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A Comparative Study on the Estimation of Wind Speed and Wind Power Density Using Statistical Distribution Approaches and Artificial Neural Network-Based Hybrid Techniques in Çanakkale, Türkiye

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Abstract: In recent years, wind energy has become remarkably popular among renewable energy sources due to its low installation costs and easy maintenance. Having high energy potential is of great importance in the selection of regions where wind energy investments will be made. In this study, the wind power potential in Çanakkale Province, located in the northwest of Türkiye, is examined, and the wind speed is estimated using hourly and daily data over a one-year period. The data, including 12 different meteorological parameters, were taken from the Turkish State Meteorological Service. The two-parameter Weibull and Rayleigh distributions, which are the most widely preferred models in wind energy studies, are employed to estimate the wind power potential using hourly wind speed data. The graphical method is implemented to calculate the shape (k) and scale (c) parameters of the Weibull distribution function. Daily average wind speed estimation is performed with artificial neural network–genetic algorithm (ANN-GA) and ANN–particle swarm optimization (ANN-PSO) hybrid approaches. The proposed hybrid ANN-GA and ANN-PSO algorithms provide correlation coefficient values of 0.94839 and 0.94042, respectively, indicating that the predicted and measured wind speed values are notably close. Statistical error indices reveal that the ANN-GA model outperforms the ANN-PSO model.

Keywords: wind speed estimation; artificial neural network; genetic algorithm; particle swarm optimization; weibull distribution; rayleigh distribution

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1. Introduction

In recent years, the energy consumption of countries has risen due to the rapid development of technology and population growth. The increasing need for energy and the depletion of fossil fuels such as coal, oil, and natural gas have revealed the demand for renewable energy sources (RESs). Wind energy, which is one of the most widely used RESs, has attracted attention since it is a cost-effective and eco-friendly alternative to fossil fuels. Having high energy potential is of great importance in the selection of regions to be invested in wind energy. Therefore, the proper estimation of wind energy potential has become an important research issue that researchers have also focused on. Owing to the variable and unpredictable nature of wind energy, several methods have been developed to estimate wind speed and wind power potential using measured wind data.

There have been numerous research studies on the topic of wind speed estimation methods to realize investments effectively by evaluating the wind power potential of a region. Table 1 summarizes the prominent studies on wind speed estimation in the literature in terms of the time granularity, estimation method, and error metrics. It is seen that four main categories are highlighted for the estimation of wind power when the current studies are evaluated: (i) physical models, (ii) statistical models, (iii) artificial intelligence (AI)-based models, and (iv) hybrid approaches [1,2].

Physical models, which are based on the use of weather data such as temperature, humidity, pressure, terrain, and obstacles, are preferred to achieve more accurate results for long-term prediction. It should be noted here that Santhosh et al. [3] divided the wind speed forecasting process into four classes according to time horizons: very short-term, short-term, medium-term, and long-term. If the prediction is made for less than 30 min, it is called very short-term prediction; if it is 30 min to 6 h, it is called short-term prediction; if it is 6 h to 24 h, it is called medium-term prediction; and if it is 1 day to 7 days, it is called long-term prediction. These models require large computational resources, since complicated mathematical equations are implemented. Numerical Weather Prediction (NWP) is one of the best-known examples of this type of model in the literature. Most of the early studies performed in the literature on wind speed estimation are based on physical models. A review of the use of NWP models for wind energy assessments is presented by Al-Yahyai et al. [4]. Statistical methods are generally appropriate for the short-term prediction of wind data. In statistical methods, large amounts of data are analyzed to determine the relationship between historical wind data and weather, and then this relationship is used to forecast future wind values. Unlike physical methods, there is no requirement to use complex mathematical equations in statistical methods. The Weibull and Rayleigh distribution models are the two most widely used types of this approach. Several studies have been conducted on the estimation of wind speed and wind power by using Weibull and Rayleigh probability density functions (PDFs) [5]. It has been emphasized in [6,7] that the Weibull function gave more accurate results in the estimation of wind energy potential when compared with the Rayleigh function. To determine the shape (k) and scale (c) parameters of the Weibull function, different techniques existing in the literature were reviewed, and the most frequently used techniques in the literature are the Maximum Likelihood Method (MLM) [8–17], the Graphical Method (GM) [8,10–12,14–16,18,19], the Energy Pattern Factor Method (EPFM) [9,15,16,18,20] and the Least-Squares Regression (LSR) method [11–13,16].

Recent studies have shown that AI methods, which reveal the best prediction results in most cases, are one of the main interests in the topic of wind speed and wind power estimation. Many studies on wind speed and wind power estimation have been conducted using AI methods such as artificial neural networks (ANNs), deep learning, and machine learning. In studies by Brahimi et al. [21] and Dumitru et al. [22], a feedforward ANN is implemented to predict daily wind speeds using meteorological measurement data. Kumar and Malik [23] introduced a Generalized Regression Neural Network (GRNN) and Multi-Layer Perceptron (MLP) for long-term wind speed estimation. It has been shown that the GRNN gives a better result than the MLP as a result of the comparison of these two models using the mean square error (MSE) metric [23]. Navas et al. [24] developed a wind speed prediction model using different ANNs, such as the Multi-Layer Perceptron Neural Network (MLPNN) and Radial Basis Function Neural Network (RBFNN). Demolli et al. [25] performed wind power prediction based on daily wind speed data for different locations by using various machine learning algorithms, namely Least Absolute Shrinkage Selector Operator (LASSO) Regression, k-Nearest Neighbor Regression, Extreme Gradient Boost Regression, Random Forest Regression (RFR), and Support Vector Regression (SVR). Lawan et al. [26] proposed a topographic machine learning-based wind speed estimation model for the evaluation of onshore wind power potential and presented the comparison of the developed terrain-based ANN model and the Support Vector Machine (SVM).

Various research papers have been published on the prediction of wind speed and wind power using hybrid approaches that combine statistical techniques, AI models, machine learning algorithms, deep learning algorithms, and optimization algorithms. Hybrid approaches that exploit the advantages of different techniques provide improved prediction accuracy and performance. Alencar et al. [27] presented a hybrid algorithm composed of the Seasonal Autoregressive Integrated Moving Average (SARIMA) and Neural Network (NN) for multi-step-ahead wind speed forecasting using explanatory variables. The suggested hybrid algorithm was verified by comparing it with other well-known techniques in the literature, such as the NN, SARIMA, and SARIMA + Wavelet. Mohammed et al. [28] utilized a short-time-period wind speed forecasting method based on Variational Mode Decomposition—ANN (VMD-ANN). Ozkan et al. [29] introduced a short-term wind power forecast model, Statistical Hybrid Wind Power (SHWIP), and compared it with well-known models such as the ANN and SVM in the literature. Zhang et al. [30] addressed a prediction model combined with an NN, Particle Swarm Optimization (PSO), and SVR. Khosravi et al. [31] employed three machine learning algorithms called a Multi-Layer Feed-Forward Neural Network (MLFFNN), SVR with a Radial Basis Function (SVR-RBF), and the Adaptive Neuro-Fuzzy Inference Systems (ANFISs) optimized with PSO (ANFIS-PSO) to estimate the wind speed, wind direction, and output power of a wind turbine. Asghar et al. [32] adopted a hybrid intelligence learning-based ANFIS to estimate the Weibull PDF with available wind speed data, and then compared the results with five well-known methods: the GM, the Empirical Method of Justus (EMJ), the Empirical Method of Lysen (EML), the Method of Moments (MOM), and the EPFM. Saeed et al. [33] introduced an AI optimization approach based on the Chebyshev metric to estimate the Weibull PDF parameters. This algorithm was then evaluated together with four different AI optimization algorithms (the Grey Wolf Optimizer (GWO), Bat Optimization (BOA), the Genetic Algorithm (GA), and the Artificial Bee Colony (ABCOA)) to obtain the optimum Weibull distribution parameters. Aly et al. [34] proposed hybrid deep learning clustered models for the prediction of wind speed and wind power using various combinations of the Recurrent Kalman Filter (RKF), the Fourier Series (FS), the Wavelet Neural Network (WNN), and the ANN for optimal performance. Lin et al. [35] carried out a study using both time-series data and multivariate regression data to forecast wind speeds in Taiwan. The SARIMA method and the Least-Squares Support Vector Regression for Time Series with Genetic Algorithms (LSSVRTSGA) were applied to forecast wind speed in a time series, and the Least-Squares Support Vector Regression with Genetic Algorithms (LSSVRGA) and Deep Belief Network with Genetic Algorithms (DBNGA) models were utilized for the prediction of wind speed in a multivariate format. Fazelpour et al. [36] analyzed four methods (ANN with RBF, ANFIS, ANN-GA, and ANN-PSO) based on AI to forecast short-term wind speed data. An AI approach composed of a hybrid NN modified by GA and PSO, which functioned as a model predictor, was recommended to forecast maritime weather variables an hour ahead by Arifin et al. [37].

