it provides best conclusions in forecasting the wind speed and wind power potency of a certain area. The Weibull distribution is widely used because it is easy to calculate only two parameters, its accuracy can be proven, it is suitable for monitoring wind speed distributions, and its pliability features. In this study, Weibull and Rayleigh distributions were utilized to obtain the power output of WPPs. The shape and scale parameters that determine distributions can be computed by many methods. Employing the hourly average wind speed data collected for each station, the standard deviation, average speed, most likely speed, the speed that contributes the most to the energy generation and average power density were calculated depending on the Weibull and Rayleigh shape and scale parameters.

2.1. Weibull distribution

The mostly used statistical approach in determining the distribution of wind speed data is the Weibull probability density function. The Weibull distribution is a distribution with higher sensitivity and more flexibility than other distributions. The Weibull distribution is a two-parameter distribution. The two-parameter Weibull probability density function can be expressed as in Eq.1.

$$f_v(v) = \left(\frac{k}{c}\right)\left(\frac{v}{c}\right)^{k-1} e^{-\left(\frac{v}{c}\right)^k}, \;\; 0 < v < \infty \tag{1}$$

Where (v) denotes the wind speed probability, (k) and (c) denote the shape and scale coefficients, respectively. It is the probability of measured wind speed, expressed as $f_v(v)$.
The dimensionless shape parameter (k) in Eq. 1 is the parameter that expresses the frequency of wind blowing. If the wind speed in a region does not fluctuate much over time, that is, if it blows at an approximately constant speed, the shape parameter (k) takes a large value. If the changes in wind speed are large, that is, if

it does not blow at a constant speed, the shape parameter takes a small value. The other parameter in Eq.1 is named the scale parameter (c), which has the identical unit as the wind speed. The scale parameter varies contingenting on the average speed. This change occurs in direct proportion. In other words, a high average speed means that the scale parameter is also high. The Weibull cumulative distribution function (cdf) is expressed as in Eq.2.

$$F(v) = 1 - e^{-(\frac{v}{c})^k},\ \ 0 < v < \infty \tag{2}$$

The Weibull cdf indicates the probability of wind speeds smaller than (v) speed.

2.2. Rayleigh distribution

Another statistical approach used to determine the distribution of wind speed data is the Rayleigh distribution. Rayleigh distribution refers to the situation where the shape parameter of the Weibull distribution is taken as constant "2". The biggest advantage of the Rayleigh distribution is that the distribution is determined only by the average wind speed. In this case, the Rayleigh PDF is expressed by Eq. 3.

$$f_R(v) = \left(\frac{2v}{c^2}\right) e^{-(\frac{v}{c})^2},\ \ 0 < v < \infty \tag{3}$$

The Rayleigh cdf is expressed by Eq.4.

$$F_R(v) = 1 - e^{-(\frac{v}{c})^2},\ \ 0 < v < \infty \tag{4}$$

2.3. Wind power and wind power density (WPD)

Wind power can be expressed mathematically as in Eq. 5.

$$Pw(v) = \frac{1}{2}\rho A V^3 \tag{5}$$

In the context provided, Pw represents the generated wind power in watts (W), where ρ denotes the air density at a specific altitude measured in kilograms per cubic meter kg/m^3, A signifies the swept area of the rotor blade measured in square meters (m^2) and v stands for the wind speed measured in meters per second m/s. The standard density of air at sea level under conditions of 15.55 C and 1 atmosphere of atmospheric pressure is denoted as $\rho 0$ =1.225 kg/m^3. It is notable that both pressure and temperature vary with altitude, consequently leading to alterations in air density (ρh). It should be emphasized that the air density (ρh) observed at a certain height does not equate to the air density at sea level. Depending on the air density at sea level, the corrected air density at height h (ρh) is calculated as in Eq. 6.

$$\rho h = \rho 0 - (1{,}194\ 10^{-4} h) \tag{6}$$

WPD denoted as the power per square meter of area m^2. It can be computed utilizing the formula provided in Eq. 7.

$$P_{wpd} = \frac{1}{2}\rho V^3 = \frac{\sum_i^N \frac{1}{2}\rho V^3}{N} \tag{7}$$

In this context, P_{wpd} denotes the wpd within each square meter of area m^2, $vi\ ith$ represents the wind speed measured per hour, and N refers to the total number of wind speed measured in the sequences.

Extrapolation is a statistical technique used to estimate values beyond the range of observed data points. Extrapolation involves establishing a direct proportionality between wind speed and altitude, considering that wind speeds are typically measured at a level under than the height of the wind turbine. This process accounts for the fact that wind speeds generally increase with height due to reduced surface friction and other atmospheric factors. Therefore, it becomes necessary to adjust the measured wind speeds to correspond with the height of the turbine casing. Eq.8 is used for extrapolation.

$$v_h = v_r \left(\frac{Z_h}{Z_r}\right)^{\propto}$$
(8)

In this equation, v_h refers to the wind speed at the height Z_h to be determined, v_r is the wind speed measured at the height Z_r, and $\propto$ stands for the Helman coefficient, which signifies the surface roughness coefficient. It is conventionally accepted as 0.143 under specific circumstances.

3. Method

In the modeling of complex high-dimensional stochastic wind power, although it can be solved with various mathematical approaches, it is quite leisurely in searching for the optimum point, since there are generally large-scale power systems containing many generators, buses, planning periods and non-linear stochastic variables. Most of the time the solutions are far from the truth. On the other hand, obtaining stochastic wind power is a composite optimization problem that is hard to resolve by direct mathematical methods. Additionally, because of their nonlinear properties, these methods cannot ensure successful results. Consequently, heuristic methods have now substituted classical mathematical methods in obtaining wind parameters. The advantage of heuristic methods compared to classical methods is that they can produce efficient solutions in a shorter time and with greater precision. Heuristics are often stimulated by certain laws of nature, biological characteristics, or mutual behaviors revealed by living things. Therefore, in this study, Symbiosis Organisms Search (SOS) and Artificial Bee Colony (ABC) algorithms, which are the main metaheuristic algorithms, were used to investigate the accuracy of wind power parameter calculations. According to the results obtained, error analyzes were calculated and the accuracies of the methods were compared. In this study, the RMSE method was used in error analysis to determine which one of the Weibull and Rayleigh parameters computed by the EPFM and the MLM would be appropriate for the actual wind speed. Thus, according to the results obtained using different Weibull parameter estimation methods, the accuracies of the methods were compared.

