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Article

Comparative Analysis for Evaluating Wind Energy Resources Using Intelligent Optimization Algorithms and Numerical Methods

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Abstract: Statistical distributions are used to model wind speed, and the two-parameters Weibull distribution has proven its effectiveness at characterizing wind speed. Accurate estimation of Weibull parameters, the scale (c) and shape (k), is crucial in describing the actual wind speed data and evaluating the wind energy potential. Therefore, this study compares the most common conventional numerical (CN) estimation methods and the recent intelligent optimization algorithms (IOA) to show how precise estimation of c and k affects the wind energy resource assessments. In addition, this study conducts technical and economic feasibility studies for five sites in the northern part of Saudi Arabia, namely Aljouf, Rafha, Tabuk, Turaif, and Yanbo. Results exhibit that IOAs have better performance in attaining optimal Weibull parameters and provided an adequate description of the observed wind speed data. Also, with six wind turbine technologies rating between 1 and 3 MW, the technical and economic assessment results reveal that the CN methods tend to overestimate the energy output and underestimate the cost of energy ($/kWh) compared to the assessments by IOAs. The energy cost analyses show that Turaif is the windiest site, with an electricity cost of $0.016906/kWh. The highest wind energy output is obtained with the wind turbine having a rated power of 2.5 MW at all considered sites with electricity costs not exceeding $0.02739/kWh. Finally, the outcomes of this study exhibit the potential of wind energy in Saudi Arabia, and its environmental goals can be acquired by harvesting wind energy.

Keywords: Weibull distribution; conventional numerical methods; intelligent optimization algorithms; wind resource exploration and exploitation; cost of energy ($/kWh)

1 Introduction

The rising demand for sustainable energy sources, such as solar and wind, has accelerated the pace of integrating renewable resources into power grids. Power extraction from wind is inexhaustible, and many countries started to embrace this technology. However, the uncertain nature of wind leads to variations in wind power generation, which causes severe obstacles to the power system operators attempting to maximize its penetration levels. For instance, wind power variability influences power systems' reliability, stability, operation, design, and cost of power systems [1,2]. Therefore, to reduce the risk of ambiguity and to better analyze the potential of wind energy at any location, it is essential to have accurate assessments of wind energy and an understanding of the distribution of wind speeds [3].

The frequency distribution of the wind speed is required to be thoroughly comprehended to provide an accurate assessment of the wind energy potential. Different Probability Density Functions (PDF) have been used in the literature to model wind speed, such as three parameters Weibull [4], Rayleigh [5], Lognormal [6,7], Gamma [6,8,9], Inverse Weibull [10], Generalized Gamma [11], Kappa [11], Burr [7], Logistic [6,12], inverse Gaussian [7], Beta [5], etc. The two parameters Weibull PDF is the most famous distribution worldwide to describe wind speed frequencies and assess the wind speed potential. The Weibull distribution is adaptable, has just two parameters, simple to estimate, and has a closed-form formulation [5,13]. Therefore, Weibull distribution is in use in this paper.

Weibull distribution is defined by its two parameters: scale (c) and shape (k). Therefore, attaining the optimal combination of c and k is essential for successful fitting accuracy and evaluating wind energy. Several methods have been used to estimate these parameters, such as the Conventional Numerical (CN) methods, including the Maximum Likelihood Method (MLM) [9,14,15], Method of Moment (MOM) [6,9,14], Energy Patter Method (EPM) [14,15], Power Density Method (PDM) [16,17], Empirical Method (EM) [14,15], and Graphical Method (GM) [18]. Recently, Intelligent Optimization Algorithms (IOA) have been applied by researchers to evaluate their performance in tuning Weibull parameters and assess the wind energy potential. Such methods include Particle Swarm Optimization (PSO) [9,14,16], Genetic Algorithms (GA) [11,16,19], Cuckoo Optimization Algorithm (COA) [6,9], Differential Evolution (DE) [12,16], and Batt Algorithm (BA) [9].

1.1 Related Work

For instance, the study in [20] conducts a technical assessment in two sites in Galati county, Romania. The wind speed data are characterized using Weibull and Rayleigh distributions, where the MOM is used to estimate their parameters. Study results reveal that the Weibull distribution best fits the wind speed in the two sites, while the Rayleigh distribution generates significant fitting errors. Bidaoui et al. [21] employ Weibull and Rayleigh distributions to evaluate the potential of wind energy in five remote areas in Northern Morocco, namely Larach, Tangier, Tetuan, Al-Hocima, and Nador. The Weibull distribution shows the superiority in accurately fitting the observed wind speed data at all the considered sites with low Root Mean Square Error (RMSE) values ranging between 0.0022 to 0.0004 m/s. The authors in [22] utilize Weibull distribution to analyze the wind speed in the Al-Salman site, Iraq. The shape and scale parameters of the Weibull PDF are estimated using the MLM. Results show that c and k values varied from 1.8 to 3.2 and from 5.93 to 8.3 m/s over various periods, respectively. On the other hand, results indicate that the average wind speed at 50 m above ground level (AGL) is 5.93 m/s.

Weibull distribution has been utilized in the techno-economic feasibility analysis of wind energy generation to evaluate the wind temporal and spatial variability and justify wind energy projects. The technical analyses use Weibull distribution to determine the best wind turbine technology for a specific location, wind power density, yearly energy output, and capacity factor (CF). In addition, Weibull distribution helps the economic assessments in determining the energy cost and the payback period of wind projects. For instance, the authors in [23] utilize EM, MLM, MLMLM, EPM, and GM to estimate Weibull parameters. These parameters are employed to determine the energy cost, CF, yearly energy yield, and wind power density for Hawke's Bay in China. Statistical analysis shows that at

30, 60, and 80 m AGL, the yearly wind speeds are 5.04, 5.84, and 6.05 m/s, respectively, while the average power densities are 184.0, 231.5, and 307.5 W/m^2. The lowest energy cost based on 2.3 MW wind turbine generators (WTG) is 0.056 US$/kWh. In [24], the authors also evaluate the potential of wind power generation in the central region of Thailand. Weibull distribution is used to carry out techno-economic assessments and accurate feed-in-tariff of a 15 MW wind farm. Results exhibit that the annual wind speed at the study location is 5.8 m/s at 120 m AGL, while annual energy production (AEP) and CF for the 15 MW power plant are speculated to be 41 GWh/year and 30%, respectively. Finally, the Levelized Cost of Energy (LCOE) is determined at 0.093 US$/kWh.

In addition, wind energy for electricity is assessed in the Republic of Djibouti by authors in [25]. Wind speed data were collected at five meteorological stations from 2015 to 2019. Weibull distribution is used to evaluate the economic and technical feasibility of five wind farms with a capacity of 450 MW. The mean wind speed is between 5.52 and 9.01 m/s for the selected five locations. The estimated annual electrical energy output from the proposed wind farms is 1739 GWh, with LCOE varying from 6.94 to 13.30 US cents/kWh. Adnan et al. [26] use GM, EM, EPF, and MLM to obtain the two parameters of Weibull distribution in the Umerkot and Sujawal districts of Pakistan. Results show low statistical errors with EM, EPF, and MLM. Accordingly, the optimal combination of the shape and scale parameters are used to analyze the energy production of various wind turbine technology with rated power ranging between 600 to 2500 kW. Regarding the wind turbines, Nordes N90/2500 produces the most wind energy in Umerkot and Sujawal, with associated energy costs of 0.074 and 0.056 $/kWh, respectively. From the above studies, however, the literature lacks a study that compares the performance of CN and IOA to assess the technical and economic feasibility of wind energy production. Younis et al. [27] examine the efficacy of various WTG when used in various Sultanate of Oman locations. The authors calculate internal and external factors and show how they influence small-scale energy WT using a fuzzy analytical hierarchy process technique. According to the research, the small WTG technology has the potential to be useful for irrigation, homes, schools, and colleges.