In this study, a comprehensive and detailed comparison is made by using four different wind speed and wind power estimation approaches. For the first time in the literature for the Çanakkale region, both hourly and daily wind speed estimations are realized using these four methods. Two different statistical methods are utilized to determine the hourly wind speed: the Weibull and Rayleigh distributions. In addition, the ANN-GA and ANN-PSO hybrid approaches are proposed for daily estimation. After evaluating the performances of these four methods separately, wind power density estimation is performed for all methods on a daily basis and a comparison is established. Meteorological data, including the average wind speed and direction at an altitude of 10 m, the wet bulb temperature, the actual pressure, the maximum and minimum temperature, the relative humidity, the average temperature, the total global solar radiation, the areal precipitation, the amount of cloudiness, the sea water temperature, and the hours of sunshine, are taken from the Turkish State Meteorological Service for a 12-month time frame and analyzed in detail.

There is a lack of publications on wind speed and wind power estimation for the Çanakkale region using hybrid and AI-based methods. It is found that the hybrid ANN-GA and ANN-PSO methods are not applied together with the Weibull and Rayleigh techniques and the performance comparison of these methods has not been presented previously in the few existing studies carried out for this region. With the aim of filling the gap in the literature, this paper is proposed and organized into four sections. After this introduction, which presents a comprehensive literature review, theoretical calculations and an analysis of wind data in Çanakkale are provided in Section 2. The analysis results and discussion are given in Section 3. Finally, the conclusions of this study are presented in Section 4.

Table 1. Comparison of the time granularity, estimation method, and error metrics of the studies on wind speed forecasting.

References	Measurement Period/Sampling Interval	Location	Proposed Estimation Method	Error Calculation Technique
[27]	June 2016–May 2017	Brazil	SARIMA—NN	MAE, MAPE, RMSE
[28]	15 min time interval	Liaoning, China	VMD—ANN	MAE, RMSE, R
[30]	10 min time interval	China	PSO-SVR-NN	MAE, MAPE, RMSE
[31]	2008–2016	Bushehr, Iran	MLFFNN, SVR-RBF, ANFIS-PSO	RMSE, R, MSE
[26]	2007–2016	Sibu, Malaysia	Terrain-Based ANN	R, MAPE
[1]	2013–2014	Ankara, Türkiye	Weibull Function	-
[38]	10 min periods, 30 min periods	Penglai, China	NN-Linear Combination	RMSE, MAE, MAPE
[24]	April 2006–March 2007	Coimbatore, Tamil Nadu, India	MLPNN, RBFNN	R^2, MSE
[21]	May 2013–July 2016	Saudi Arabia	ANN	R, RMSE
[6]	2000–2016	Incheon, South Korea	Weibull and Rayleigh	RMSE, R^2, X^2
[8]	1995–2002,2012–2013	Giruliai, Lithuania	Weibull—MLM, Weibull—MSSDM	RMSE, R^2, X^2
[22]	4 years	Romania	Feedforward ANN	RMSE
[39]	-	-	ANN with BP, ANN with ELM	RMSE, R^2, R
[32]	-	-	ANFIS-Weibull	RMSE
[9]	2004, 2005, 2006, 2009	Florya, Yalova, Gebze, Biga	MUOM-Weibull	R^2, KS, RMSE, X^2, PDE
[40]	2014, 2016	Xinjiang, China	SSA, Hybrid Laguerre NN	RMSE, MAE
[18]	2016–2018	Northern Pakistan	MOM, EML, EMJ, EPFM, MMLM, GM	RMSE, R^2, MBE
[10]	2009–2013	Hatay, Osmaniye, Türkiye	Weibull with GM, MLM, EML, EPM, MOM	RMSE, R^2, MPE
[5]	January 2008–August 2011	Osmaniye, Türkiye	Weibull and Rayleigh with GM	-
[19]	2013	Osmaniye, Türkiye	Weibull and Rayleigh with GM, MOM	-
[11]	2008–2012	Jubail, Saudi Arabia	Weibull with MLM, LSR	RMSE, R^2, MAE, MBE
[7]	12 months	Northern Morocco	Weibull and Rayleigh	RMSE, R^2, MBE
[12]	September 2014	Southern India	Weibull with GM, MOM, EMJ, EML, LSR, MLM, MMLM, PDM, AMLM	RMSE, MAPE, R^2, X^2
[13]	Period of a year	Saudi Arabia	Weibull with MOM, LSR, MLM	MSE
[41]	1971–2000	Poland	Two and three-parameter Weibull	R^2, SE
[42]	2010–2014	Bohawian, China	Weibull-AI (GWO, PSO, CS, EMJ, EML, EPFM, MLM)	RRMSE, R^2
[43]	September 2014	Kayathar, Tamil Nadu, India	Weibull with nine different methods	RMSE, MAPE, R^2, X^2
[44]	1960–1978	Faya-Largeau, Chad	Weibull	-
[33]	April 2016–December 2018	Coastal region ofPakistan	Weibull-AI (GWO, BOA, GA, ABCOA)	RMSE, R^2, MBE
[45]	2009–2013	Southern region of Türkiye(Adana, Osmaniye, Hatay)	Weibull with the PDM	R^2, MPE, RMSE
[14]	Period of a year	Hawke's Bay region of Pakistan	Weibull with EM, MLM, MMLM, EPM, GM	RMSE, R^2

Table 1. *Cont.*

References	Measurement Period/Sampling Interval	Location	Proposed Estimation Method	Error Calculation Technique
[15]	2007–2013	Bafoussam, Cameroon	Weibull with EMJ, EML, MOM, GM, Mmab, MLM, EPFM, MMLM, EEM, AMLM	RMSE, R^2, X^2
[16]	2018	İzmir, Türkiye	Weibull with GM, MLM, EPFM	RMSE, R^2, X^2
[17]	2014	Lithuania	MLM, MMLM, WAsP, Rayleigh	MSE, R^2, X^2, RE
[20]	2014–2018	Punjab, Pakistan	Weibull with EPFM	RMSE, R^2
[25]	4 years	Niğde, Cesme, Mamak, Bozcaada, and Silivri, Türkiye	Machine Learning Algorithms(LASSO, KNN, xGBoost, SVR, RFR)	RMSE, R^2, MAE
[34]	-	-	Hybrid Deep Learning Models(RKF, FS, WNN, ANN)	MAPE, nRMSE
[35]	January 2017–December 2017	Taiwan	DBNGA, SARIMA, LSSVRTSGA, LSSVRGA	MAPE, RMSE
[36]	Period of a year with 1 h intervals	Tehran, Iran	ANN-RBF, ANFIS, ANN-GA, ANN-PSO	RMSE, MSE
[37]	May 2014–April 2015	Madura Strait, Java Sea	Hybrid NN-GA, NN-PSO	RMSE, MAPE, SDE, SSE
[46]	24 h ahead	Beijing, China	PSO-ANN	-
[47]	March–May 2009	Mongolia	ANN, Hybrid Model	RMSE
[23]	Period of a year	Western region of India	GRNN, MLP	MSE
[29]	3 months	Türkiye	SHWIP	nMAE

2. Methodology

2.1. Information about Study Region

Çanakkale Province, located in the Marmara region, is among the places with the highest wind energy potential in Türkiye [48]. There are 25 wind power plants in operation and 7 wind power plants under construction in the region. The total installed power of the operational power plants is 891 MW. At the end of June 2022, the installed power based on wind energy in Türkiye was 10.976 MW, approximately 8% of which is located in Çanakkale. In addition, the Saros Wind Power Plant, one of the ten largest wind power plants in Türkiye with an installed capacity of 138 MW, is located in this region. The hourly time-series wind data consist of the average wind speed and direction at an altitude of 10 m; the temperature, relative humidity, and actual pressure of Çanakkale are analyzed in detail for a 12-month period (2019 year). Çanakkale Province is one of the geopolitically strategic cities in Türkiye, which is located on the in the coast of the Aegean Sea in West Anatolia, and is surrounded by Balıkesir from east, the Aegean Sea in the west, Edirne in the northwest, and Tekirdag and the Marmara Sea in the north. The coordinates from the Northern Hemisphere are 40.14 north latitude and 26.40 east longitude. The altitude of Çanakkale is 2 m, and its distance from the sea is 12 km. The location of Çanakkale Province, as well as its annual average wind speed and annual average wind power density distribution, is shown in Figure 1.