3.1. Meta heuristic (MHS) optimization algorithms

There are two basic requirements that meta-heuristic search algorithms must meet in order to be successful. These are neighborhood (exploitation) and exploration tasks. The exploitation mission entails a delicate search conducted in the vicinity of reference locations, often referred to as fine-tuning or intensification in the literature. Various simple yet efficient statistical methods exist for exploring the neighborhood of a related location, making intensification a process that Metaheuristic Search (MHS) algorithms execute adeptly. The primary determine of the performance of MHS algorithms lies in their exploration capabilities. Exploration, crucial for averting local solution traps during the search process, is paramount. Local solution traps pose a significant challenge in solving optimization problems, particularly in non-convex and multidimensional search spaces, where numerous local solutions abound. While MHS algorithms excel in their exploitation task, they often become ensnared in these local solution traps. In such instances, it is the exploration operators that rescue the algorithms from these predicaments. Unlike intensification, the diversification process lacks well-known and potent mathematical methods. Furthermore, as the complication of optimization problems escalates, MHS algorithms encounter difficulties in effectively executing the exploration process. For these myriad reasons, successful completion of the MHS process requires having a powerful exploration ability. Consequently, in this study, experimental studies were carried out using SOS and ABC algorithms, which are among the successful MHS algorithms in the literature for parameter estimation methods.

3.1.1 Symbiosis organisms search algorithm

Similar to other population-based algorithms, the SOS algorithm is a population-based iterative method to find the overall best solution in the search space. The name given to the population in the SOS algorithm is ecosystem. In the initial population creation phase, a group of organisms is randomly initialized in the search space. Each organism represents a candidate solution to the problem. Each organism within the ecosystem has a best fitness value that indicates its degree of compatibility with the desired goal.

In general, all meta-heuristic algorithms subject the solutions they obtain at the end of each iteration to a replacement process to determine the new generations to be produced in the next step.
In the SOS algorithm, the new generation is produced by imitating the biological interaction between two organisms in the ecosystem. The process, which resembles real-life biological interaction and consists of three phases: is modeled as a mutual benefit phase, a unilateral benefit phase, and a phase where one benefits and the other is harmed.

The character of the interaction defines the main principle of each universe. In the mutualism phase, interactions provide benefits to both parties. In the commensalism phase, while one side gains, it has no effect on the other. In the parasitism phase, one side gains and the other side suffers. In all stages, each organism interacts with the others in a random manner. The process continues until the termination criterion is met.

3.1.2. Artificial bee colony algorithm (ABC)

ABC algorithm is one of the algorithms based on swarm intelligence. Bee Colony, like other swarm intelligence-based algorithms, has the ability to divide labor and organize itself. This algorithm explores both the global and regional spaces based on the neighborhood rule. Within the colony, bees are partitioned into three groups:

1-Worker Bees: Worker bees employ the neighborhood principle to search for food sources abundant in nectar. There is one worker in each food source. Therefore, the number of worker bees is equal to the number of food sources.

2-Onlooker Bees: Onlooker bees wait in the hive and after sharing the food sources and information of other bees with them through dance, they turn to the food source where nectar is abundant.
3-Scout Bees: At the beginning of the foraging process, scout bees disperse randomly and start searching for food.

Steps for Artificial Bee Colony:

1-Initialization of the Algorithm: This stage is the stage of generating random food resources in the environment. It corresponds to the algorithm producing a random starting value between the lower and upper limits of the parameter.

2-Identification of New Sources: Identification of new sources is carried out according to the neighborhood principle. The worker bee identifies a new food source in the neighborhood of the food source.

3- Determining the Quality of the Source: A best value is appointed to the parameter vectors corresponding a new source, followed by the application of a greedy selection process. If the new source is of better quality than the other, the old source is deleted from memory and the new source is stored in memory.

4-Selecting the Source: When worker bees return to the hive, they convey information to the onlooker bees about the quality of the source through dance. Accordingly, onlooker bees choose the source for themselves. Sources with high nectar quality (fitness value) are more likely to be selected.

3.2. Statistical methods

In this study, the EPFM and MLM, which are statistical methods, were employed to determine the parameters of Weibull and Rayleigh distributions.

Energy pattern factor method

Energy Pattern Factor Method is defined mathematically as in Eq. 9, depending on the average wind speed data.

$$E_{pf} = \frac{\overline{V^3}}{(\overline{V})^3} \tag{9}$$

Where E_{pf} is computed using the average of the cube of the speed and the cube of the average of the speed. After E_{pf} is calculated, the shape (k) and scale (c) parameters can be easily calculated with Eq. 10 and Eq. 11.

$$k = 1 + \frac{3,69}{(E_{pf})^2} \tag{10}$$

$$c = \frac{\overline{V}}{\Gamma(1+\frac{1}{k})} \tag{11}$$

Maximum likelihood method

The shape (k) and scale (c) parameters can be computed using the Maximum Likelihood Method, as described by Eq. 12 and Eq. 13.

$$k = \left(\frac{\sum_{j=1}^{N} V_j^k \ln(V_j)}{\sum_{j=1}^{N} V_j^k} - \frac{\sum_{j=1}^{N} \ln(V_j)}{N}\right)^{-1} \tag{12}$$

$$c = \left(\frac{\sum_{j=1}^{N} V_j^k}{N}\right)^{\frac{1}{k}} \tag{13}$$

Where, N represents the total wind speed data, while V_j ⊠⊠$h$mentions to the wind speed measured for the hour.

Error analysis

Error analysis is necessary to determine which one of the Weibull and Rayleigh parameters, computed using the EPFM and MLM, are appropriate for the actual wind speed data. Various established analysis methods, like root mean square error (RMSE), mean square error (MSE), mean absolute error, chi-square, and coefficient of determination are employed in this error analysis process. In this study, the RMSE method given in Eq.14 was used.

$$RMSE = \left[\frac{1}{N}\sum_{i=1}^{n} (y_{i,m} - x_{i,w})^2\right]^{1/2} \tag{14}$$

4. Analysis Studies And Results

In this study, the wind speed distribution was appraised for sample wind speed data by utilizing the Weibull and Rayleigh distribution method to acquire the power output of WPPs.

To accomplish this, wind speed data collected on an hourly basis at a height of 10 meters from previous years (2017-2023) were utilized for sampling. To augment the sample size, monthly wind data for each year were used for the analysis of the month in which the study would be carried out. Thus, a total of 210 samples (30x7) were obtained for each month. In addition, in the study, a total of 2520 samples (12x30x7) were obtained for each year to perform annual wind speed density analysis The hub height of the Wind Power Plants (WPPs) considered in this study is 60 meters. Firstly, wind speeds measured at 10 meters were extrapolated to a height of 60 meters using Eq.8.