Saudi Arabia has roughly 16% of the total world's oil reserves and is the largest oil producer and exporter of the total petroleum liquid [28]. On the other hand, Saudi Arabia has the potential for wind and sun energy. For wind energy, the process of wind data recording and collection in Saudi Arabia began in 1970 [29]. The first work concerning wind data was done by Ansari et al. [30]. Rehman et al. [29] evaluated the potential of wind energy by assessing the cost of wind power utilizing three WTG at 20 locations in Saudi Arabia. The results showed that the minimum cost of kWh utilizing 2500, 1300, and 600 kW WTG was 0.0234, 0.0295, and 0.0438 US$/kWh at Yanbo, while the maximum appeared in Nejran with values of 0.0706, 0.0829, and 0.121 US$/kWh. In addition, Rehmana et al. [31] studied the potential of wind for pumping water in isolated areas not connected to the main power grid of Saudi Arabia. Results point out that a wind turbine with a size of 2.5 kW is the most suitable for powering the water pump at all the selected sites. It is also found that the cost of water pumping at the three locations is as low as 1.28 US cents/m^3.

1.2 Motivation and Contributions

Most wind energy assessments in Saudi studies use CN methods to estimate Weibull parameters and accordingly evaluate the techno-economic assessments of wind energy production. Nevertheless, the advent of the IOAs revealed their capacity to obtain optimal Weibull parameters and represent wind speed data more accurately, thus, more precise wind energy evaluation. Therefore, the main objective behind this research is to conduct technical and economic feasibility studies for five sites in northern Saudi Arabia. This study proposes six wind turbine technologies with different wind speed characteristics and rated powers. The primary contributions of this research work are as follows:

1. Develop a framework to calculate the characteristics of the Weibull distribution to describe the wind speed at five different locations in Saudi Arabia: Aljouf, Rafha, Tabuk, Turaif, and Yanbo.
2. Compare the performance of five CN methods and five IOAs in obtaining Weibull parameters. The CN methods used in this study are LSM, MLM, MOM, EM, and EPFM, while IOAs are PSO, GA, Differential Evolution (DE), COA, and Social Spider Optimization (SSO). Results demonstrate that IOAs outperform CN approaches in determining the best parameters, providing a trustworthy account of the actual frequency of wind speed.
3. Evaluate the energy output and recommend the optimal wind turbines for the selected sites. This study analyzes the installation of six wind turbine technologies rated between 1 and 3 MW.
4. Estimate the cost of energy to justify the wind turbines' economic viability over their life span.
5. Even though this work aims to characterize wind speeds in Saudi Arabia, the established framework can be used to describe wind speeds in many geographical areas with varied wind regimes.

The paper is organized as follows: Section 2 explains the framework of the study and wind speed data source. In Section 3, Weibull PDF is presented together with the estimation approaches: CN and IOA. Section 4 describes the statistical indicators used to evaluate the accuracy of the study models. Section 5 discusses the wind power extrapolation at hub height, while Section 6 exhibits the economics analysis of wind turbines. The discussions and results of the comparison are presented in Section 7. Finally, the study concludes in Section 8.

2 Methodology

This section provides a complete explanation of the methodology employed in this research. Initially, the problem description and framework of the proposed methods are described. An introduction about Weibull distribution and CN and IOA methods are then presented, along with the technical and economic assessment of the used procedure.

2.1 Problem Description

The main goal of this study is to present a framework for assessing the wind energy potential at five locations in northern Saudi Arabia, namely Aljouf, Rafha, Tabuk, Turaif, and Yanbo. The proposed framework evaluates the performance of five CN and IOA estimation methods in obtaining the two parameters of Weibull distribution. In addition, a comparative analysis is conducted using technical and economic feasibility studies to assess the wind energy resources at the considered sites. Therefore, the proposed framework is shown to be accurate, reliable, simple to implement, and can help evaluate wind energy in different geographic areas.

2.2 Study Framework

This feasibility study conducts a comparative analysis between five CN and five IOA methods to estimate Weibull distribution parameters. Fig. 1 presents the overall framework adopted. The main steps of the proposed framework are as follows:

Step 1: Data collection: the wind speed data are initially collected. Afterward, the data preprocessing techniques are applied to organize the data by looking for missing values, noisy data, and other abnormalities before running the estimation methods.

Step 2: Statistical characteristics: the main objective of this step is to provide insights into the wind regimes in each site and approve the performance of the proposed algorithms.

Step 3: Weibull parameters estimation: the CN and IOA methods are applied to estimate c and k of the Weibull distribution.

Step 4: Building the estimation models: by using the best parameters mentioned in ***Step 3,*** ten models are generated for each considered site.

Step 5: Results comparison: the models generated by CN and IOA methods are evaluated utilizing RMSE, Coefficient of Determination (R^2), and Mean Absolute Error (MAE).

Step 6: Annual energy: based on the comparison in ***Step 5***, the best Weibull PDF function findings are used to estimate the annual energy produced by wind turbines.

Step 7: Energy cost: the feasible energy cost per kilowatt hour (kWh) for the chosen wind turbine is then calculated using the annual energy estimate.

The subsections below provide a detailed explanation of each step.

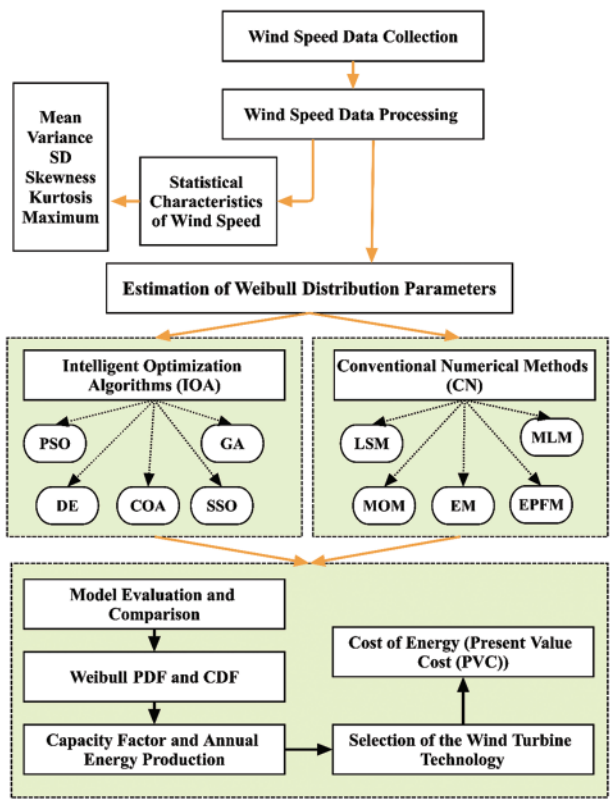


Figure 1: The framework of the study

2.3 Wind Data Source

The wind data used in this study is obtained from the National Climatic Data Center, USA, Department of Commerce [32]. In this study, the wind speed regimes of five Saudi areas located in the northern parts are investigated, namely Aljouf, Rafha, Tabuk, Turaif, and Yanbo. These locations are chosen for the wind analysis primarily because they are spread out geographically in the northern parts of Saudi Arabia, where the wind speed is predominant. To accomplish a very accurate assessment of wind power, avoid uncertainty in the wind, and justify the economic feasibility of wind deployment, long-term averaged-daily wind speed data are considered in this study covering 40 years (1977–2017). Table 1 exhibits the geographic information and anemometer height at each site. Fig. 2 displays the Saudi Arabia wind speed map, while Fig. 3 shows the monthly mean of wind speed data at the five study locations.