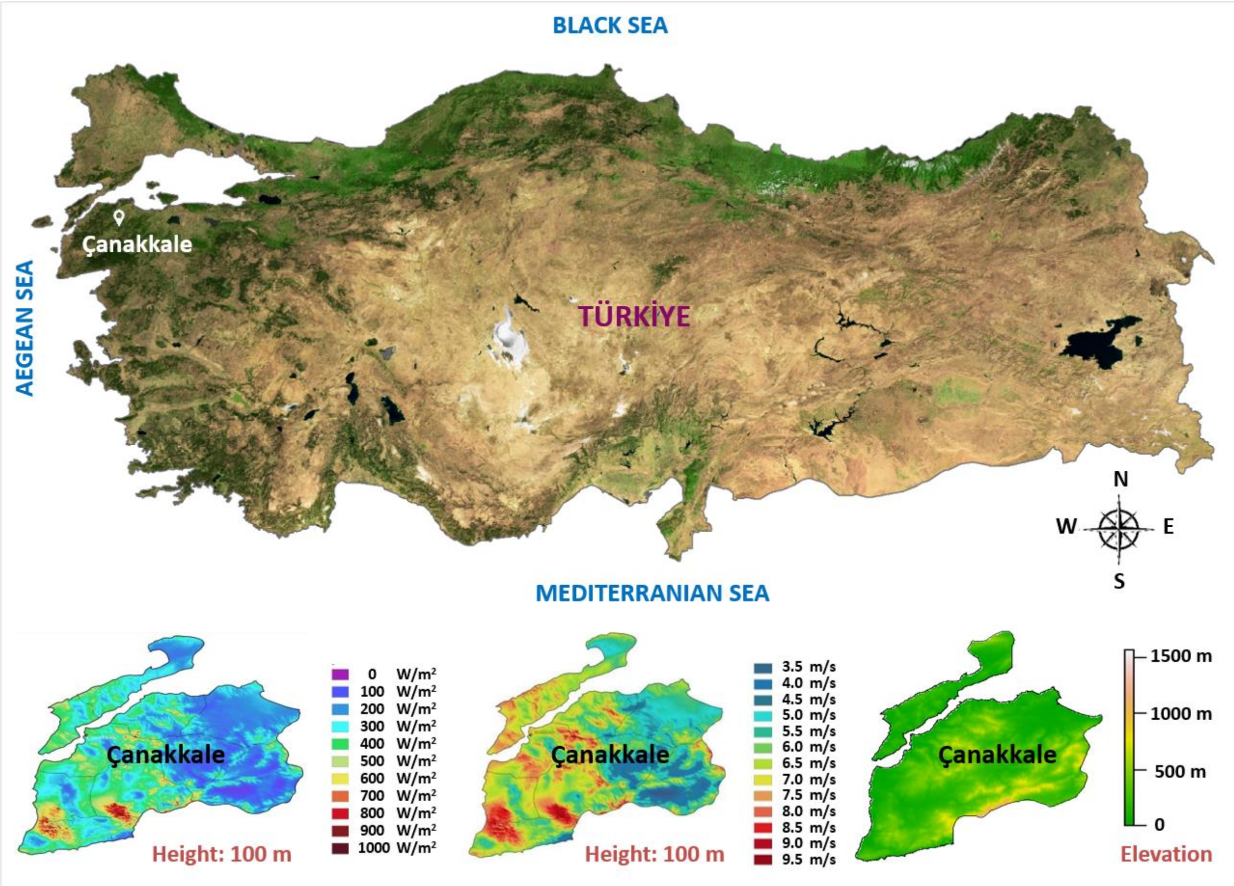

Figure 1. Location, elevation, annual average wind speed, and wind power density distribution of Çanakkale [49].

2.2. Weibull and Rayleigh Distribution Functions

Weibull and Rayleigh are the two most widely used and simplest distribution models for estimating wind power potential by expressing the PDF of wind speed data. Several techniques have been used to attain the shape (k) and the scale (c) parameters, which play a significant role in the Weibull distribution function. Each of these techniques existing in the literature has advantages and drawbacks. In this study, GM, which is a practical and effective way to find these parameters, is preferred.

2.2.1. Weibull Distribution

The mean wind speed and standard deviation values of observed time-series wind data were calculated using Equations (1) and (2):

$$v_m = \frac{1}{N}\left[\sum_{i=1}^{N} v_i\right] \tag{1}$$

$$\sigma = \frac{1}{N-1}\left[\sum_{i=1}^{N} (v_i - v_m)^2\right]^{1/2} \tag{2}$$

where v is wind speed, v_m is the mean wind speed (m/s), σ is the standard deviation (m/s), and N is the number of hours within the time period. To evaluate the mean wind speed values accurately, it is essential to know the number of hours during a given time interval per month or year. Estimation of the wind power potential of any region is realized using previously measured data. In general, this process is performed through wind speed distribution functions. First of all, hourly wind speed values in a time-series format are observed and then converted into the frequency distribution format for probability modelling because of the convenience [5]. Weibull distribution can be defined as the PDF, $f_w(v)$, and the cumulative distribution function, $F_w(v)$, as follows:

$$f_w(v) = \frac{k}{c}\left(\frac{v}{c}\right)^{k-1} \exp\left[-\left(\frac{v}{c}\right)^k\right] \tag{3}$$

$$F_w(v) = 1 - \exp\left[-\left(\frac{v}{c}\right)^k\right] \tag{4}$$

where $f_w(v)$ is the probability of a wind speed of v (m/s) occurring, v (m/s) is the measured wind speed, k (dimensionless) is the shape parameter, and c (m/s) is the scale parameter of the Weibull distribution. It is essential to know and interpret wind speed distributions for wind speed estimation. The data organized in the time-series format are rearranged in the frequency distribution format to make it more suitable for statistical analysis [5]. The following equation [5] describes the relationship between the Weibull scale parameter (c), the Weibull shape parameter (k), and the mean wind speed, v_m:

$$v_m = c\Gamma\left(1 + \frac{1}{k}\right) \tag{5}$$

Γ is the gamma function, which can be determined by the standard equation below:

$$\Gamma(x) = \int_0^\infty t^{x-1} \exp(-t)dt \tag{6}$$

By transforming Equation (4) into a logarithmic form, Equation (7) can be defined as

$$\ln[-\ln(1 - F_w(v))] = k \ln v - k \ln c \tag{7}$$

Here, if $x = \ln v$, $y = \ln[-\ln(1 - F_w(v))]$, $A = k$, and $B = -k\ln(c)$ are assumed [50], a linear equation is obtained from the function. Then, $y = Ax + B$ is acquired from Equation (7). Furthermore, the equation of $c = \exp(-B/A)$ is computed from the equation of $B = -k\ln(c)$. Then, A and B are calculated using the Least-Squares Method:

$$A = \frac{\sum\limits_{i=1}^{N} (x_i - \overline{x})(y_i - \overline{y})}{\sum\limits_{i=1}^{N} (x_i - \overline{x})^2}, B = \overline{y} - A\overline{x} \tag{8}$$

Here, $\overline{x}$ (average of x values) and $\overline{y}$ (average of y values) are obtained from Equation (9):

$$\overline{x} = \frac{1}{n}\sum_{i=1}^{N} f_i x_i,\ \overline{y} = \frac{1}{n}\sum_{i=1}^{N} f_i y_i \tag{9}$$

A straight line should result when plotting $\ln v$ against $\ln[-\ln(1 - F_w(v))]$. The line's slope is k and its y-axis intersection point is $-k\ln(c)$. The captured graph as an example for 2019 is given in Figure 2. Using wind speed data from Çanakkale Province, the Weibull parameters k and c in Equation (4) can be determined as 1.33 and 3.06, respectively.