Table 1.Monthly Weibull parameters and error rates

Month	**Method**	**k**	**c (m/s)**	**Total Absolute Error PDF)**
1	EPFM	1.717411459	8.67863556	1.057163145
	MLM	1.893688801	8.780044354	1.072190066
	SOS	1.93790154	8.426067466	1.029933202
	ABC	1.93790154	8.426067466	1.029933202
2	EPFM	1.664487508	8.485753366	1.217339419
	MLM	1.839293457	8.601385704	1.221227883
	SOS	1.772402485	7.731485147	1.187690659
	ABC	1.772402485	7.731485147	1.187690229
3	EPFM	1.660331232	8.526912911	1.200393361
	MLM	1.848815707	8.633043177	1.209073163
	SOS	2.535576968	7.24714609	1.020983218
	ABC	2.535576968	7.24714609	1.020980205
4	EPFM	2.28637684	7.504895939	1.161691776
	MLM	2.400027209	7.501433401	1.186059408
	SOS	2.991909833	6.798685873	0.904142669
	ABC	2.991909833	6.798685873	0.904141737
5	EPFM	2.154721077	8.065113452	1.079968581
	MLM	2.26397308	8.073843755	1.074433314
	SOS	3.057083425	7.161685369	0.877583603
	ABC	3.057083425	7.161685369	0.877581742
6	EPFM	2.636954789	8.941351355	1.02255627
	MLM	2.72188761	8.939281583	1.036578088
	SOS	2.938431072	8.249564957	1.022011556
	ABC	2.93843212	8.249566059	0.982279277
7	EPFM	2.824861796	10.47225927	0.869551938
	MLM	2.969093713	10.47311463	0.889549484
	SOS	2.803249784	10.16567707	0.860841843
	ABC	2.803249659	10.16567742	0.860841848
8	EPFM	2.757587495	11.72821533	0.982064225
	MLM	2.885180007	11.73811724	1.007545094
	SOS	2.500539326	11.37318236	0.942404509
	ABC	2.494763278	11.40699189	0.942525427
9	EPFM	2.061162654	9.019482043	1.11356985
	MLM	2.171788742	9.049960909	1.113006916
	SOS	2.523388861	8.571365917	1.021959869
	ABC	2.523525868	8.571404076	1.021959871
10	EPFM	1.716321095	7.848924512	0.959466217
	MLM	1.763831225	7.887966999	0.960614025
	SOS	1.686378108	8.131140252	0.946971951
	ABC	1.615935565	8.413819769	0.947260968
11	EPFM	1.390579972	6.858483495	1.404128669
	MLM	1.523624512	6.976649336	1.371037576
	SOS	1.644921194	6.192311987	1.342020413
	ABC	1.645575281	6.194206006	1.342043041
12	EPFM	1.547648146	7.588513891	1.023703576
	MLM	1.601892705	7.640100392	1.023121314
	SOS	1.527209518	8.037642206	1.023142593
	ABC	1.527749909	8.038734949	1.023142626

EPFM and MLM, which are statistical methods, were used to compute the Weibull and Rayleigh distribution parameters. In addition, SOS and ABC algorithms, which are the main metaheuristic algorithms, were used to investigate the accuracy of parameter calculations. Thus, error analyzes were calculated according to the results obtained using different Weibull parameter estimation methods and the accuracies of the methods were compared.

Table 1 includes 12-month Weibull parameters and error values for sample speed data. Table 2 includes Rayleigh parameters and error values for 12 months for sample speed data. Additionally, Tables 3 and 4 include Weibull and Rayleigh distribution parameters and error values for all years for sample speed data.

Table 2.Monthly Rayleigh parameters and error rates

Month	Method	k	c (m/s)	Total Absolute Error PDF)
1	EPFM	2	8.731662084	1.047152591
	MLM	2	6.300343352	1.366081151
	SOS	2	5.84163526	1.212501768
	ABC	2	8.275893334	1.032868932
2	EPFM	2	8.556390518	1.238829739
	MLM	2	6.226544481	1.497560071
	SOS	2	7.610389021	1.206364316
	ABC	2	7.610389021	1.206326739
3	EPFM	2	8.599539774	1.128228634
	MLM	2	6.240416653	1.399599897
	SOS	2	7.708630802	1.102799364
	ABC	2	7.708630802	1.102799364
4	EPFM	2	7.50176564	1.24470644
	MLM	2	5.118123337	1.43945807
	SOS	2	6.48436174	1.150452937
	ABC	2	6.48436174	1.150452937
5	EPFM	2	8.059460861	1.147406513
	MLM	2	5.564677206	1.456989053
	SOS	2	7.784568174	1.14330202
	ABC	2	7.784568079	1.14330202
6	EPFM	2	8.965232692	1.125957118
	MLM	2	6.027069385	1.472964291
	SOS	2	9.271317852	1.119462978
	ABC	2	9.271317852	1.119462978
7	EPFM	2	10.52574397	0.984574222
	MLM	2	7.020762202	1.124358562
	SOS	2	10.15707544	0.971734021
	ABC	2	10.15707544	0.971734021
8	EPFM	2	11.777429	1.035611668
	MLM	2	7.883916162	1.198967896
	SOS	2	11.92195684	1.034259069
	ABC	2	11.92195684	1.034259069
9	EPFM	2	9.015531887	1.133806407
	MLM	2	6.286225309	1.439087393
	SOS	2	8.227730338	1.103912681
	ABC	2	8.227730338	1.103912681
10	EPFM	2	7.897205394	1.066779905
	MLM	2	5.763936027	1.535197342
	SOS	2	8.034220489	1.06405699
	ABC	2	8.034220489	1.06405699
11	EPFM	2	7.061048885	1.40451224
	MLM	2	5.410238036	1.585324399
	SOS	2	6.322905066	1.352756353
	ABC	2	6.322905066	1.352756353
12	EPFM	2	7.702498833	1.099015125
	MLM	2	5.768359904	1.473046301
	SOS	2	7.724976848	1.098921919
	ABC	2	7.724976848	1.098921919

Table 3. Annual Weibull parameters and error rates

Year	Method	k	c (m/s)	Total Absolute Error PDF)
2018	EPFM	2.250149	8.534181	0.897163043
	MLM	2.358513	8.543171	0.9145299
	SOS	2.821013	7.843502	0.808812755
	ABC	2.821013	7.843502	0.808812755
2019	EPFM	1.857433	9.614972	0.980346637
	MLM	1.994699	9.694583	1.04043706
	SOS	1.809924	8.065538	0.810631753
	ABC	1.809924	8.065538	0.810631753
2020	EPFM	2.142101	9.59528	1.054014657
	MLM	2.237293	9.639677	1.071148791
	SOS	1.938589	9.258395	1.028914645
2021	ABC	1.938628	9.258457	1.02891552
	EPFM	2.140984	9.285866	1.072734491
	MLM	2.250454	9.326096	1.124340203
	SOS	1.887262	8.528088	1.002346029
2022	ABC	1.888214	8.529815	1.002355878
	EPFM	1.991107	8.7342	0.808026101
	MLM	2.089238	8.767511	0.833448118
	SOS	2.413021	7.580767	0.680924857
	ABC	2.413021	7.580767	0.680924857
2023	EPFM	1.324577	6.438738	0.794619966
	MLM	1.413673	6.544893	0.818395018
	SOS	1.391989	5.695548	0.769080567
	ABC	1.388009	5.732565	0.769250984

