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Particle Swarm Optimization method for estimation of Weibull parameters: A case study for the Brazilian northeast region

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ABSTRACT

In this paper the application of the Particle Swarm Optimization (PSO) method to estimate the Weibull parameters for wind resources in the Brazilian Northeast Region (BRNER) is reported. For the present research, wind speed data from three 80 m towers installed at different sites in the region were collected. The measuring periods for each tower site are: February 2012 to January 2013 for Maracanaú, August 2012 to July 2013 for Parnaíba, and May 2012 to March 2013 for Petrolina. Aiming to compare with the PSO performance, five numerical methods are applied to calculate the Weibull distribution parameters. Best performance for all analyzed sites is achieved by the PSO method, with a correlation higher than 99% and an error close to zero. PSO proves to be a valuable technique for characterization of the particular wind conditions found in the BRNER.

1. Introduction

For decades, Brazil has been giving priority to large hydro-power plants as a base of the country's electricity generation matrix. The Brazilian power station structure at the end of the year 2014 shows that the greatest fraction belongs to large and medium hydro-power plants (ca. 67% of the total electrical power) [1], giving to the country leadership positions as regards to the use of renewable energy sources to generate electrical energy. Despite the significant participation, the proportional share of such hydro-power plants in the Brazilian electricity generating structure is slowly decreasing in recent years. In practice, there is no more significant potential for new large hydro-power plants. Although a large theoretical potential exists in the northern region (Amazon basin), its use is very debatable for ecological reasons.

In recent years, the Brazilian government has been developing policies to diversify the country's electricity generation matrix. One of the strategies was the so-called “Incentive Programme for Alternative Energy Sources” (PROINFA), a governmental programme to promote the use of wind power, biomass fuels and small hydro-electric power plants. Success was obtained mainly in the wind sector. In 2014, the figures for the wind sector achieved a nominal power output of 3838 MW, a share of 2.88% of total power generation capacity, according to the Brazilian Agency for Electric Energy (ANEEL).

As observed in Refs. [2,3], the main characteristics associated with BRNER wind resources are a well defined seasonal pattern for wind speed, with typically low speed values during the first half of the year and higher speeds along the second half. BRNER is located in the continuous trade winds paths, triggered by the sub-equatorial atmospheric circulation and intensified by sea breezes along the shoreline. Trade winds are caused by the mid-latitude surface air masses moving (converging) towards heated low pressure equatorial latitudes. This movement is deflected westward, opposite to Earth rotation, due to the principle of conservation of angular momentum (Coriolis effect). Additional deflections may occur near the coast line due to thermal sea-land and inland gradients and to orographic influences. In the case of BRNER trade winds come free from obstacles from a very large oceanic surface, thus having remarkable intensity, constancy and low turbulence.

Trade winds from both terrestrial hemispheres converge to an equatorial region known as Intertropical Convergence Zone (ITCZ). In their travel to the lower equatorial pressures, trade winds air masses become warm and humid, resulting in, deep convective clouds, showers and thunderstorms along the ITCZ. ITCZ latitude migrates seasonally, reaching the BRNER from March to May and bringing its main and usually only rainy season. ITCZ returns to and remains at equatorial latitudes for the remaining 9 months of the

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year resulting in prevailing dry climate for large areas of the region, which is associated. With remarkably strong and constant wind speeds. The cyclic alternating wet-dry periods caused by the ITCZ annual migration induce a remarkable seasonality in wind speeds, reaching maximum fluctuations of ca. ±30 around the annual average [4].

To evaluate the wind energy potential in a region, a modeling of the wind stochastic behavior is required, making possible to identify seasonality patterns and to predict the wind resource behavior [5]. There are several probabilistic frequency distributions used to represent wind speed data, such as Weibull, Gamma, Normal and Log-Normal; the well-known Weibull distribution is the standard function used by the wind energy community to model wind speed frequency distribution all over the world. However, studies have shown that some methods to determine the Weibull parameters lead to an unsatisfactory adjustment capability to the used wind distribution histograms [3]. In this way, alternative methods to calculate the Weibull parameters should be investigated [6].

The use of computational intelligence techniques can optimize determination of the Weibull parameters and hence reduce estimation errors of wind turbines electricity production. Therefore, the present work describes the use of the PSO technique to estimate the Weibull parameters adjusted for the wind conditions found in the BRNER. The methodology presented is innovative for the particular wind conditions considered, characterized by a well-defined seasonal pattern. The need for further research for that specific wind regime is demonstrated in Refs. [3,6].