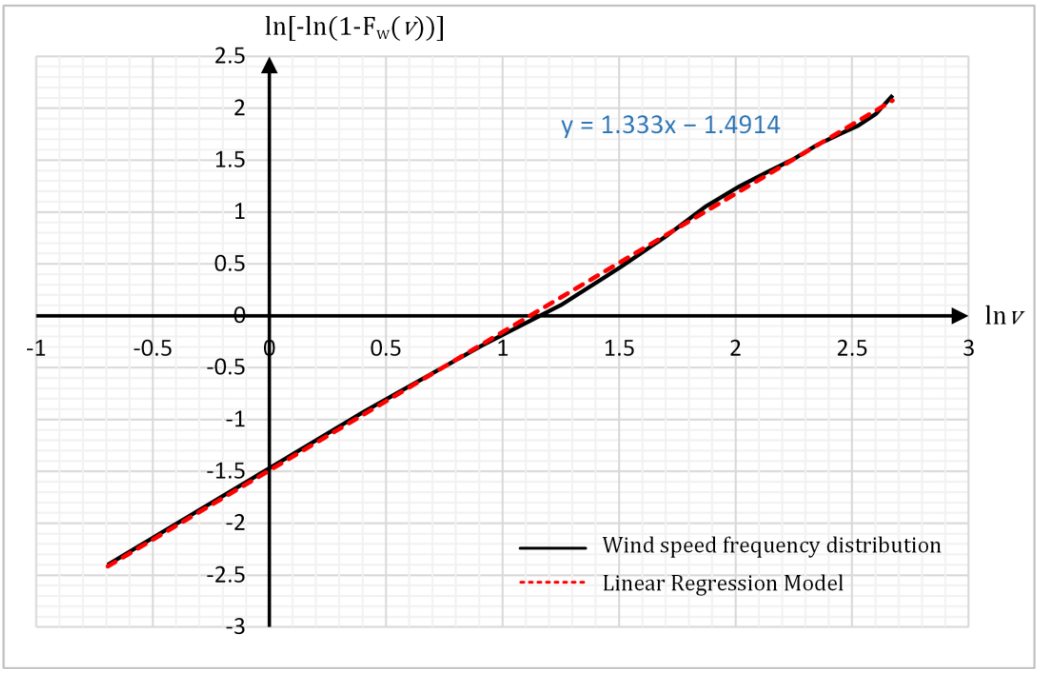

Figure 2. Graphical method of determining Weibull parameters.

The calculated parameters of shape (k), scale (c), the mean wind speed (v_m), and the standard deviation are listed by month in Table 2. The scale factor, c, ranges from 2.45 to 4.04 m/s, according to the Weibull parameters outlined in Table 1, while the shape factor, k, is between 0.95 and 2.12. October and November have the lowest values of the scale parameter, indicating that they are the least windy months of the year. The value of the scale parameter is lowest in January and February, which means that these two months are the windiest months of 2019 year in Çanakkale Province.

Table 2. The monthly average mean wind speed, standard deviation, and Weibull parameters calculated using wind speed data of Çanakkale Province.

		Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
v_m (m/s)	2019	4.06	4.06	3.90	3.06	3.05	2.89	3.08	3.85	3.32	2.73	3.03	3.23
σ (m/s)	2019	2.66	2.34	2.12	1.79	2.06	1.61	1.59	1.58	1.64	1.74	2.52	2.90
c (m/s)	2019	4.04	3.81	3.38	2.89	2.67	2.58	2.88	3.64	3.10	2.45	2.46	2.68
k	2019	1.41	1.57	1.47	1.50	1.28	1.50	1.78	2.12	1.59	1.31	0.95	0.98

2.2.2. Rayleigh Probability Density Function

Another statistical approach used to determine the wind speed, and thus, the wind power potential, is the Rayleigh distribution function. The situation where the shape parameter is equal to 2 in the Weibull function is accepted as a Rayleigh distribution [6]. The PDF of the Rayleigh model, $f_R(v)$, is as given below:

$$f_R(v) = \frac{\pi}{2} \frac{v}{v_m^2} \exp\left[-\left(\frac{\pi}{4}\right)\left(\frac{v}{v_m^2}\right)^k\right] \tag{10}$$

2.3. Calculations of Wind Power

The wind power, $P(v)$, whose unit is Watts, passing through a blade sweep area (A) at speed v rises as the cube of its velocity, and is calculated as follows [5,6,51]:

$$P(v) = \frac{1}{2}\rho A v_m^3 \tag{11}$$

where ρ is the standard air density ($\rho = 1.225\ \mathrm{kg/m^3}$). The wind power density per unit area ($\mathrm{W/m^2}$) in a region is obtained with the following formula for the Weibull function [5]:

$$P_{Weibull} = \frac{1}{2}\rho c^3 (1 + \frac{3}{k}) \tag{12}$$

The wind power density per unit area ($\mathrm{W/m^2}$) in a region for the Rayleigh function is expressed as follows [5]:

$$P_{Rayleigh} = \frac{3}{\pi}\rho A v_m^3 \tag{13}$$

The wind power densities of the Weibull and Rayleigh functions were calculated using the equations above. The monthly variation in the mean wind power densities, based on the Weibull and Rayleigh distribution functions, as well as actual (measured) data for Çanakkale, are illustrated in Figure 3. As stated in the literature [6,7], and as seen from the figure, the Weibull PDF provides results that are closer to the actual value for wind power density estimation than the Rayleigh PDF.

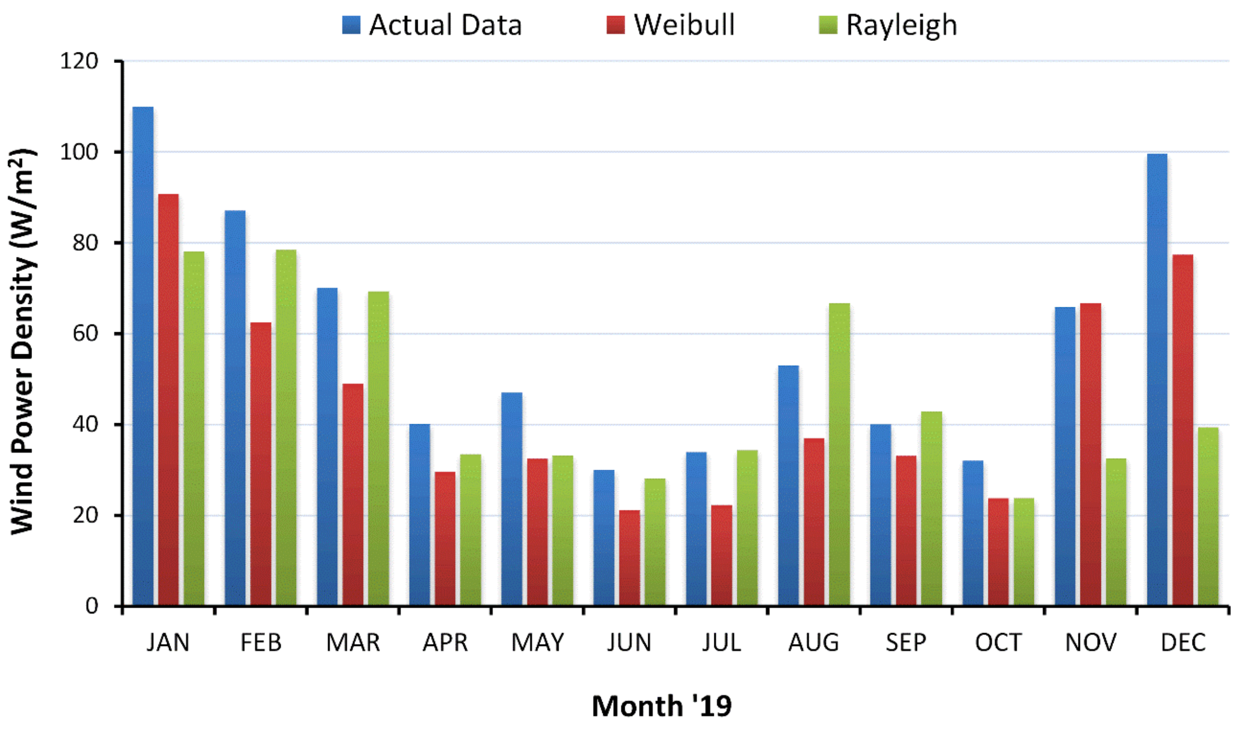

Figure 3. Monthly variation in mean wind power densities ($\mathrm{W/m^2}$) for the Çanakkale Province.

2.4. ANN-Based Hybrid Models for Wind Speed Estimation

ANNs are intelligent systems that work by mimicking the biological nervous system and are inspired by the electrochemical information processing technique of the human brain. An ANN model is comprised of neurons that use inputs across the network and transform inputs using transfer functions to produce results [52]. In this study, a Multi-Layer Feed-Forward Backpropagation ANN structure, as demonstrated in Figure 4, is utilized for the estimation of wind speed. Each cell in an ANN is called a neuron, which connect with each other through connections of different weights. Sets of neurons form layers that are divided into three layers: input, output, and hidden. As seen in Figure 4, 12 neurons (x_1, x_2, x_3, ..., x_{12}) representing the wind direction, wet bulb temperature, actual pressure, maximum and minimum temperature, relative humidity, average temperature, total global solar radiation, areal precipitation, amount of cloudiness, sea water temperature and hours of sunshine are used in the input layer, whereas one neuron (y_1) is employed In the output layer, denoting the daily average wind speed.