Table 4.Annual Rayleigh parameters and error rates

Year	Method	k	c (m/s)	Total Absolute Error PDF)
2018	EPFM	2	8.529405	0.953625763
	MLM	2	5.848135	1.085541793
	SOS	2	8.008161	0.93396745
	ABC	2	8.008161	0.93396745
2019	EPFM	2	9.635003	1.003059886
	MLM	2	6.859567	1.220425539
	SOS	2	7.911173	0.8375703
	ABC	2	7.911173	0.8375703
2020	EPFM	2	9.588652	1.042193133
	MLM	2	6.660969	1.333532937
	SOS	2	9.307622	1.031107434
2021	ABC	2	9.307622	1.031107434
	EPFM	2	9.279463	1.049004291
	MLM	2	6.434743	1.300527507
	SOS	2	8.47798	1.009771258
2022	ABC	2	8.47798	1.009771258
	EPFM	2	8.734933	0.80703664
	MLM	2	6.139414	1.138353325
	SOS	2	7.968295	0.750608413
	ABC	2	7.968295	0.750608413
2023	EPFM	2	6.68556	1.153322329
	MLM	2	5.247191	1.401980124
	SOS	2	5.841635	1.056066522
	ABC	2	5.841635	1.056066522

When Tables 1, 2, 3 and 4 are surveyed, It can be observed that metaheuristic algorithms give supeiror results than statistical methods. In this content, hourly average speed (Vavg), most likely speed (Vmls), maximum speed and wind power density (WPD) were delibareted utilizing the parameters idenitified by the probability method. Average speed, most likely speed, Vmax and WPD values are specified in Tables 5, 6.

Table 5. Monthly wind speed and power values

Month	Vavg (m/s)	Vmls (m/s)	Vmax (m/s)	Standard Deviation (σ)	Power Density (P/A)	Turbine Power Output (W)
1	7.738234	4.585011516	30.9488277	4.428751217	58.66914426	294.871.12
2	7.582904	4.96709581	24.0713105	4.489829158	74.59265622	374.902.69
3	7.621144	5.731264396	29.0384063	4.462153762	114.5881724	575.920.15
4	6.648267	4.96709581	20.6325518	2.869962061	74.59265622	374.902.69
5	7.142511	6.495432982	21.7788047	3.31282396	166.8064269	838.369.10
6	7.945231	5.731264396	16.8117089	3.094777948	114.5881724	575.920.15
7	9.328198	5.731264396	18.7221304	3.410198699	114.5881724	575.920.15
8	10.43747	6.495432982	20.2504675	3.931218476	166.8064269	838.369.10
9	7.989807	5.731264396	22.9250576	3.909109217	114.5881724	575.920.15
10	6.998716	4.585011516	20.2504675	4.190261331	58.66914426	294.871.12
11	6.257692	3.82084293	25.9817319	4.414853274	33.95205108	170.643.01
12	6.826162	3.438758637	26.7459005	4.478762328	24.75104523	124.398.75

Table 6. Annual wind speed and power values

Month	Vavg (m/s)	Vmls (m/s)	Vmax (m/s)	Standard Deviation (σ)	Power Density (P/A)	Turbine Power Output (W)
2018	7,55898816	5,731264396	26,74590051	3,360655982	114,5881724	575.920,15
2019	8,53879884	5,731264396	30,94882774	4,610257326	114,5881724	575.920,15
2020	8,49772171	6,113348689	25,98173193	4,070751859	139,0676012	698.953,76
2021	8,22371015	7,259601568	22,54297329	3,901810491	232,8771183	1.170.440,40
2022	7,74113246	6,495432982	24,07131046	3,937277433	166,8064269	838.369,10
2023	5,92492356	3,82084293	29,03840627	4,473940855	33,95205108	170.643,01

In this study, the Nordex N60 model turbine, one of the most commonly utilized turbine types in Turkey, was employed to estimate wind power based on the 12-month average speed derived from the sampled wind data. The rated power of the Nordex N60 turbine is 1300 kW, the casing length is 60 m, the blade diameter is 60 m, and taking these technical specifications into consideration, the power output of a WPP with an installed power of 1.3 MW was calculated using Eq. 5. The results obtained are given in Tables 5 and 6.

The probability density function f(V) indicates the probability of observing speed V at any moment, and the cumulative distribution function F(V) indicates the probability that the speed observed at any moment is equal to or less than speed V. From Figure 1 to Figure 8, the probability density distributions of the Weibull and Rayleigh distribution corresponding to the wind speed of the 1st, 2nd and 3rd months and probability distributions for a sample year are shown. Although in this study, analyzes were made for 12 months and all years, functions were calculated and distribution graphs were prepared, only the graphs for the 1st, 2nd and 3rd months are given in the study. Other analyzes are also given in the appendix of the study. Calculation of Weibull and Rayleigh distribution parameters, average wind speed, maximum wind speed, pdf and cdf was performed with MATLAB R2019a.

When the graphs and tables given in the study are examined, it is seen that the absolute error values of the Weibull and Rayleigh parameters calculated with metaheuristic algorithms are quite small. When the obtained test results are compared with the real wind speed data, it is clearly seen that they are effective and accurate. In addition, as can be seen from the graphs, it is understood that the probability density distributions calculated with metaheuristic algorithms have a more successful and uniform distribution.