Table 1: Characteristics and geographic features of five sites

City	Region	Latitude (*N*)	Longitude (*E*)	Elevation (m)	Station height (m)
Aljouf	North	+29.785	+040.100	+0689.2	7
Rafha	North	+29.626	+043.491	+0449.3	12
Tabuk	Northwest	+28.365	+036.619	+0777.5	9
Turaif	North	+31.693	+038.731	+0854.4	8
Yanbo	Northwest	+24.144	+038.063	+0007.9	10

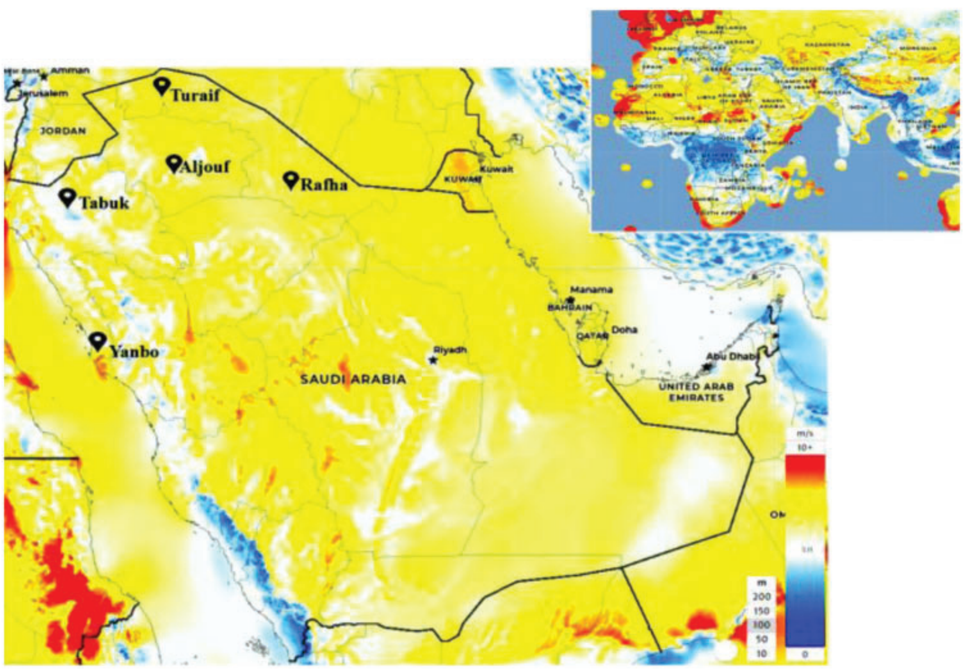


Figure 2: Map of Saudi selected sites. This map is obtained from Global Wind Atlas. Please visit https://globalwindatlas.info

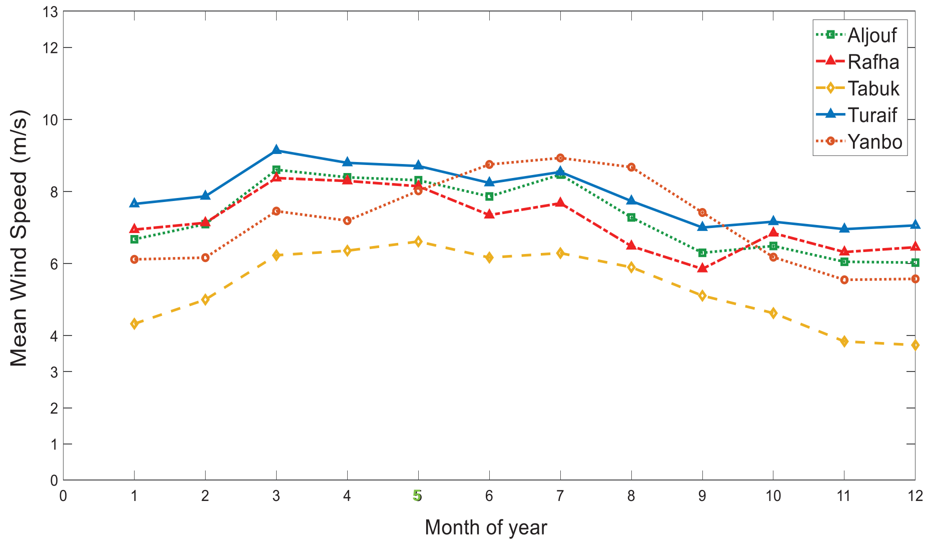


Figure 3: Monthly mean of wind speed at the study sites

2.4 *Wind Speed Characteristics*

Some statistics are calculated at the measurement heights to comprehend and analyze the wind speed data. Table 2 lists the statistics values, including Mean, Variance, Standard Deviation, Skewness, Kurtosis, and Maximum wind speed value. The Mean value tells about the central tendency of the wind speed data. Variance and Standard Deviations (SD) provide information about how observed wind speed deviate from the central value. In addition, to understand the pattern of the observed frequency distribution, Skewness and Kurtosis are utilized. The symmetrical characteristic of the wind speed data is measured by Skewness, while the steep degree of data is described by the Kurtosis value [12].

Table 2: Statistical characteristics of wind speed at study sites

City	Aljouf	Rafha	Tabuk	Turaif	Yanbo
Mean (m/s)	7.525934	7.387378	5.511694	8.152232	7.393027
Variance (m/s)	11.56876	10.36447	6.249976	10.07062	7.903882
SD (m/s)	3.401289	3.21939	2.499995	3.173425	2.811384
Skewness	0.993003	0.739382	1.012287	0.828774	0.770616
Kurtosis	4.82901	3.636315	5.92581	4.383357	3.859248
Maximum (m/s)	31	25.3	25.2	27.1	23.7

3 Two-Parameters Weibull Model

Weibull PDF showed its popularity worldwide to represent the wind speed frequency distribution. Weibull distribution proved its efficiency in representing wind data as it provides a good fit for the wind speed data at the ground surface and upper layers [33]. Weibull distribution is characterized by its PDF, $f(v)$, and its Cumulative Distribution Function (CDF), $F(v)$, as follows [34]:

$$f(v;\mathrm{k},\mathrm{c}) = \left(\frac{\mathrm{k}}{\mathrm{c}}\right)\left(\frac{v}{\mathrm{c}}\right)^{\mathrm{k}-1}\exp\left(-\left(\frac{v}{\mathrm{c}}\right)^{\mathrm{k}}\right) \tag{1}$$

$$F(v) = \int_0^v f(v)\ dv = 1 - exp\left(-\left(\frac{v}{\mathrm{c}}\right)^{\mathrm{k}}\right) \tag{2}$$

where, v: wind speed (m/s), c: Weibull scale parameter (m/s), and k: Weibull shape parameter.

3.1 Conventional Numerical Estimation Methods

The following subsections explain the CN methods used to estimate the shape k and the scale c parameters of the Weibull PDF [35–37].

3.1.1 Least Square Method

The wind speed data should be represented in a cumulative frequency distribution arrangement to use LSM [38]. The logarithmic transformation is fundamental to LSM. Therefore, the linearization of Weibull distribution, for example, is accomplished by taking the logarithm of its CDF to obtain the following expression [39]:

$$ln[-ln(1-F(v))] = k\,ln(v) - k\,ln(c) \tag{3}$$

This equation represents a straight line as follows: $y = ax + b$, Where: $y = ln[-ln(1-F(v))]$, $a = k,\ x = ln(v),\ b = -k\,ln(c)$.

By linear regression formula, the least square estimator of Weibull distribution parameters k and c are as follows:

$$k = \frac{N\sum_{i=1}^{N}x_iy_i - \sum_{i=1}^{N}x_i\sum_{i=1}^{N}y_i}{N\left(\sum_{i=1}^{N}x_i^2\right) - \left(\sum_{i=1}^{N}x_i\right)^2} \tag{4}$$

$$c = \exp\left(\frac{\sum_{i=1}^{N}x_i\sum_{i=1}^{N}x_iy_i - \sum_{i=1}^{N}x_i^2\sum_{i=1}^{N}y_i}{N\sum_{i=1}^{N}x_iy_i - \sum_{i=1}^{N}x_i\sum_{i=1}^{N}y_i}\right) \tag{5}$$

3.1.2 Maximum Likelihood Method

The MLM is known as the likelihood function of the wind speed data [35]. The MLM can be solved by numerical iteration to compute the two Weibull parameters. According to maximum likelihood estimation theory, the Weibull parameters are calculated from Eqs. (6) and (7) [40]:

$$k = \left(\sum_{i=1}^{n}\left(v_i^k ln v_i\right) \Big/ \sum_{i=1}^{n} v_i^k - \sum_{i=1}^{n} ln\left(\frac{v_i}{n}\right)\right)^{-1} \tag{6}$$

$$c = \left(\frac{1}{n}\sum_{i=1}^{n} v_i^k\right)^{1/k} \tag{7}$$

After determining the value of k in Eq. (6) through a numerical iteration algorithm, such as Newton Raphson, the value of c can be computed from Eq. (7).