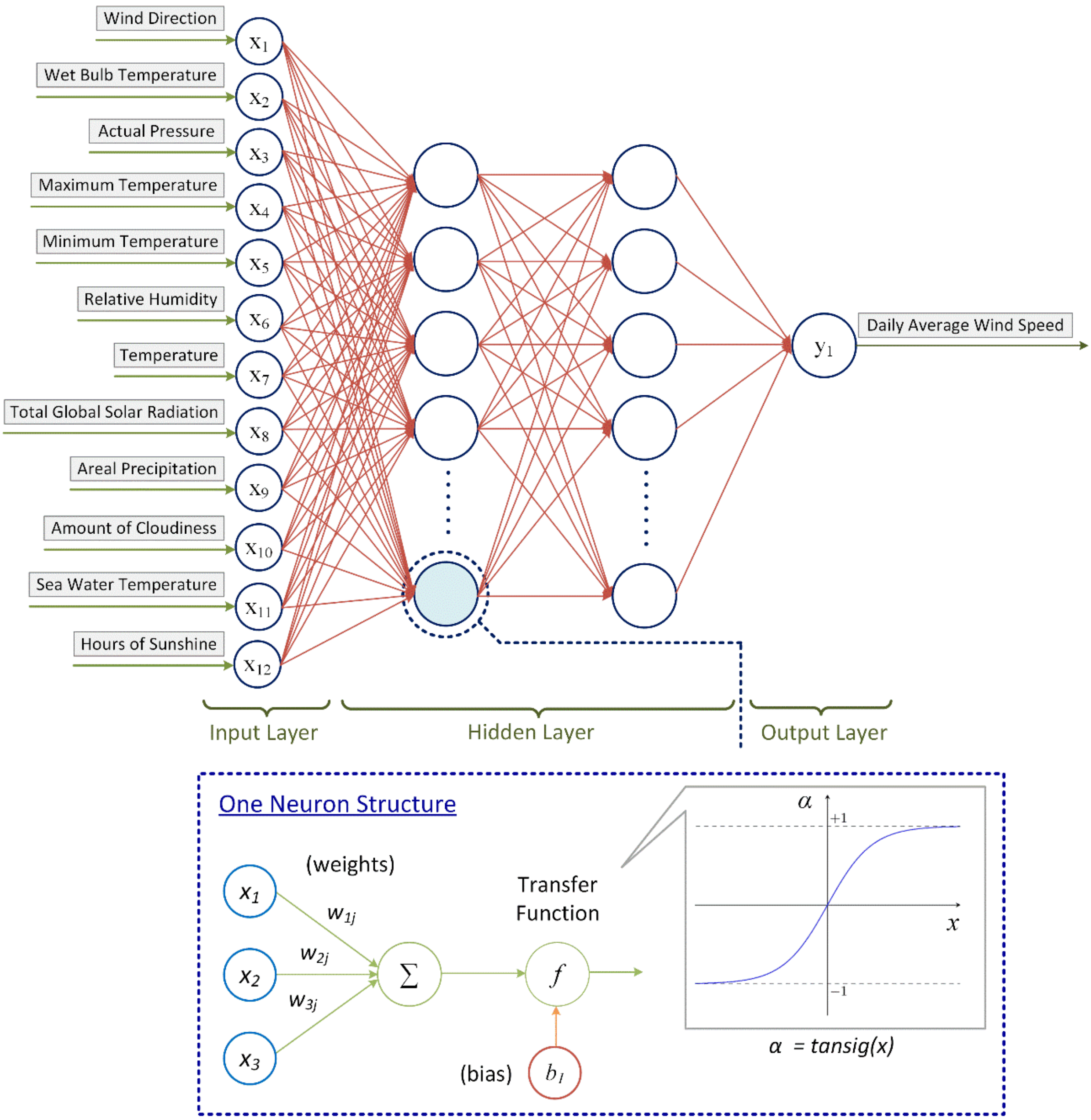

Figure 4. Feed-forward backpropagation ANN structure with two hidden layers.

Each neuron's input is determined by adding a bias term to the weighted sum of its previous layer's outputs [53]. The inputs of each neuron are processed by a transfer function, from which the linked neuron's output is produced. The sigmoid and hyperbolic tangent functions are the most frequently used activation functions [52]. The hyperbolic tangent sigmoid (tansig) is preferred as the transfer function in that configuration because the relation between input and output neurons is nonlinear. Equation (14) can be employed to mathematically define the output of the network.

$$\hat{y} = f_3\left(\sum_{k=1}^{p} w_{ks}.f_2\left(\sum_{j=1}^{m} w_{jk}.f_1\left(\sum_{i=1}^{n} w_{ij}.\, x_i + \varphi_j\right) + \varphi_k\right) + \varphi_s\right) \tag{14}$$

where x_i represents the input values and $\hat{y}$ is the output values of the network; w_{ij} represents the weights used to establish connections between the ith node of the input layer and the jth node of the first hidden layer; w_{jk} is the weights used to establish connections between the first and second hidden layers; and w_{ks} denotes the weights used to establish connections between the output layer and the second hidden layer. The transfer function is represented by f_1, f_2, and f_3, whereas the biases on the nodes of the first hidden, second hidden, and output layers are indicated by φ_j, φ_k, and φ_s, respectively.

One of the main objectives and novelties of this study is to introduce two hybrid approaches consisting of ANNs' dual combinations with GA and PSO algorithms to predict the wind speed and wind power potential. These hybrid approaches are more effective than the conventional ANN method alone. To overcome the lack of a single ANN model, the parameters of the ANN model are optimized by GA and PSO, resulting in higher prediction performance. Most recent studies have focused on hybrid approaches, where an ANN and metaheuristic optimization methods have been combined [54–57].

A network of interconnected artificial neurons that have been trained utilizing a learning algorithm is known as an ANN. In the ANN-GA hybrid model, a GA is used as a learning algorithm and trains the ANN in order to optimize the estimation technique. Similarly, in the ANN-PSO hybrid model, PSO is employed as a learning algorithm and trains the ANN to optimize the model and learning parameters. Figure 5 illustrates the flowchart of the presented hybrid ANN-GA and ANN-PSO algorithms. The performance of the ANN model depends on the number of hidden layers, the number of neurons in hidden layer, the rate division of the data (training and testing), the number of iterations, and the training function. The coefficient of determination (R^2), mean square error (MSE), root mean square error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE) are used to evaluate the accuracy of the presented models. The presented models are implemented using MATLAB software (2022b version). The ANN design parameters for MATLAB implementation are listed in Table 3.

Table 3. ANN design specifications for MATLAB implementation.

Parameter	Specifications
Neural network type	Feed-forward backpropagation
Number of neurons in input layer	12
Number of neurons in output layer	1
Number of hidden layers	2
Data division	70% Training, 30% Testing
Learning Rate	[0.7]
Transfer function	logsig (Log–sigmoid function) tansig (Tangent sigmoid function)
Training function	trainlm (Levenberg–Marquardt)
Performance function	Mean squared error (MSE)
Iteration number	70
Normalized range	[–1, 1]