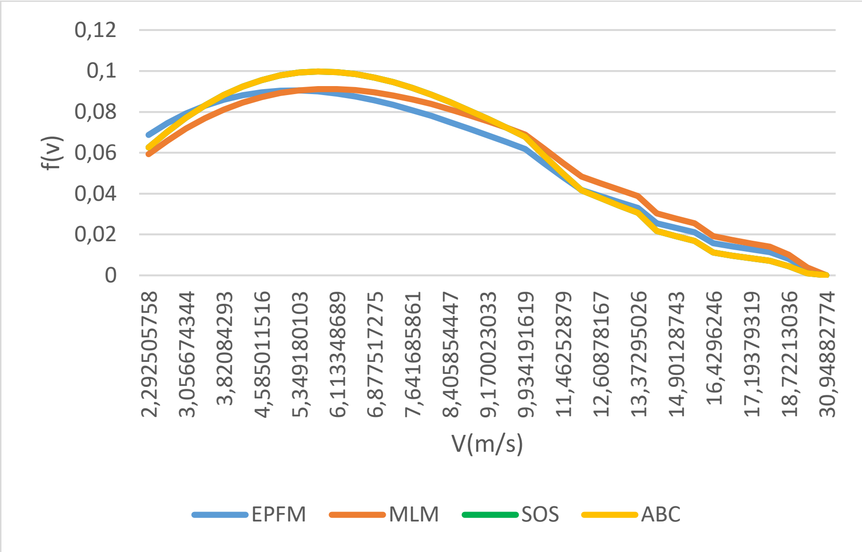

Figure 1. Weibull distribution probability density functions for the 1st month

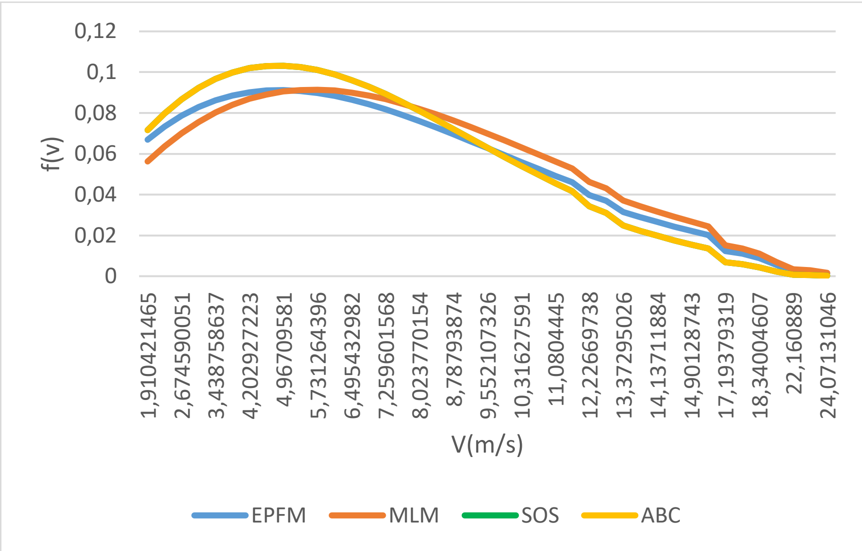

Figure 2. Weibull distribution probability density functions for the 2nd month

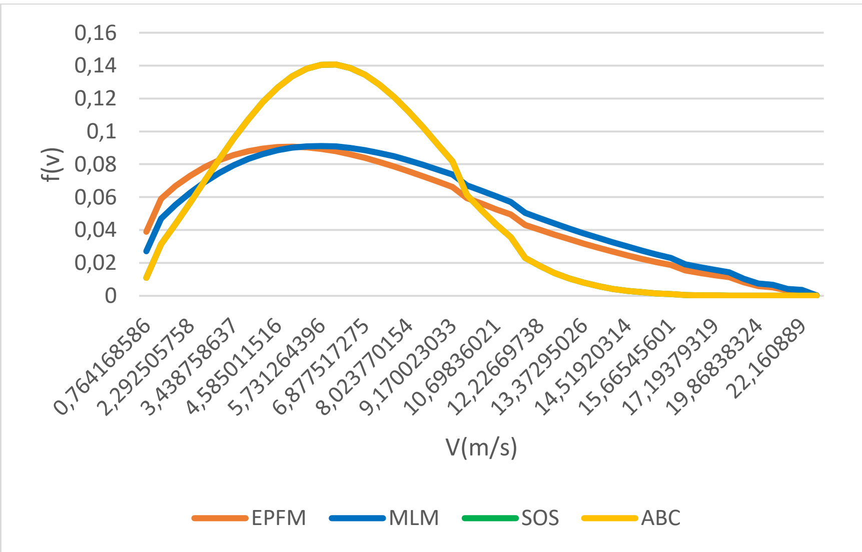

Figure 3. Weibull distribution probability density functions for the 3rd month

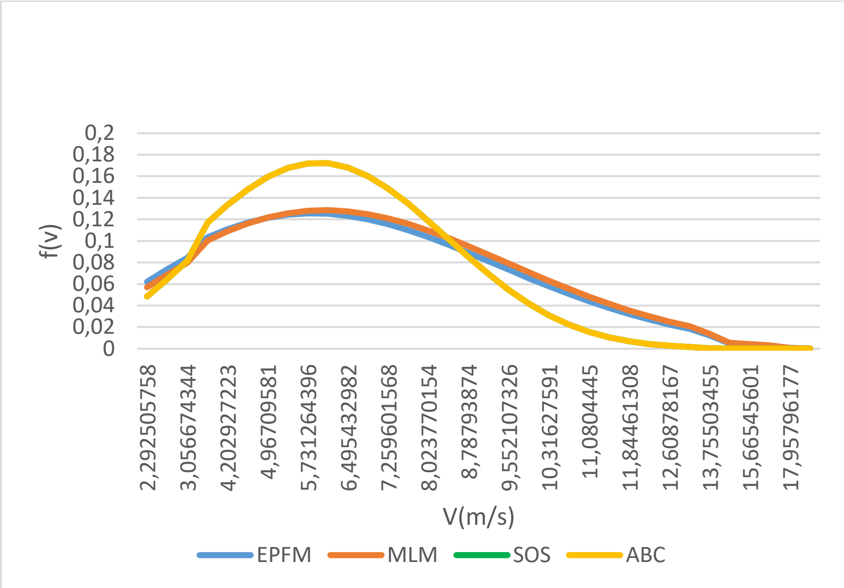

Figure 4. Weibull distribution probability density functions for the 4th month

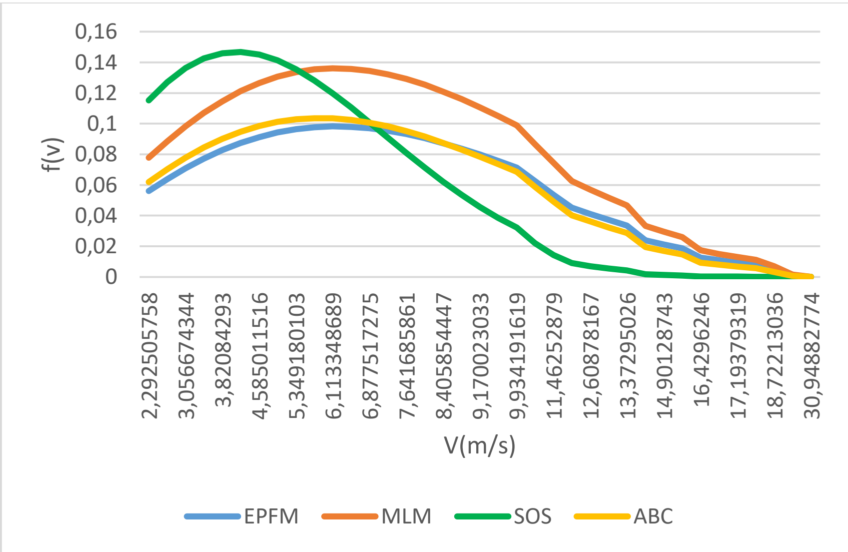

Figure 5. Rayleigh distribution probability density functions for the 1st month

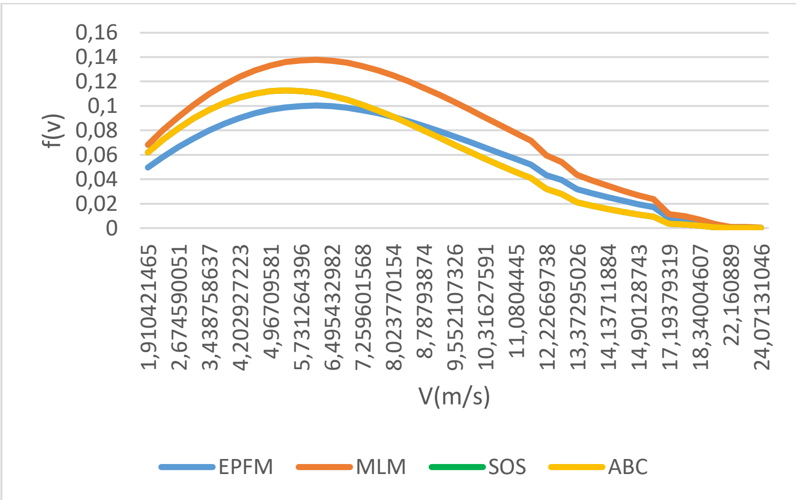

Figure 6. Rayleigh distribution probability density functions for the 2nd month

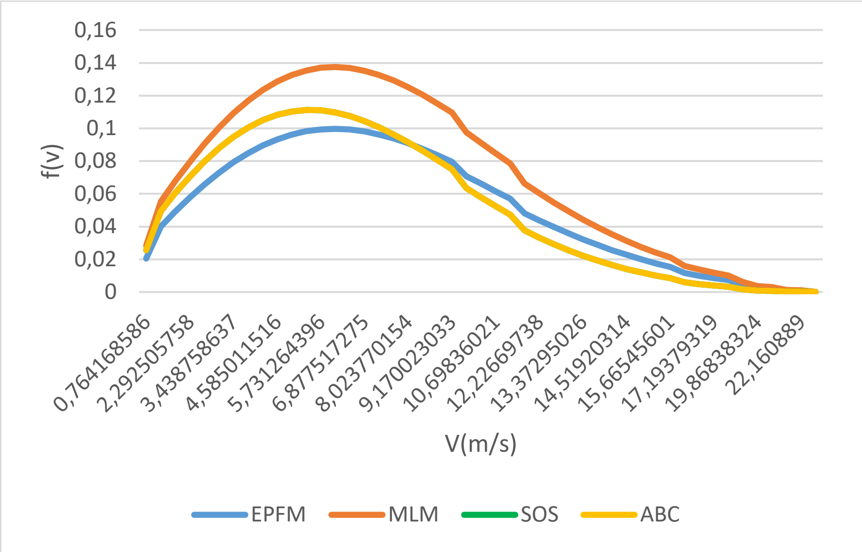

Figure 7. Rayleigh distribution probability density functions for the 3rd month

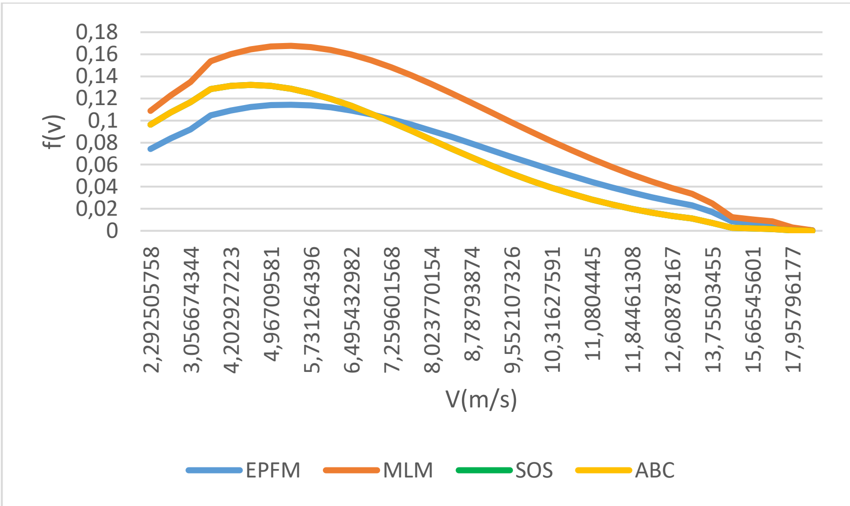

Figure 8. Rayleigh distribution probability density functions for the 4th month

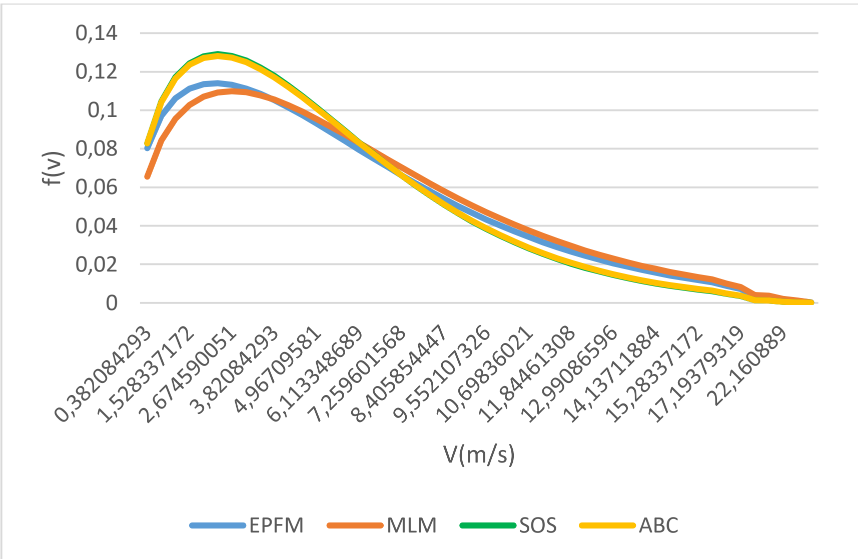

Figure 9. Annual Weibull distribution probability density functions

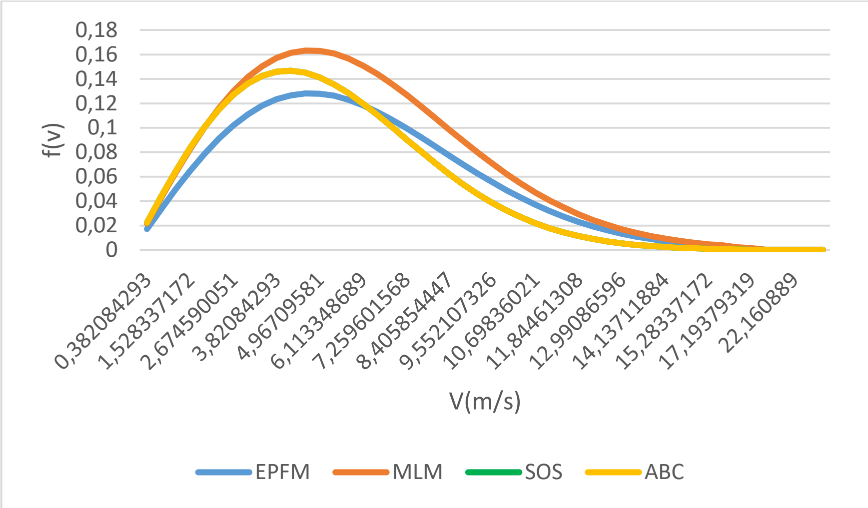

Figure 10. Annual Rayleigh distribution probability density functions

5. Discussion

In this section, firstly, a study was conducted to verify the effectiveness of the proposed methods. Then, comparison test results were given on the graphs to make the solutions of the experimental results of the proposed algorithms understandable. The parameters of stochastic wind energy were solved using both statistical methods and SOS and ABC metaheuristic algorithms. Thus, error analyzes were calculated according to the results obtained using different Weibull parameter estimation methods and the accuracies of the methods were compared.