3.1.3 Method of Moment

The MOM uses the mean of the observed wind speed $\overline{V}$ and the standard deviation of the wind data σ to estimate the Weibull parameters [36]. The Weibull parameters k and c are computed by the following equations [36]:

$$c = \frac{\overline{V}}{\Gamma\left(1 + \frac{1}{k}\right)} \tag{8}$$

$$k = \left(\frac{0.9874\overline{V}}{\sigma}\right)^{1.0983} \tag{9}$$

where: $\overline{V} = \sum_{i=1}^{n} \left(f\left(v_i\right) . v_i\right)$, Variance $= \sum_{i=1}^{n} f\left(v_i\right) . \left(v_i - \overline{V}\right)^2$, Standard Deviation: $\sigma = \sqrt{Variance}$, and n is the number of wind speed bins. $\Gamma\left(x\right)$ is the Gamma function and for random variable z, it is defined as $\Gamma\left(z\right) = \int_0^\infty v^{z-1} \exp\left(-v\right) \, dv$.

3.1.4 Empirical Method

The EM is a special case of the MOM [35]. The Two Weibull parameters are estimated in this method by using the following equations [41]:

$$c = \frac{\overline{V}}{\Gamma\left(1 + \frac{1}{k}\right)} \tag{10}$$

$$k = \left(\frac{\sigma}{\overline{V}}\right)^{-1.089} \tag{11}$$

3.1.5 Energy Pattern Factor Method

The EPFM is generated from the average data of the wind speed and is represented as follows [36]:

$$E_{pf} = \frac{\left(v^3\right)_m}{\overline{V}^3} = \frac{\left(\frac{1}{n}\sum_{i=1}^{n} v_i^3\right)}{\left(\frac{1}{n}\sum_{i=1}^{n} v_i\right)^3} \tag{12}$$

where E_{pf} is the energy pattern factor. As the E_{pf} is determined, the Weibull parameters k and c are estimated from Eqs. (13) and (14).

$$k = 1 + \left(\frac{3.69}{E_{pf}^2}\right) \tag{13}$$

$$c = \frac{v_m}{\Gamma\left(1 + \frac{1}{k}\right)} \tag{14}$$

3.2 Intelligent Optimization Algorithms

The metaheuristic optimization algorithms are nature-inspired techniques. The examined algorithms include PSO, GA, DE, COA, and SSO. With these algorithms, this study attempts to minimize the difference between the measured frequency distribution of the wind speed and theoretical values generated by the considered PDFs. Hence, the objective function is as follows:

$$Fitness\left(v_i\right) = \frac{1}{2}\sum_{i=0.5}^{n} \left(f_m\left(v_i\right) - f_{PDF}\left(v_i, \theta_i\right)\right)^2 \tag{15}$$

where $f_m\left(v_i\right)$ is the measured frequency distribution of wind speed class, $f_{PDF}\left(v_i, \theta_i\right)$.

Fig. 4 depicts the process of optimizing the Weibull parameters from the scope of the PSO algorithm. The c and k are generated, and their values evolve until we obtain the lowest error values, represented by Eq. (15). The optimization algorithms are compared to estimate the Weibull parameters. The outcomes of the algorithms are considered after 50 runs, each with 1000 iterations. The median values of the 50 runs were used to select the final fitness values. Fig. 7 displays the convergence rates of the algorithms to obtain the optimal set of Weibull parameters in the selected sites.

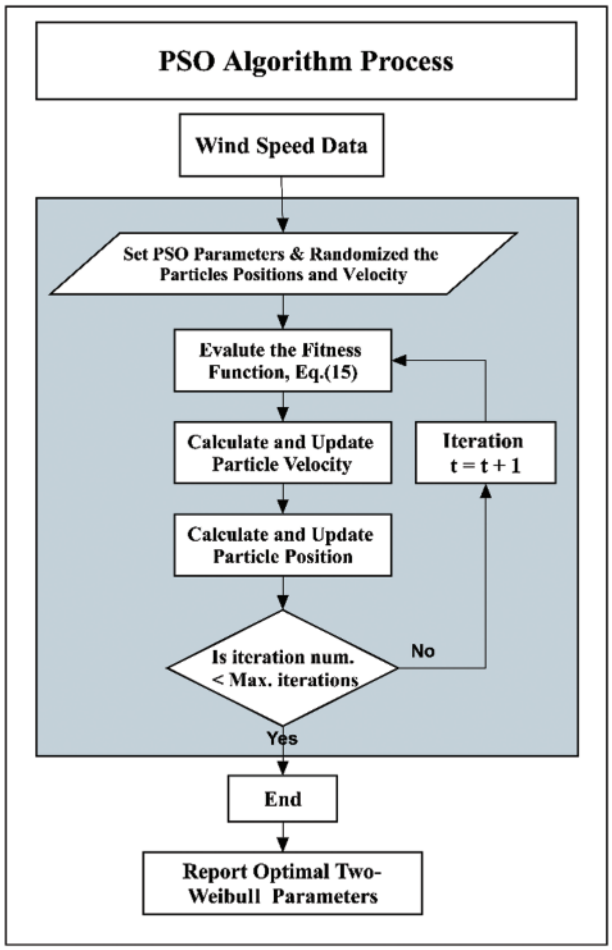


Figure 4: The process of optimizing Weibull parameters from the scope of PSO

4 The Goodness of Fit Tests

The accuracy and efficiency of the considered numerical and optimization methods to show how close the theoretical frequency distribution is to the empirical frequency distribution are evaluated using some statistical indicators: RMSE, R^2, and MAE [42].

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{n}(v_i - w_i)^2} \tag{16}$$

$$R^2 = \frac{\sum_{i=1}^{n}\left(v_i - \overline{V}\right)^2 - \sum_{i=1}^{n}\left(v_i - w_i\right)^2}{\sum_{i=1}^{n}\left(v_i - \overline{V}\right)^2} \tag{17}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|v_i - w_i| \tag{18}$$

where: v_i is the actual wind speed data, w_i is the estimated data using the study distribution, $\overline{V}$ is the mean value of v_i, and the n is the number of all wind bin classes. RMSEmeasures the deviation between actual values and forecasted values [43], and R^2 is the proportion of variation of the predicted values generated by PDF models and the observed wind speed data variation. Finally, MAEdetermines the average error between empirical and theoretical PDFs considered in this study.

5 Wind Power Extrapolation at Turbines Height

Wind speeds are collected at station height while the wind turbines are functioning and designed to operate at hub heights (h). That is, the wind speed values increase as height increases from the anemometer level. Therefore, through employing the power law expression, Eq. (19), the wind behavior at different heights can be captured and comprehended [44].

$$\frac{v}{v_o} = \left(\frac{h}{h_o}\right)^{\alpha} \tag{19}$$

where v and v_o are the wind speed at the wind turbine hub height and station height (m/s), respectively. h is the hub height in meters, while h_o represents the station height. α represents the surface roughness coefficient.