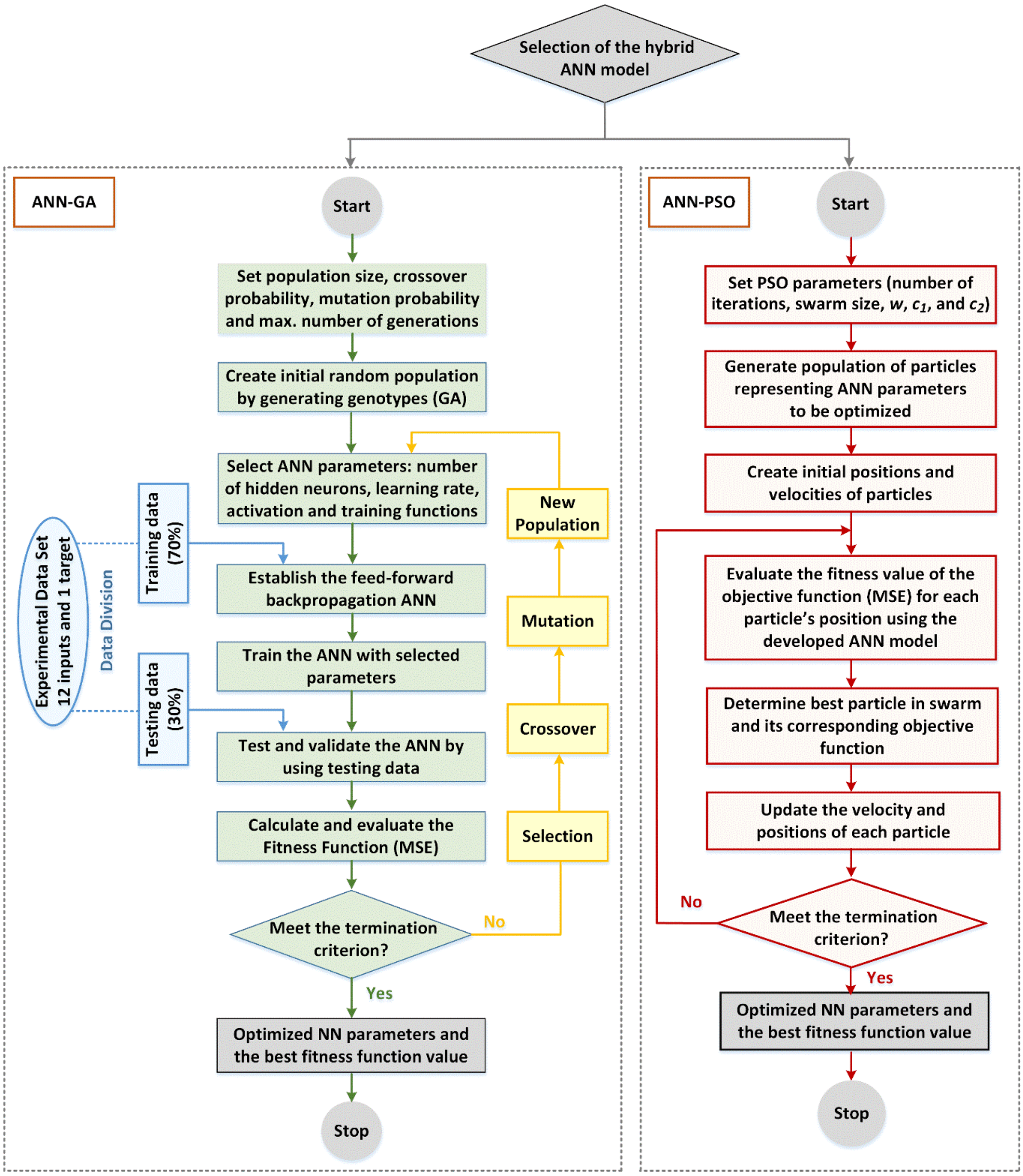

Figure 5. Flowchart of the hybrid ANN-GA and ANN-PSO algorithms [53].

3. Results and Discussions

The main purpose of this study is to examine the Weibull and Rayleigh distribution functions, which are statistical methods for the daily average wind speed and wind power potential estimation of Çanakkale Province, as well as the hybrid artificial intelligence-based ANN-GA and ANN-PSO methods, and then to present a comparison of these four methods. The gap in the literature was filled by using the ANN-GA and ANN-PSO methods for the first time to estimate the wind speed and wind power density in Çanakkale Province. The statistical error indices listed in Table 4 were used to evaluate the accuracy of the presented estimation techniques and to determine the error rates. The error rates were calculated with the formulas for the five most commonly used statistical error indices given in this table: R^2, MSE, RMSE, MAE, and MAPE. In these formulas, n is the number of observations, y_i

and x_i represent the estimated and measured test data, respectively, and z_i represents the mean of the measured data.

Table 4. The mathematical formulas of the statistical error indicators.

Error Metrics	Definitions	Formulas
R^2	Coefficient of Determination	$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - x_i)^2}{\sum_{i=1}^{n}(y_i - z_i)^2}$
MSE	Mean Square Error	$MSE = \frac{\sum_{i=1}^{n}(y_i - x_i)^2}{n}$
$RMSE$	Root Mean Square Error	$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(y_i - x_i)^2}{n}}$
MAE	Mean Absolute Error	$MAE = \frac{1}{n}\sum_{i=1}^{n}\lvert y_i - x_i \rvert$
$MAPE$	Absolute Percentage Error	$MSE = \frac{\sum_{i=1}^{n}(y_i - x_i)^2}{n}$

Figure 6 depicts the mean, minimum, and best fitness values (MSE) in relation to the generation size of the GA. The best MSE for the testing data was reached during the GA's 52nd iteration as 0.3653, while the correlation was computed as 0.94839. Figure 7 demonstrates the linear correlation between the actual and estimated outcomes for the training and testing data. As seen in that figure, the regression line of the test and the estimated data are provided as y = 0.81 × T + 0.62. The error between the estimated result and actual data and a comparison of them are also shown in Figure 7. As can be observed from the figure, the error graph has a few peak points, but overall, the error rate is close to zero, which leads one to deduce that the proposed ANN-GA algorithm performs successfully.

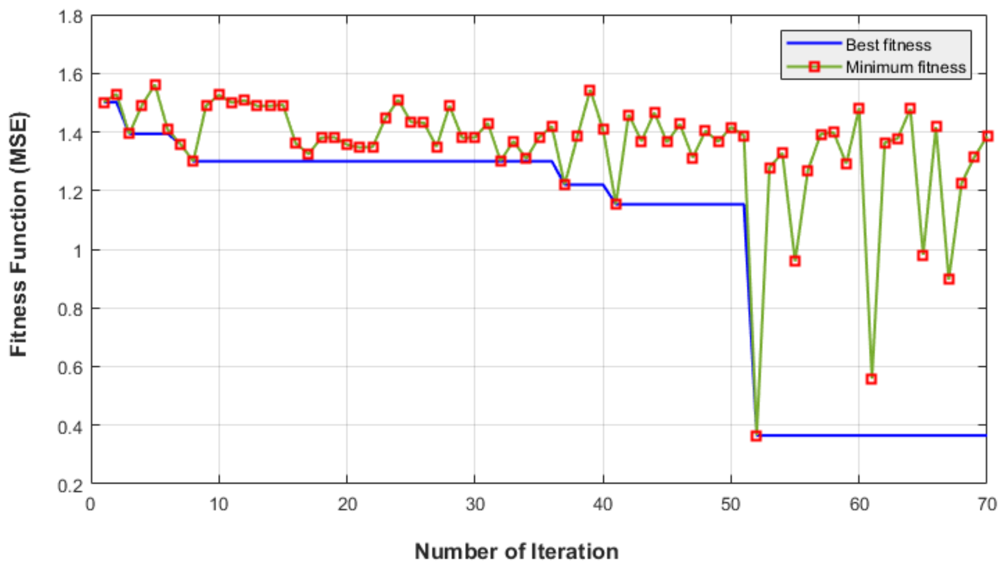

Figure 6. The minimum and best values of fitness with respect to the generation size of GA.

Figure 8 represents the mean, minimum, and best fitness values (MSE) in relation to the generation size of PSO. The best MSE for the testing data was 0.4721, while the correlation was obtained as 0.94042. Figure 9 illustrates the linear correlation between the actual and estimated values for the training and testing data. The regression line of the test and the predicted data are provided as y = 0.78 × T + 0.81. The error between the predicted and actual results and a comparison between them is also shown in that figure. According to Figure 9, the test and training errors are both quite low, which implies that the suggested ANN-PSO technique works satisfactorily.