The stochastic situation of modern power systems has been in existence for many years and continues to be one of the most fundamental problems today. In this study, since the wind speed is uncertain for any time interval, Weibull probability density function (PDF) is used to estimate the wind speed. In the solution of the problem, the effectiveness of the methods is investigated by using metaheuristic-based methods and statistical methods. Since the discovery and neighborhood search ability of the algorithm is improved in metaheuristic methods, local optimum traps are avoided and optimum values are increased. When the proposed MHS algorithms are applied to the test functions, it is clearly seen that the algorithms are successful in calculating the stochastic wind power parameters and provide effective and accurate results. In summary, as a result of the comprehensive experimental study, the proposed MHS algorithms are presented to the literature as one of the effective MHS methods that can be used in obtaining the stochastic wind power parameters.

6. Results

In the designing and modeling of modern power systems, both the power ranges of the load and the power ranges of generation are utilized as input variables. While the capacity factor is traditionally taken into account in the generation of power ranges of dispatchable power plants for generation series, the implementation of probabilistic approaches in generating power series for wind and solar sources is crucial for ensuring accurate modeling of power systems.

In this study, probabilistic approaches such as the Weibull and Rayleigh distribution methods were utilized to derive the power series of WPPs. The accuracy of the methods was investigated by using statistical methods and metaheuristic algorithms to calculate the parameters of these distribution methods. In order to achieve this objective, wind speed data measured in daily periods for previous years (2017-2023) for Turkey were used as an example. With these data, 12-month average wind speed, maximum wind speed, power density and wind power were determined using both Weibull and Rayleigh distribution. Probability density functions and cumulative distribution functions obtained from different statistical and