The Weibull distribution parameters values k_{ho} and c_{ho} are calculated at the station's height (ho) AGL. To alter k_{ho} and c_{ho} values to any desired WTG heights (k_h and c_h), the following relations are used [44]:

$$k_h = k_{ho}\left[1 - 0.0881\ln\left(\frac{h_o}{10}\right)\right] \Big/ \left[1 - 0.0881x\ln\left(\frac{h}{10}\right)\right] \tag{20}$$

$$c_h = c_{ho}\left(\frac{h}{ho}\right)^{\alpha_h} \tag{21}$$

The value of α is usually unknown. Yet, by attaining the two parameters of Weibull distribution at station height, the surface roughness coefficient at station height $\left(\alpha_{h_o}\right)$ at any desired height (α_h) can be calculated utilizing the following equations [44]:

$$\alpha_{h_o} = 0.37 - 0.0881 ln\left(c_{ho}\right) \tag{22}$$

$$\alpha_h = \alpha_{h_o} / \left[1 - 0.0881x\ln\left(\frac{h}{10}\right)\right] \tag{23}$$

The performance of Wind turbines is subjected to different criteria that are essential to evaluate their efficiency. CF is a significant criterion since it refers to the overall performance of the wind turbine over the desired time interval. The energy output E_{out} over a period (T) can be expressed as follows [34]:

$$E_{out} = T\int_{v_c}^{v_r} P(v) f(v)\, dv + T = T\left[\int_{v_c}^{v_r} P_r\left(\frac{v^2 - v_c^2}{v_r^2 - v_c^2}\right) f(v) + \int_{v_r}^{v_f} P_r f(v)\, dv\right] \tag{24}$$

where $f(v)$ is the Weibull PDF, P_r is the rated power of the wind turbine, while v_c, v_r, and v_f are the cut-in speed, rated speed, and furling speed of the wind turbine, respectively. The capacity factor can be calculated after integrating Eq. (24) to get the following equation [45]:

$$CF = \frac{E_{out}}{E_{rated}} = \frac{\exp\left(-\left(\frac{v_c}{c_o}\right)^{k_o}\right) - \exp\left(-\left(\frac{v_r}{c_o}\right)^{k_o}\right)}{\left(\frac{v_r}{c_o}\right)^{k_o} - \left(\frac{v_c}{c_o}\right)^{k_o}} - \exp\left(-\left(\frac{v_f}{c_o}\right)^{k_o}\right) \tag{25}$$

where $E_{rated} = T * P_{rated}$, is the rated energy of the wind turbine, and for a lifetime of n years, the rated energy can be computed as follow:

$$E_{rated} = (n\ years)\,(365\ day)\,(24\ h)\,(P_{rated}) \tag{26}$$

After determining the capacity factor and the rated power of the wind turbine, the output power of the WTG over its lifetime can be then calculated from the following equation:

$$E_{out} = CF \times E_{rated} \tag{27}$$

6 Economic Analysis of Wind Turbines

The energy cost analysis is vital to justify the economic viability of wind turbines over their life span. The technical assessment (Maximum capacity factor) is insufficient to select the ideal wind turbine technologies and site. Hence, the minimum cost of energy ($/kWh) provides a reliable evaluation of the selection process.

Several factors influence the cost of the WTG, including initial investment cost, location, and operating conditions where the wind turbines are implemented [45]. Prices of wind turbines are set by manufacturers depending primarily on the rated power of the wind turbines; see Table 3 [45,46]. Usually, for wind turbines with a size greater than 200 kW, the price is between $1000 to $1600 per kW [45]. Present Value Cost (PVC) is selected in this study to speculate the cost of wind energy production in the five Saudi sites. The cost of kWh of energy is computed by dividing the PVC values by E_{out} of the wind turbine over its lifetime [18,34,45]. The process of accomplishing the cost of energy has been done by adhering to the following five assumptions:

- Wind turbines' lifetime (n) is assumed to be 20 years.
- The interest rate (r) and inflation rate (i) are set to be 8% and 6%, respectively.
- The operation, maintenance, and repair cost (C_{omr}) is 25% of the annual cost of the turbine (machine price/lifetime).
- Scrap or Salvage value (S) is set to be 10% of the turbine price and civil work.
- Investment (I) includes the turbine price plus 20% additional cost for the civil work and other connections.

Table 3: Describes the characteristic of wind turbines used in this study

	WT1	WT2	WT3	WT4	WT5	WT6
Hub height (m)	70	71	67	80	80	80
Rated power (MW)	1	1.65	2	2.5	2.5	3

(Continued)

Table 3: Continued

	WT1	WT2	WT3	WT4	WT5	WT6
Rotor diameter (m)	62	80	80	88	80	90
Cut-in speed (m/s)	3	3	4	3	3	3
Rated speed (m/s)	15	14	16	15	12.5	21
Cut-off speed (m/s)	25	30	25	25	25	25
Price (US $)	1,600,000	2,640,000	3,200,000	4,000,000	4,000,000	4,800,000

Therefore, under previous assumptions, PVC is calculated for each WTG at each site as follows:

$$PVC = I + C_{omr}\left[\frac{1+i}{r-i}\right]\left[1-\left(\frac{1+i}{1+r}\right)^{n}\right] - S\left[\frac{1+i}{1+r}\right]^{n} \tag{28}$$

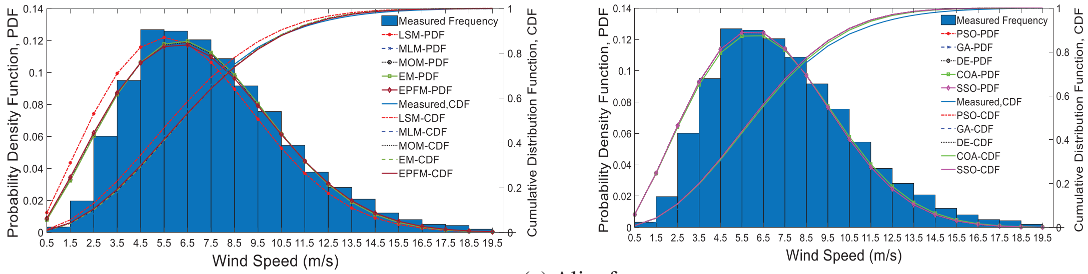
7 Results and Discussion

In this study, a comparative analysis is conducted between the performance of five CN and IOA methods in the accurate estimation of Weibull parameters and in assessing wind energy resources in five locations in Saudi Arabia. First, the histograms of the observed wind speed frequency distributions are initially constructed for the considered sites. Next, the c and k are estimated using CN methods and IOA. After that, the performance of the theoretical PDFs is examined according to the RMSE, R^2, and MAE. The results of the best estimation approach based on both CN methods and IOA are then compared in assessing the wind energy potential with six wind turbines in all the selected locations.

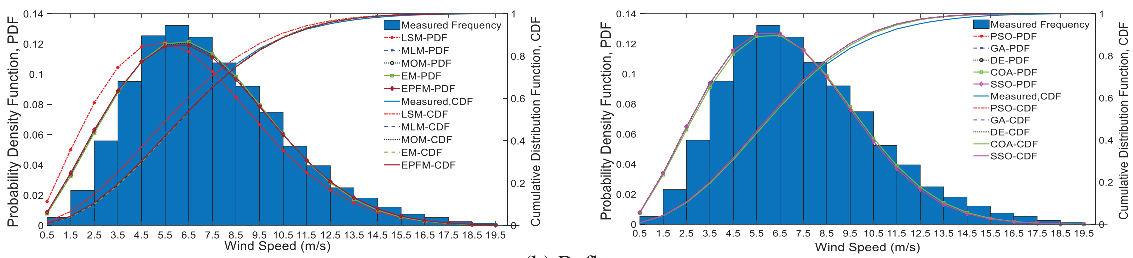
7.1 Analysis of Weibull PDF Estimation Methods

Fig. 5 shows the Weibull frequency distribution using CN methods and IOA with the original wind speed data histogram. Comparing the performance of CN methods and IOAs and according to Tables 4 and 5, which summarize the goodness of fit tests results of theoretical Weibull distributions, the IOAs outperformed CN methods in obtaining the optimal two-Weibull parameters and in describing the frequencies of actual wind data. In Table 4, the results of CN methods indicate that LSM is the least precise method among other approaches, while the best CN estimation methods for all five sites are ranked as EM, MOM, MLM, and EPFM, respectively.