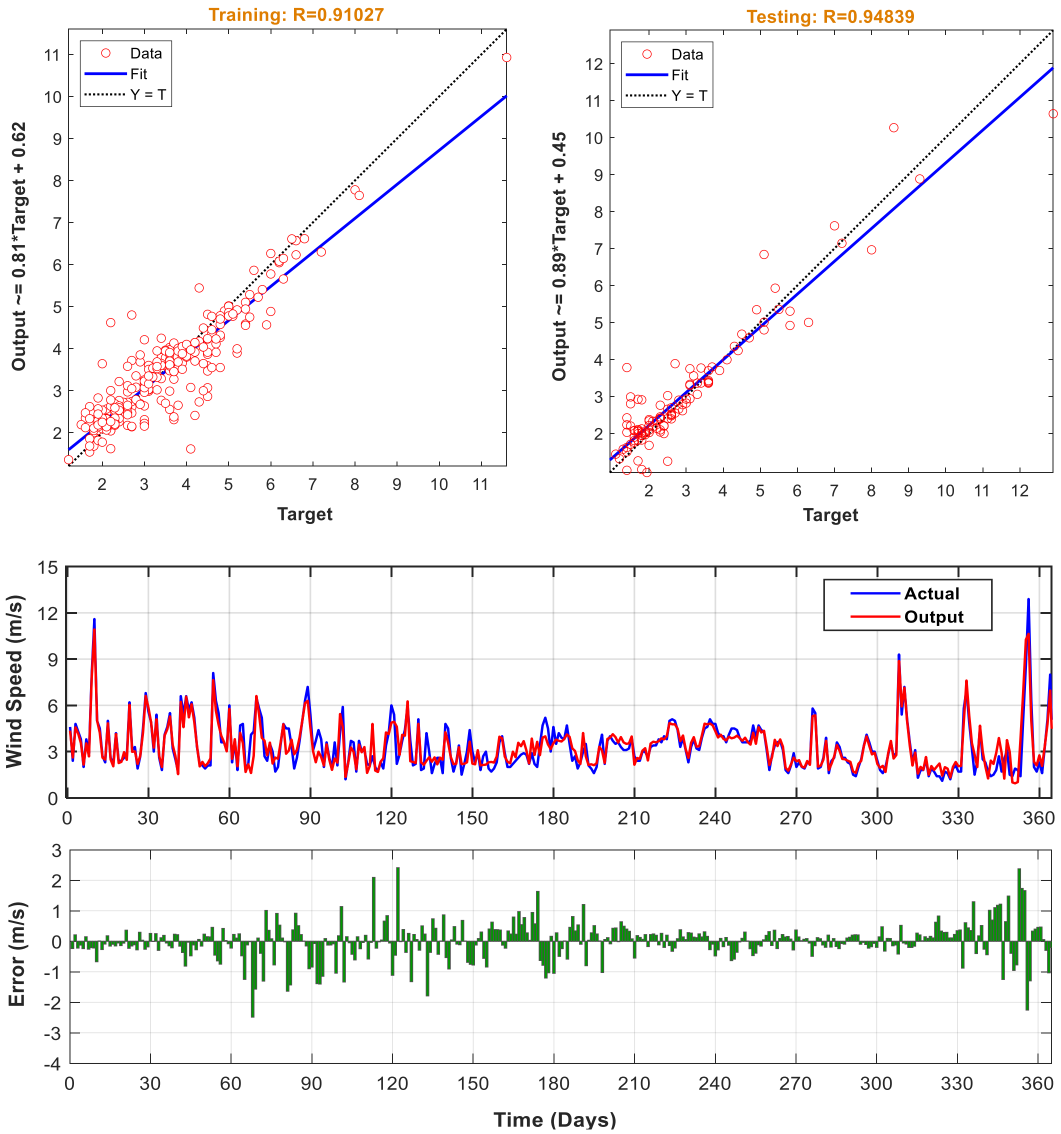

Figure 7. Correlation between target and predicted results for the training and test data (ANN-GA).

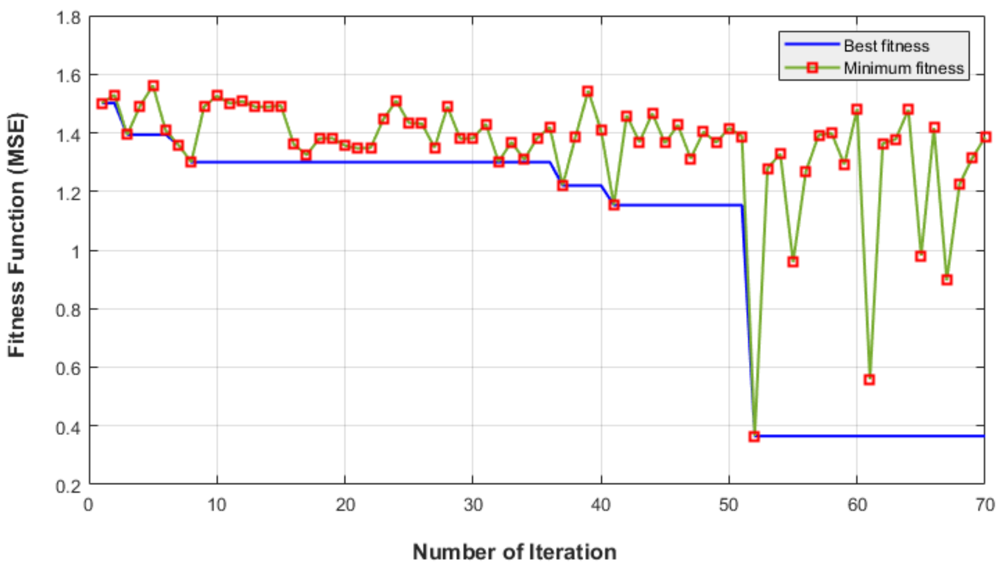

Figure 8. The minimum and best values of fitness with respect to the generation size of PSO.

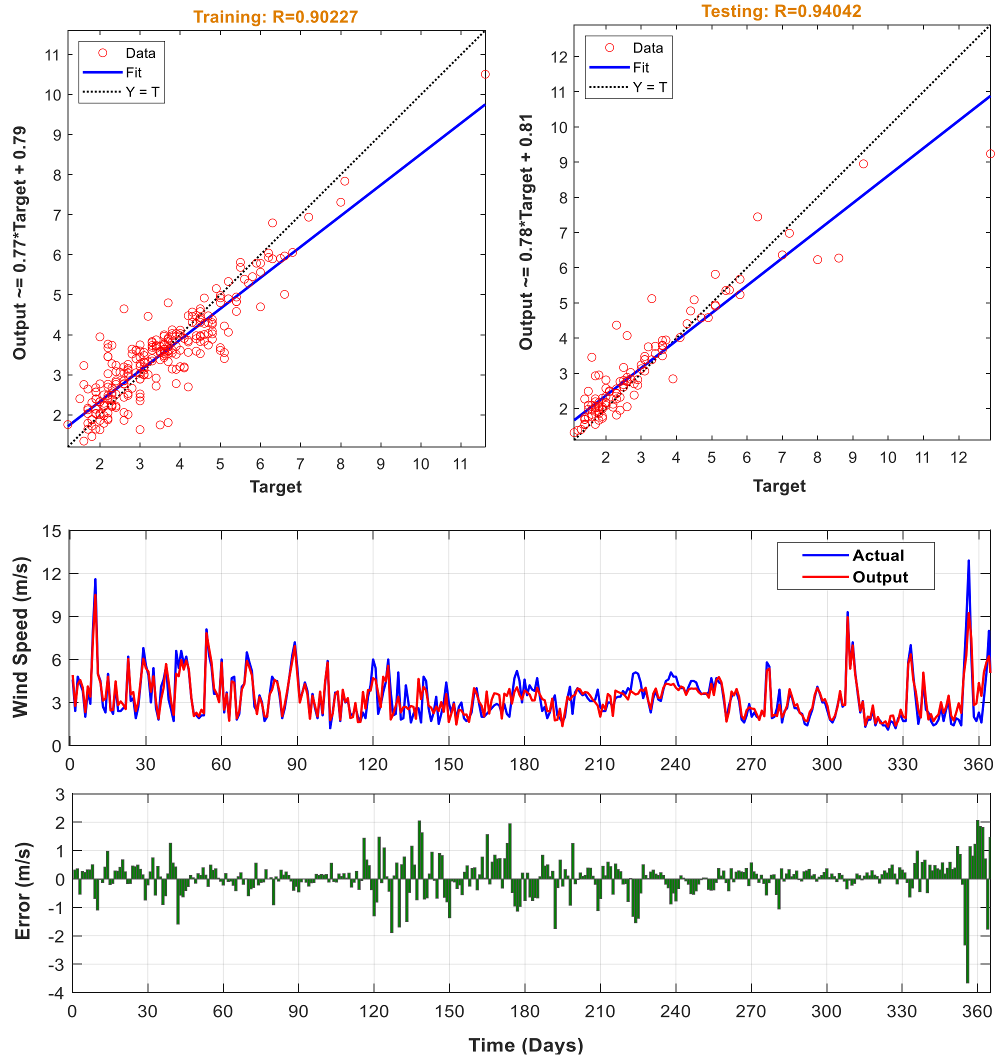

Figure 9. Correlation between target and predicted results for the training and test data (ANN-PSO).