2. Brazilian northeast region (BRNER) wind potential

2.1. Analysis of the wind speed data

The BRNER has an area of 1.5 million km^2 (18% of Brazilian territory), the size of France, Italy, United Kingdom and Germany put together, and an estimated population of 53 million inhabitants or 28% of the Brazilian population [7]. For the present project, wind speed data were collected in 80 m measurement towers installed in three sites of three states in the BRNER: Parnaíba (state of Piauí), Maracanaú (state of Ceará) and Petrolina (state of Pernambuco) (Fig. 1). The measurement periods for the three sites are: February 2012–January 2013 for Maracanaú, August 2012–July 2013 for Parnaíba, May 2012–March 2013 for Petrolina.

For each tower, the following sensors were installed: three anemometers (Maximum #40) at 78, 50 e 20 m height; a wind direction sensor (#200P) at 78 m; an ambient temperature sensor (#110S) and a pyranometer (LI-200SZ) at 14 m. Additionally, a data logger (NRG Symphonie PLUS) collects the data every 2 s and gives 10 min average values for the analysis. The collected data are used for the development of a statistical analysis to characterize the wind potential of the mentioned sites in the BRNER.

Statistical analysis allows understanding of the future behavior of the stochastic process associated with the wind speed, aiming to estimate the electricity generation and the capacity factor of wind turbines, wind potential assessment of regions of interest and the impacts associated with operation of electrical systems. In this way, this statistical analysis of wind speed series is performed to detect seasonality patterns and behaviors that may assist in the description of the stochastic process.

Fig. 2 shows characteristic days for the mentioned period in Maracanaú, with each day representing the average of the days of the specific month (wind speed values measured at 78 m). The analysis of the generated surface allows to identify wind speed daily and monthly patterns and consequently, thinking in terms of WECs connected to the grid in the Brazilian case, to evaluate the wind potential as a complementary source to hydroelectric plants. The wind resource seasonal characteristic, complementary to the

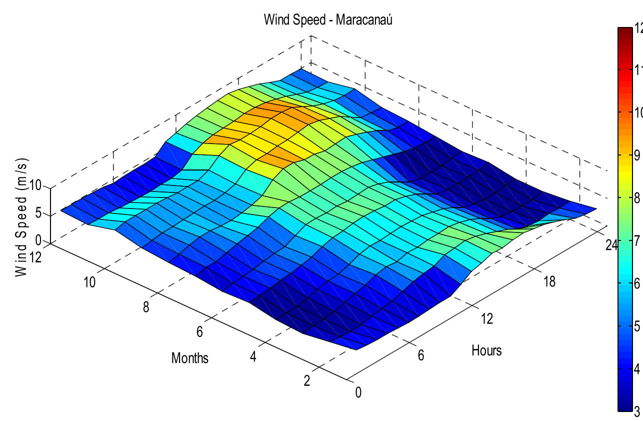

Fig. 2. Characteristic days for Maracanaú.

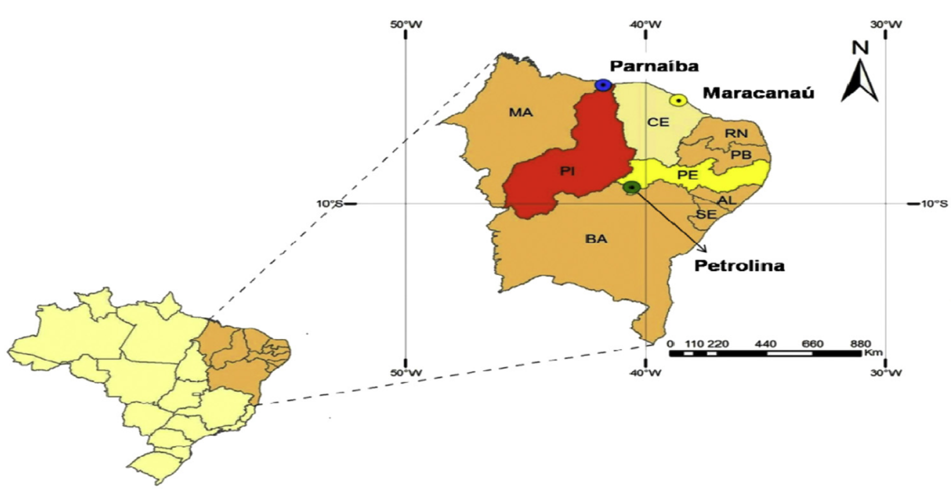

Fig. 1. Measurement towers sites.

seasonal hydro regime, is easily identified: lowest wind speed values are found during the rainy period (January–April), while the highest wind speed values (between 5 m/s and 7 m/s) occur in the dry period (July–October). Considering the daily curves, the highest values are found between 10 am and 5 pm in all the observed months.