metaheuristic methods were created for the data used. Accordingly, it has been clearly seen that metaheuristic algorithm methods provide more effective results in estimating the parameters of stochastic wind energy. Based on these significant experimental findings, metaheuristic algorithms can indeed be employed to address various power system challenges within larger power systems that integrate diverse renewable energy sources. In summary, as can be understood from the comprehensive experimental study, it has been presented to the literature that effective MHP methods can be used in solving power systems problems.

Conflict of Interest Statement

The authors declare that there is no conflict of interest.

References

[1] J. Wang, J. Hu and K. Ma, ''Wind speed probability distribution estimation and wind energy assessment,'' *Renew. Sustain. Energy Rev.*, vol. 60, pp. 881–899, 2016.

[2] J. Zhang, Y. Wei, Z. Tan, K. Wang and W. A Tian, ''Hybrid method for short-term wind speed forecasting,'' *Sustainability*, vol. 9, no.4, pp. 1-10, April 2017.

[3] Z.R. Shu, Q.S. Li and P.W. Chan, ''Investigation of offshore wind energy potential in Hong Kong based on weibull distribution function,'' *Appl. Energy*, vol.156, pp. 362–373, 2015.

[4] M. Elshahed, M. M. Elmarsafawy and H. Z. Eldin, ''Stochastıc chance constraınt wıth dıscrete probabılıtıes of wınd sources ın economıc dıspatch,'' International Conference on Renewable Power Generation, April 2016. doi:10.1049/cp.2015.0389

[5] N. Masseran and A.M. Razali, ''Modeling the wind direction behaviors during the monsoon seasons in peninsular Malaysia,'' *Renew. Sustain. Energy Rev.*, vol. 56, pp. 1419–1430, 2016.

[6] J.F. Manwell, J.G. Mccowan and A.L. Rogers, ''Wind Energy Explained: Theory, Design and Application,'' Second Edition; JohnWiley & Sons, New York, NY, USA, 2010.

[7] P.K. Goyal and T.K. Datta, ''Effect of wind directionality on the vulnerability of rural houses due to cyclonic wind.'' *Nat. Hazards Rev.*, vol. 14, pp. 258–267, 2013.