The comparison graph for the prediction of the 2019 daily wind power density for the Weibull distribution, Rayleigh distribution, hybrid ANN-GA, and ANN-PSO algorithms is depicted in Figure 10. The estimated and measured (actual) wind power density results are shown and compared in the figure. The actual wind power density is represented by the blue curve, while the ANN-GA, ANN-PSO, Rayleigh, and Weibull results are represented by green, red, purple, and yellow curves, respectively. As can be seen from Figure 10, the Weibull distribution, which is one of the statistical methods, shows a superior performance compared to the Rayleigh distribution. However, it is understood that ANN-based hybrid algorithms give much better results in WP estimation than these two statistical methods. Then, considering Table 5, when the proposed ANN-based hybrid techniques were evaluated internally, it was observed that the ANN-GA model performed superior to the ANN-PSO model. According to Table 5, an MSE of 0.3653, an RMSE of 0.6044, an MAE of 0.3994, and an MAPE of 16.66% were obtained, and a correlation of 94.839% was achieved for the ANN-GA model. For the ANN-PSO model, an MSE of 0.4721, an RMSE of 0.6871, an MAE of 0.4304, and an MAPE of 17.07% were acquired, and a correlation of 94.042% was accomplished. The results show that the proposed ANN-GA model improves the prediction accuracy better than ANN-PSO. As a result, it is understood that the ANN-GA method has the best prediction results among the four methods for wind speed and wind power density.

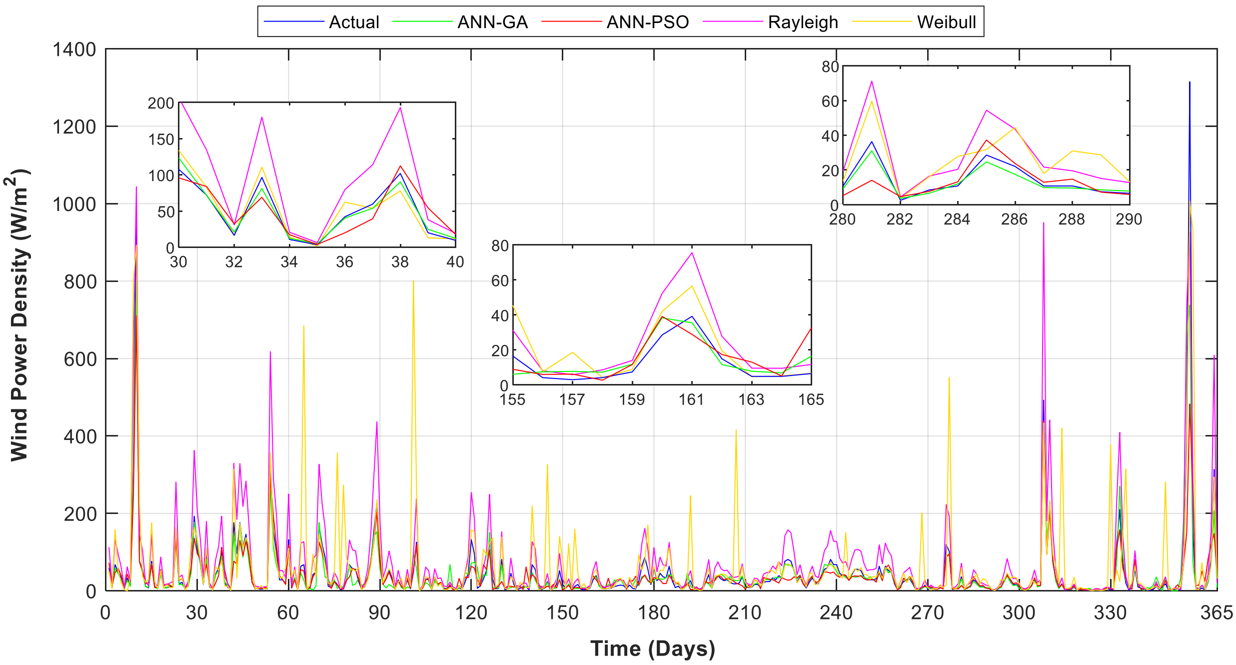

Figure 10. Prediction of daily wind power density for ANN-GA, ANN-PSO, Weibull distribution, and Rayleigh distribution.

Table 5. The statistical error performance result of ANN-based hybrid models.

Method	Statistical Error Performance Result					
	R	R^2	MSE	RMSE	MAE	MAPE
Presented ANN-PSO	0.94042	0.866	0.4721	0.6871	0.4304	17.07%
Presented ANN-GA	0.94839	0.896	0.3653	0.6044	0.3994	16.66%

Moreover, Table 5 is given to compare the performance of the presented ANN-based hybrid estimation techniques in this study. The performance of the proposed algorithms was evaluated using error metrics such as R^2, RMSE, MSE, MAE, and MAPE. The range of RMSE, MSE, and MAE is $(0, +\infty)$; smaller values of these parameters mean that the estimation model has higher accuracy. In addition, $10\% < \text{MAPE} < 20\%$ indicates a good prediction result. As understood from Table 5, ANN-GA exhibited a more satisfactory performance compared to ANN-PSO.

4. Conclusions

In this paper, a performance comparison of statistical methods and ANN-based hybrid methods for daily average wind speed and wind power estimation in Çanakkale is presented. Four estimation techniques were used: Weibull distribution, Rayleigh distribution, ANN-GA, and ANN-PSO algorithms. The accuracy of the proposed hybrid ANN-based methods was calculated using the statistical error indices R^2, RMSE, MSE, MAE, and MAPE. Among the statistical methods presented, the Weibull distribution yielded better results than the Rayleigh distribution, whereas the ANN-GA gave better results than ANN-PSO. The obtained results of R^2, MSE, RMSE, MAE, and MAPE were 0.896, 0.3653, 0.6044, 0.3994, and 16.66%, respectively, for the ANN-GA model. It was seen that the ANN-GA model realized the wind speed and wind power density estimation of Çanakkale Province with 94.839% accuracy. The results indicate that the proposed hybrid approaches provide reasonable wind speed and wind power density predictions. Consequently, thanks to the presented study, it is expected that better planning and a more effective evaluation can be made for investments in the wind sector in the region. In further studies, by using different

AI-based hybrid methods to predict the wind speed of the region and more favorable datasets, results with higher accuracy can be achieved.

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Abbreviations

ABCOA	Artificial Bee Colony Algorithm
AI	Artificial Intelligence
AMLM	Alternative Maximum Likelihood Method
ANFIS	Adaptive Neuro-Fuzzy Inference System
ANN	Artificial Neural Network
BOA	Bat Optimization Algorithm
BP	Back-Propagation
CS	Cuckoo Search Algorithm
DBNGA	Deep Belief Network with Genetic Algorithms
EEM	Equivalent Energy Method
ELM	Extreme Learning Machine
EM	Empirical Method
EMJ	Empirical Method of Justus
EML	Empirical Method of Lysen
EPFM	Energy Pattern Factor Method
EPM	Energy Pattern Method
FS	Fourier Series
GA	Genetic Algorithm
GM	Graphical Method
GRNN	Generalized Regression Neural Network
GWO	Gray Wolf Optimizer
KNN	K-Nearest Neighbor
KS	Kolmogorov–Smirnov Distance
LASSO	Least Absolute Shrinkage Selector Operator
LSR	Least-Squares Regression
LSSVRGA	Least-Squares Support Vector Regression with Genetic Algorithms
LSSVRTSGA	Least-Squares Support Vector Regression for Time Series with Genetic Algorithms
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MBE	Mean Bias Error
MLFFNN	Multi-Layer Feed-Forward Neural Network
MLM	Maximum Likelihood Method
MLP	Multi-Layer Perceptron
MLPNN	Multi-Layer Perceptron Neural Network
Mmab	Mabchour's Method
MMLM	Modified Maximum Likelihood Method
MOM	Method of Moments
MPE	Mean Percentage Error
MSE	Mean Square Error

MSSDM	Mean Speed and Standard Deviation Method
MUOM	Method of Multi-Objective Moments
nMAE	Normalized Mean Absolute Error
NN	Neural Network
NWP	Numerical Weather Prediction
nRMSE	Normalized Root Mean Square Error
PDE	Power Density Error
PDF	Probability Distribution Function
PDM	Power Density Method
PSO	Particle Swarm Optimization
R	Correlation Coefficient
R^2	Coefficient of Determination
RBF	Radial Basis Function
RBFNN	Radial Basis Function Neural Network
RE	Relative Error
RES	Renewable Energy Sources
RFR	Random Forest Regression
RKF	Recurrent Kalman Filter
RMSE	Root Mean Square Error
RRMSE	Relative Root Mean Square Error
SARIMA	Seasonal Autoregressive Integrated Moving Average
SDE	Standard Deviation of Error
SE	Standard Error
SHWIP	Statistical Hybrid Wind Power
SSA	Singular Spectrum Analysis
SSE	Sum Squared Error
SVM	Support Vector Machine
SVR	Support Vector Regression
VMD	Variational Mode Decomposition
WNN	Wavelet Neural Network
X^2	Chi-Square Error
xGBoost	Extreme Gradient Boost

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