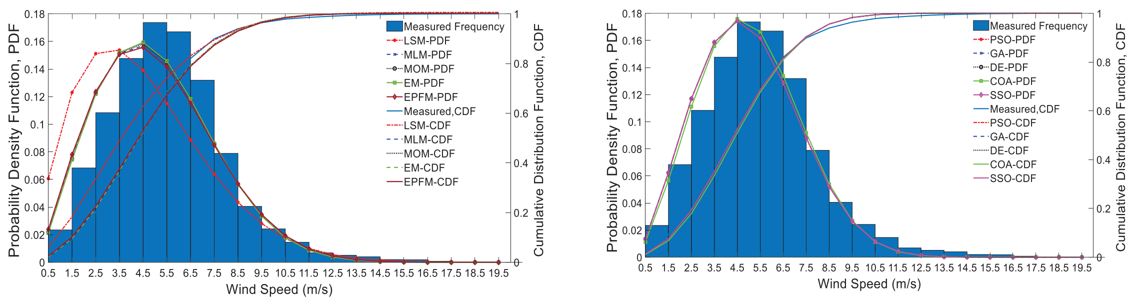
In Table 5 and Fig. 7, results revealed that COA is the less accurate and the slowest algorithm to obtain the Weibull parameters. Yet, it performs better in tuning c and k than all CN methods. PSO, GA, DE, and SSO algorithms have similar performance in estimating Weibull parameters, resulting in high fitting accuracy. In Aljouf, for example, the RMSE, R^2, and MAEare 0.00565, 0.98453, and 0.00429, respectively. Therefore, for CN methods, the scale and shape parameters of Weibull for all five areas, Aljouf, Rafha, Tabuk, Turaif, and Yanbo, are determined by EM to carry out the technical and economic assessments and to compare its results with those obtained by SSO. Table 6 lists the Weibull parameters and PLC attained from EM and SSO at all Saudi sites. Fig. 6 shows the coefficient of determination values of the Weibull distribution using different models. The R^2 values of Weibull using LSM, EM, PSO, and COA are 0.916643, 0.961082, 0.980825, and 0.980280. This indicates that the models generated by IOAs are more accurate than CN methods.



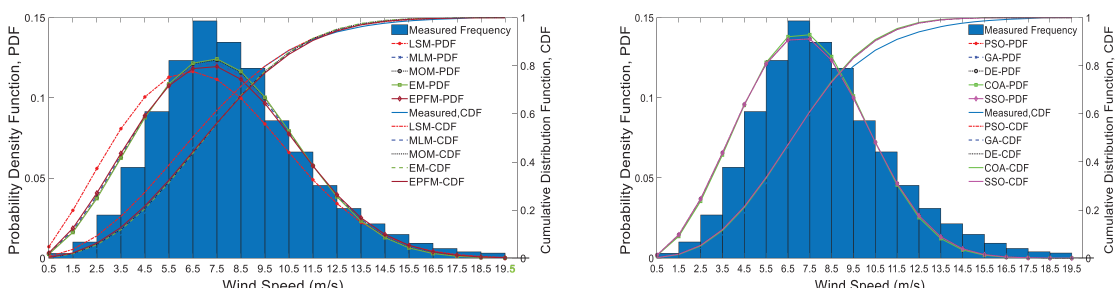
(a) Aljouf



(b) Rafha

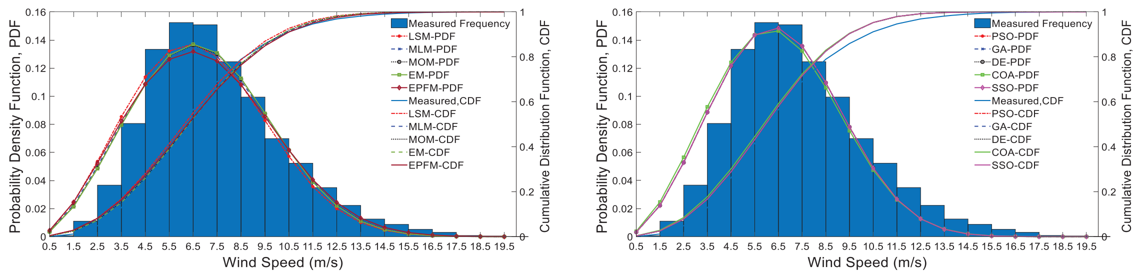


(c) Tabuk



(d) Turaif

Figure 5: (Continued)



(e) Yanbo

Figure 5: Histogram of observed wind speed and Weibull PDF using CN methods (left) and IOA (right)

Table 4: Weibull parameters and goodness of fit results using CN methods

			Aljouf			
	c (m/s)	k	RMSE (m/s)	R^2	MAE (m/s)	PLC
LSM	7.434099	2.16958	0.007496	0.972775	0.005125	0.193265
MLM	7.923815	2.291896	0.00702	0.976122	0.004919	0.187644
MOM	7.910796	2.293257	0.006927	0.976754	0.004874	0.187789
EM	7.910178	2.308859	0.006916	0.976825	0.004893	0.187796
EPFM	7.912037	2.255381	0.007049	0.975926	0.00483	0.187775
			Rafha			
	c (m/s)	k	RMSE (m/s)	R^2	MAE (m/s)	PLC
LSM	7.261949	2.081876	0.010132	0.951791	0.007187	0.195329
MLM	7.825857	2.300983	0.006573	0.979707	0.004938	0.18874
MOM	7.817703	2.308492	0.006488	0.980229	0.00491	0.188832
EM	7.817037	2.324068	0.006445	0.980493	0.004918	0.188839
EPFM	7.81901	2.272702	0.006679	0.979051	0.004912	0.188817
			Tabuk			
	c (m/s)	k	RMSE (m/s)	R^2	MAE (m/s)	PLC
LSM	5.087887	1.737512	0.02478	0.831763	0.01511	0.226673
MLM	5.704691	2.140518	0.009659	0.974438	0.006535	0.216592
MOM	5.712004	2.169808	0.009016	0.977727	0.00623	0.21648
EM	5.711959	2.185594	0.008679	0.979362	0.006058	0.21648
EPFM	5.711776	2.124218	0.01005	0.97233	0.006756	0.216483
			Turaif			
	c (m/s)	k	RMSE (m/s)	R^2	MAE (m/s)	PLC
LSM	8.169236	2.315956	0.014035	0.916643	0.009388	0.184957
MLM	8.610794	2.631643	0.010052	0.95724	0.007456	0.180319
MOM	8.608632	2.677839	0.009692	0.960248	0.007204	0.180341
EM	8.607054	2.692521	0.00959	0.961082	0.007119	0.180358
EPFM	8.618638	2.579415	0.010602	0.952439	0.007795	0.180239

(Continued)

Table 4: Continued

Yanbo						
	c (m/s)	k	RMSE (m/s)	R^2	MAE (m/s)	PLC
LSM	7.810702	2.616236	0.010941	0.957957	0.007568	0.188807
MLM	7.810499	2.628722	0.010934	0.957875	0.007538	0.188913
MOM	7.800983	2.666878	0.01072	0.959512	0.007503	0.189021
EM	7.799564	2.681593	0.010677	0.959831	0.007533	0.189037
EPFM	7.810413	2.5629	0.011317	0.954874	0.007714	0.188914

Table 5: Weibull parameters and goodness of fit results using IOAs

Aljouf						
	c (m/s)	k	RMSE (m/s)	R^2	MAE (m/s)	PLC
PSO	7.597983	2.326921	0.005651	0.984531	0.004293	0.191344
GA	7.597974	2.326931	0.005651	0.984531	0.004293	0.191344
DE	7.597983	2.326921	0.005651	0.984531	0.004293	0.191344
COA	7.689729	2.310271	0.005785	0.983786	0.004365	0.190286
SSO	7.597943	2.32665	0.005651	0.984531	0.004291	0.191344
Rafha						
	c (m/s)	k	RMSE (m/s)	R^2	MAE (m/s)	PLC
PSO	7.534124	2.360943	0.005226	0.987171	0.004246	0.192087
GA	7.534136	2.36092	0.005226	0.987171	0.004246	0.192087
DE	7.534124	2.360943	0.005226	0.987171	0.004246	0.192087
COA	7.635116	2.364884	0.005408	0.986263	0.004298	0.190914
SSO	7.534601	2.361162	0.005226	0.987171	0.004247	0.192082
Tabuk						
	c (m/s)	k	RMSE (m/s)	R^2	MAE (m/s)	PLC
PSO	5.649419	2.424155	0.005643	0.991276	0.00428	0.21745
GA	5.649408	2.424148	0.005643	0.991276	0.00428	0.21745
DE	5.649419	2.424155	0.005643	0.991276	0.00428	0.21745
COA	5.725484	2.498584	0.006228	0.989372	0.004356	0.216272
SSO	5.649196	2.423693	0.005643	0.991276	0.00428	0.217454
Turaif						
	c (m/s)	k	RMSE (m/s)	R^2	MAE (m/s)	PLC
PSO	8.182519	2.868632	0.006732	0.980825	0.005634	0.184814
GA	8.182517	2.868657	0.006732	0.980825	0.005634	0.184814
DE	8.182519	2.868632	0.006732	0.980825	0.005634	0.184814
COA	8.170147	2.923615	0.006827	0.98028	0.005737	0.184947
SSO	8.182494	2.868899	0.006732	0.980825	0.005634	0.184814