[8] T. V. Ramachandra and B. V. Shruthi, "Wind energy potential mapping in Karnataka, India, using GIS," *Energy Convers. Manag.*, vol. 46, no. 9–10, pp. 1561–1578, 2005. doi: 10.1016/j.enconman.2004.07.009

[9] E. Dokur and M. Kurban, "Wind Speed Potential Analysis Based on Weibull Distribution," *Balk. J. Electr. Comput. Eng.*, vol. 3, no. 4, pp. 231–235, 2015. doi:10.17694/bajece.72748

[10] E. C. Morgan, M. Lackner, R. M. Vogel, and L. G. Baise, "Probability distributions for offshore wind speeds," *Energy Convers. Manag.*, vol. 52, no. 1, pp. 15–26, 2011. doi:10.1016/j.enconman.2010.06.015

[11] P. Ramírez and J. A. Carta, "Influence of the data sampling interval in the estimation of the parameters of the Weibull wind speed probability density distribution: a case study," *Energy Convers. Manag.*, vol.46, no.15–16, pp.2419–2438, 2005. doi:10.1016/j.enconman.2004.11.004

[12] S. Vela, "A review of wind speed probability distributions used in wind energy analysis case studies in the Canary Islands," vol. 13, pp. 933–955, 2009. doi:10.1016/j.rser.2008.05.005

[13] O. A. Jaramillo and M. A. Borja, "Wind speed analysis in La Ventosa, Mexico: a bimodal probability distribution case," vol.29, pp.1613–1630, 2004. doi:10.1016/j.renene.2004.02.001

[14] A. Serban, L. S. Paraschiv and S. Paraschiv, "Assessment of wind energy potential based on Weibull and Rayleigh distribution models," Energy Reports, vol. 6, pp. 250–267, April 2020. doi:10.1016/j.egyr.2020.08.048

[15] P. Wais, "A review of Weibull functions in wind sector," Renew. Sustain. Energy Rev., vol. 70, pp. 1099–1107, February 2017. doi:10.1016/j.rser.2016.12.014

[16] M. Ali, M. K. Mridul and A. Al Mahbub, "Comparative wind power assessment by weibull distribution function in Faridpur," Proc.

2020 11th Int. Conf. Electr. Comput. Eng. ICECE 2020, pp. 13–16, 2020. doi:10.1109/ICECE51571.2020.9393088

[17] I. Y. F. Lun and J. C. Lam, "A study of Weibull parameters using long-term wind observations," Renew. Energy, vol. 20, no. 2, pp. 145–153, 2000. doi:10.1016/S0960- 1481(99)00103-2

[18] A. S. S. Dorvlo, "Estimating wind speed distribution," Energy Convers. Manag., vol. 43, no. 17, pp. 2311–2318, 2002. doi:10.1016/S0196-8904(01)00182-0

[19] S. H. Pishgar-Komleh, A. Keyhani and P. Sefeedpari, "Wind speed and power density analysis based on Weibull and Rayleigh distributions (a case study: Firouzkooh county of Iran)," Renew. Sustain. Energy Rev., vol. 42, pp. 313–322, 2015. doi:10.1016/j.rser.2014.10.028

[20] A.H. Shahirinia, E.S. Soofi and D.C. Yu. "Probability distributions of outputs of stochastic economic dispatch," Electrical Power and Energy Systems, vol.81, pp. 308–316, 2016.

[21] G.J. Osorio, J.M. Lujano-Rojas, J.C.O. Matias, J.P.S. Catalao, "A probabilistic approach to solve the economic dispatch problem with intermittent renewable energy sources," Energy vol. 82, pp. 949-959, 2015.

[22] T.G. Hlalele, R.M Naıdoo, J. Zhang and R.C. Bansal, "Dynamic Economic Dispatch With Maximal Renewable Penetration Under Renewable Obligation," IEEE Access, vol. 8, pp. 38794-38808, 2020.

[23] S. N. Keshmiri and W. Gao, "Multi-Objective Stochastic Economic Dispatch," IEEE, North American Power Symposium 2010, doi:10.1109/NAPS.2010.5619590

[24] J. Hetzer, D. C. Yu and K. Bhattarai, "An Economic Dispatch Model Incorporating Wind Power," Ieee Transactıons On Energy Conversıon, vol. 23, No. 2, pp. 603-611, June 2008.

[25] A. Albani and M.Z. Ibrahim, "Statistical Analysis of Wind Power Density Based on the Weibull and Rayleigh Models of Selected Site in Malaysia," Pakistan Journal of Statistics and Operation Research, Vol.9, No.4 pp. 393-406, 2014. doi:10.1234/pjsor.v9i4.580

[26] C.Peng, H. Sun, J. Guo and G. Liu, "Dynamic economic dispatch for wind-thermal power system using a novel bi-population chaotic differential evolution algorithm," Electrical Power and Energy System, vol.42, pp.119–126, 2012.

[27] H.T. Jadhav, R. Roy, "Gbest guided artificial bee colony algorithm for environmental economic dispatch considering wind power," Expert Systems with Applications, vol.40, pp.6385–6399, 2013.

[28] S. Velamuri, S. Sreejith, P. Ponnambalam, "Static economic dispatch incorporating windfarm using Flower pollination algorithm," Perspectives in Science, vol.8, pp. 260-262, 2016.

[29] E. Arriagada, E. López, M. López and J. Vannier Claudio, "A Stochastic Economic Dispatch Model with Renewable Energies Considering Demand and Generation Uncertainties," IEEE Grenoble Conference, DOI: 10.1109/PTC.2013.6652496, 2013.

[30] Z. Zhang and Y. Sun, "A versatile probability distribution model for wind power forecast errors and ıts application in economic dispatch," IEEE Transactıons on Power Systems, vol.28, no.3, pp.3114-3125 august 2013.

[31] Z. Demirkol and M. Çunkaş, "The Renewable Energy Potential for Afyonkarahisar," Selcuk University Journal of Engineering Science and Technology, May 2014. doi:10.15317/Scitech.201416130

[32] M. Kurban, Y. Kantar and F.O. Hocaoglu, "Statıstical analysis of wind speed and power densities using weibull distribution," Afyon Kocatepe University Journal of Scıence, vol.7, no.2, pp.205-218, 2007.

[33] X. Liu, "Economic load dispatch constrained bywind power availability: a wait-and-see approach," IEEE Transactıons On Smart Grıd, Vol.1, No.3, pp. 347-355, December 2010.

[34] C. Peng, H. Sun, J. Guo and G. Liu, "Dynamic economic dispatch for wind-thermal power system using a novel bi-population chaotic differential evolution algorithm," Electrical Power and Energy Systems, vol.42, pp. 119–126, 2012.

[35] H.T. Jadhav, R. Roy, "Gbest guided artificial bee colony algorithm for environmental/economic dispatch considering wind power," Expert Systems with Applications, vol.40, pp. 6385–6399, 2013.

[36] Z. Zhang, Y.Z. Sun, D.W. Gao, J. Lin and L. Cheng, "A versatile probability distribution model for wind power forecast errors and ıts application in economic dispatch," IEEE Transactions On Power Systems, vol.28, no.3, pp. 3115-3125, August 2013.

[37] F. Zia and M. Nasir, "Optimization methods for constrained stochastic wind power economic dispatch," 2013 IEEE 7th International Power Engineering and Optimization Conference (PEOCO2013), Langkawi, Malaysia. pp.1-5, June 2013.

[38] Q. Han, Z HaoHu, T. F. Chu, "Non-parametric models for joint probabilistic distributions of wind speed and direction data," Renew. Energy 2018, vol.126, pp. 1032–1042, 2018.