(Continued)

Table 5: Continued

Yanbo						
	c (m/s)	k	RMSE (m/s)	R^2	MAE (m/s)	PLC
PSO	7.369306	2.769853	0.007983	0.977544	0.006733	0.194036
GA	7.369318	2.769866	0.007983	0.977544	0.006733	0.194036
DE	7.369306	2.769853	0.007983	0.977544	0.006733	0.194036
COA	7.295453	2.704547	0.008257	0.975976	0.006834	0.194923
SSO	7.368835	2.770077	0.007983	0.977543	0.006733	0.194041

Table 6: Two-Weibull parameters at wind turbine heights using EM and SSO results

Site	Turbines	Weibull, EM			Weibull, SSO		
		c (m/s)	k	α_h	c (m/s)	k	α_h
Aljouf	WT1	13.32862	2.873364	0.226599	12.92938	2.895841	0.230879
	WT2	13.38212	2.877698	0.226941	12.98226	2.90021	0.231228
	WT3	13.16574	2.860061	0.22555	12.76842	2.882435	0.22981
	WT4	13.84758	2.91469	0.229858	13.4425	2.937491	0.2342
	WT5	13.84758	2.91469	0.229858	13.4425	2.937491	0.2342
	WT6	13.84758	2.91469	0.229858	13.4425	2.937491	0.2342
Rafha	WT1	11.68321	2.759279	0.227858	11.33847	2.803059	0.231777
	WT2	11.7282	2.763442	0.228202	11.38288	2.807287	0.232126
	WT3	11.54622	2.746505	0.226803	11.20324	2.790082	0.230704
	WT4	12.11927	2.798965	0.231135	11.76907	2.843374	0.23511
	WT5	12.11927	2.798965	0.231135	11.76907	2.843374	0.23511
	WT6	12.11927	2.798965	0.231135	11.76907	2.843374	0.23511
Tabuk	WT1	9.760799	2.661637	0.26121	9.677132	2.952159	0.26238
	WT2	9.805008	2.665652	0.261604	9.721159	2.956612	0.262776
	WT3	9.626358	2.649315	0.260001	9.543251	2.938492	0.261166
	WT4	10.19056	2.699919	0.264967	10.10516	2.994619	0.266154
	WT5	10.19056	2.699919	0.264967	10.10516	2.994619	0.266154
	WT6	10.19056	2.699919	0.264967	10.10516	2.994619	0.266154
Turaif	WT1	13.79931	3.312652	0.217623	13.27258	3.529324	0.223
	WT2	13.8519	3.317649	0.217952	13.32441	3.534648	0.223337
	WT3	13.63916	3.297316	0.216616	13.11475	3.512985	0.221968
	WT4	14.30895	3.360297	0.220753	13.7751	3.580085	0.226208
	WT5	14.30895	3.360297	0.220753	13.7751	3.580085	0.226208
	WT6	14.30895	3.360297	0.220753	13.7751	3.580085	0.226208
Yanbo	WT1	12.1572	3.235669	0.228096	11.62218	3.342165	0.234128
	WT2	12.20483	3.24055	0.22844	11.66892	3.347207	0.234481
	WT3	12.01219	3.22069	0.22704	11.47991	3.326693	0.233044

(Continued)

Table 6: Continued

Site	Turbines	Weibull, EM			Weibull, SSO		
		c (m/s)	k	α_h	c (m/s)	k	α_h
	WT4	12.61897	3.282207	0.231376	12.07553	3.390235	0.237495
	WT5	12.61897	3.282207	0.231376	12.07553	3.390235	0.237495
	WT6	12.61897	3.282207	0.231376	12.07553	3.390235	0.237495

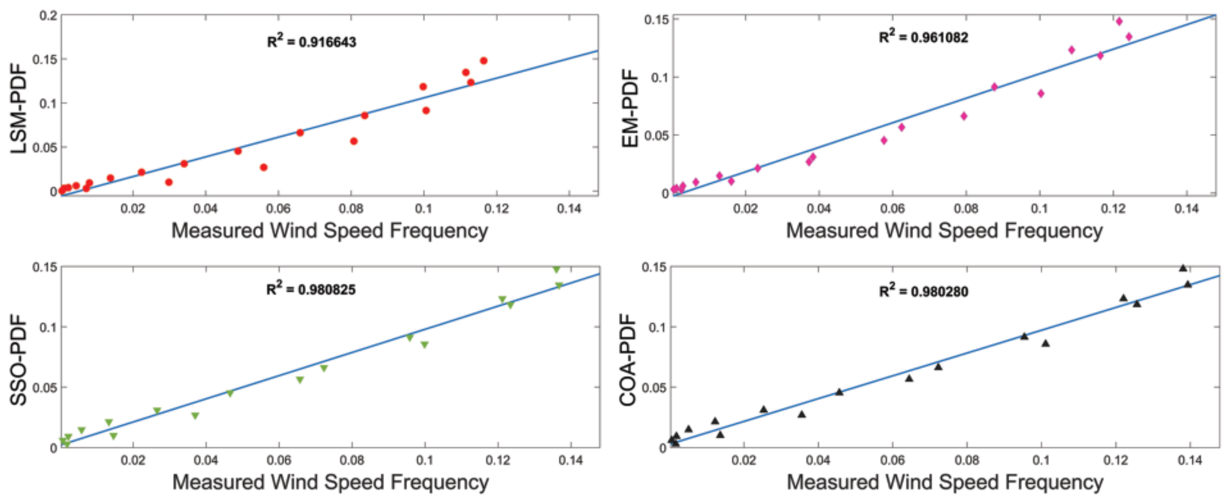


Figure 6: The coefficient of determination values of the Weibull distribution using different models

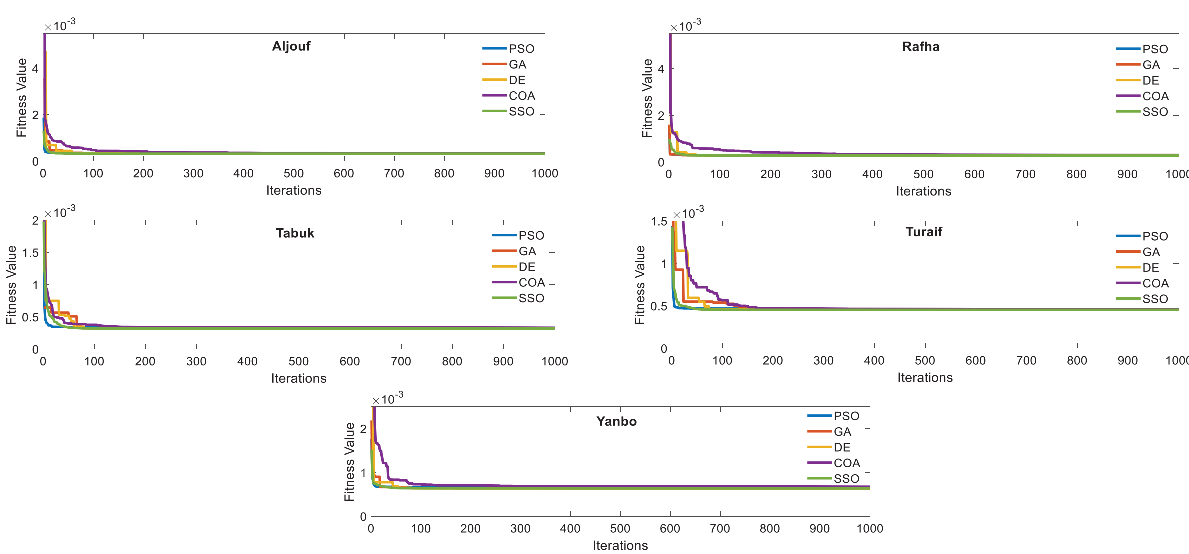


Figure 7: The convergence rate of PSO, GA, DE, COA, and SSO in optimizing Weibull parameters

7.2 *Analysis of Wind Turbine Energy Output*

Table 7 exhibits the energy output in MWh and the CF. This Table shows that the range of CF is between 10.86%–58.21% and 8.77%–56.52% using EM methods and SSO, respectively. For all Saudi sites, the CF of all six wind turbines examined in this study has higher values in the case of using Weibull parameters obtained from EM compared to those attained by SSO. That means that the annual energy output of wind turbines is overestimated with CN approaches than the intelligent optimization methods. For instance, WT4 output energy in Yanbo is 10228.71 MWh when employing values calculated from EM, while it is found to be 9140.67 MWh with SSO.

Table 7: Annual energy output and capacity factor using results obtained from EM

Site	Wind turbine	PVC	E_{out}, EM (MWh/year)	CF_{EM}	COE_{EM} ($/kWh)	E_{out}, SSO (MWh/year)	CF_{SSO}	COE_{SSO} ($/kWh)
Aljouf	WT1	$2,118,517	4647.211	0.419226	0.022793	4422.417	0.398947	0.023952
	WT2	$3,495,554	8559.119	0.467952	0.02042	8196.975	0.448152	0.021322
	WT3	$4,237,035	8075.495	0.364246	0.026234	7604.219	0.342989	0.02786
	WT4	$5,296,293	12271.16	0.442794	0.02158	11744.18	0.423778	0.022549
	WT5	$5,296,293	15279.55	0.551349	0.017331	14875.74	0.536777	0.017802
	WT6	$6,355,552	7376.146	0.221801	0.043082	6796.581	0.204374	0.046756
Rafha	WT1	$2,118,517	3736.145	0.337039	0.028352	3493.367	0.315137	0.030322
	WT2	$3,495,554	7024.072	0.384026	0.024883	6630.756	0.362522	0.026359
	WT3	$4,237,035	6291.406	0.283775	0.033673	5811.449	0.262126	0.036454
	WT4	$5,296,293	9955.433	0.359233	0.0266	9359.163	0.337717	0.028295
	WT5	$5,296,293	13166.47	0.475231	0.020113	12660.65	0.456848	0.020916
	WT6	$6,355,552	5486.219	0.164971	0.057923	4948.234	0.148794	0.06422
Tabuk	WT1	$2,118,517	2587.803	0.233446	0.040933	2284.627	0.206096	0.046365
	WT2	$3,495,554	5020.844	0.274504	0.03481	4554.522	0.249009	0.038375
	WT3	$4,237,035	4143.085	0.186874	0.051134	3571.669	0.1611	0.059314
	WT4	$5,296,293	7073.655	0.255246	0.037437	6330.055	0.228414	0.041834
	WT5	$5,296,293	10151.58	0.366311	0.026086	9668.244	0.348869	0.02739
	WT6	$6,355,552	3611.139	0.108587	0.087999	2871.378	0.087658	0.110671
Turaif	WT1	$2,118,517	4841.126	0.436719	0.02188	4453.381	0.40174	0.023785
	WT2	$3,495,554	8968.14	0.490314	0.019489	8421.666	0.460436	0.020753
	WT3	$4,237,035	8340.997	0.376221	0.025399	7469.087	0.336894	0.028364
	WT4	$5,296,293	12826.96	0.462849	0.020645	11950.02	0.431205	0.02216
	WT5	$5,296,293	16132.66	0.582132	0.016415	15664	0.565221	0.016906
	WT6	$6,355,552	6981.881	0.209946	0.045515	5720.058	0.172002	0.055555
Yanbo	WT1	$2,118,517	3794.481	0.342301	0.027916	3351.753	0.302362	0.031603
	WT2	$3,495,554	7270.107	0.397477	0.024041	6563.434	0.358841	0.026629
	WT3	$4,237,035	6270.969	0.282853	0.033783	5404.262	0.243759	0.039201
	WT4	$5,296,293	10228.71	0.369094	0.025889	9140.671	0.329832	0.028971
	WT5	$5,296,293	13947.93	0.503298	0.018986	13081.5	0.472034	0.020243
	WT6	$6,355,552	4876.671	0.146642	0.065163	3989.97	0.119978	0.079644

7.3 *Analysis of the Cost of Energy*

In addition, Table 7 illustrates that the values of the cost of energy (COE) of all wind turbines at the five Saudi locations have low $/MWh with the best model obtained by EM compared with the best model in IOA. Since SSO results provide high fitting accuracy to the original wind speed data, the COE prices are better estimated utilizing the evaluation conducted by SSO. Therefore, in terms of the annual energy output of the four wind turbines, the range is between 4422.42 to 14875.74 MW in Aljouf, 3493.37 to 12660.65 MW in Rafha, 2284.23 to 9668.24 MW in Tabuk, 4453.38 MW to 15664 in Turaif, and 3351.75 to 13081.5 MW in Yanbo. The highest annual energy output at all Saudi sites was 15664 MW in Turaif with the WT5 machine model, while the lowest was 2284.23 MW in Tabuk using WT1. WT5 generates the maximum energy for all Saudi sites compared to all other wind turbine technologies, making this WTG the optimal one to be installed.

In addition, Table 7 presents the COE at each site using the six wind turbine models. This Table shows that the lowest cost of electricity was found to be $0.016906/kW in Turaif with WT5, and the highest price was obtained to be $0.11067/kW in Tabuk with the WT6 model. Furthermore, for the WT5, the COE was found not to exceed $0.02739/kW for all five considered sites.

8 Conclusion and Future Works

The main goal of this study was to conduct a comparative analysis between conventional numerical (CN) methods and intelligent optimization algorithms (IOA) in evaluating the potential of wind energy in five Saudi cities located in the northern part, namely Aljouf, Rafha, Tabuk, Turaif, and Yanbo. The measured wind speed data at these sites are fitted using Weibull PDF to predict power density at these locations at different wind turbine hub heights. The two Weibull parameters, the shape (k) and scale (c), are estimated using five CN methods and five IOA. Moreover, the efficiency of these approaches is evaluated by the goodness of fit tests using the Root Mean Square Error (RMSE), Coefficient of Determination (R^2), and Mean Absolute Error (MAE). By analyzing the techno-economic assessments, the main findings of this study are summarized as follows:

1. Results showed that IOAs are better at calculating the optimal combination of Weibull parameters and providing an adequate description of the frequencies of observed wind data. Method of Moment appeared to be the best CN method in determining k and c. PSO, GA, DE, and SSO have almost similar performance to approximate wind speed distribution for all considered Saudi sites.
2. Comparing the CN methods and IOA in carrying out the technical and economic assessments, results indicated that CN methods overestimated the energy output and hence underestimated the cost of energy ($/kWh) of the six wind turbine technologies investigated in this study. Therefore, since IOAs provide better fitting accuracy, the results based on SSO are considered to assess wind resources in Saudi Arabia.
3. Based on the electrical output of the WTG using IOA, the capacity factor range was computed to be between 8.77% and 56.52% in all locations.
4. Furthermore, Turaif was found to be the optimal location for harvesting wind energy, followed by Aljouf and Yanbo, respectively.
5. Based on the cost of energy analysis, the WT5 model exhibited the most suitable wind turbine technology to be implemented at all considered sites with an electricity cost of less than $0.02739/kW.

The economic risk associated with the generation of wind-based electricity is thoroughly examined in this study. The proposed framework in this study can be applied to any techno-economic analysis of green wind generation in developing nations. Moreover, it might support improved planning for wind energy projects by planners and policymakers. Weibull distribution is used in this study to characterize wind speed at five Saudi locations. Nevertheless, additional analyses that consider other probability distribution functions and various numerical and contemporary optimization techniques could be investigated. Finally, this study is carried out based on daily averaged wind speed due to data availability. However, a more detailed examination would be possible with a shorter temporal resolution, such as hourly wind speed data.

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Conflicts of Interest: The author declares that he has no conflicts of interest to report regarding the present study.

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