Fig. 3 shows characteristic days for the mentioned period in Parnaíba, with wind speed values measured at 78 m. As was the case in Maracanaú, the wind resource complementary characteristic to the seasonal hydro regime is easily identified: Parnaíba shows the highest wind speed values between September and December (most of the values higher than 8.5 m/s); even in other periods, as between April and August, a good wind potential is available (values higher than 6 m/s). Considering the daily patterns, the highest values are found between 1 pm and 1 am in all the observed months.

Fig. 4 shows characteristic days for the observed months in Petrolina, with wind speed values measured at 78 m. As it can be observed, the wind resource complementary characteristic to the seasonal hydro regime is not so easily identified as was the case in Maracanaú and Parnaíba. One of the reasons of this behavior can be found in the localization of Petrolina in a central area of the BRNER, ca. 650 km far from the coastline. Considering the monthly behavior, Petrolina shows the highest wind speed values between July and November. Considering the daily patterns, the site is characterized for a low variation throughout the day in all observed months. In most of the second semester, a small decrease of the values is observed in the morning period; in the rest of the day values higher than 7 m/s are found, with low variability.

Table 1 summarizes the main statistical parameters obtained from the wind speed values of Maracanaú, Parnaíba and Petrolina. For each location three different analysis periods are considered: from January to June (first semester or 1st S), from July to December (second semester or 2nd S) and the whole year (annual), aiming to identify the influence of seasonal factors (such as rain distribution) over wind speed behavior.

The seasonality is verified in the three sites: higher wind speed values in the second semester (months with almost zero precipitation) and lower wind speeds in the first semester (rainy months). Maracanaú shows a second semester average wind speed 31% higher than the first semester average, while for Parnaíba, the second semester average is 30% higher than that for the first semester. Petrolina follows clearly another pattern: the difference between semesters is only 8.8%, confirming a low variability behavior. To remember, Petrolina is ca. 650 km far from the coastline, while Maracanaú and Parnaíba are located near to the ocean. Therefore, differences between wind speed variations measured near and far from the coast can be explained by the influence of the sea on the coastal wind regime.

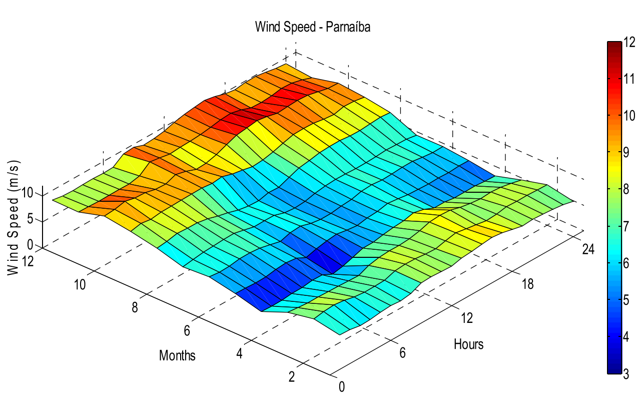

Fig. 3. Characteristic days for Parnaíba.

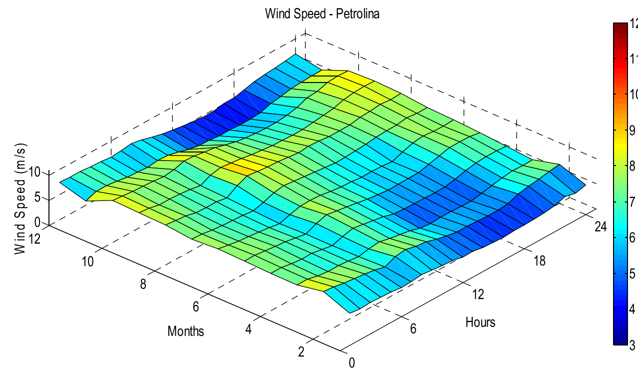

Fig. 4. Characteristic days for Petrolina.

Taking into account the standard deviation, while Maracanaú and Parnaíba show lower values in the second semester, Petrolina has no variation between the semesters and shows the lowest annual value of the three sites.

2.2. Particle Swarm Optimization method

The solution of different optimization problems involving Artificial Intelligence (AI) techniques are widely used in different applications [8]. Optimization heuristic techniques include probabilistic models developed from the observation of natural phenomena aiming to find the optimal solution of a function. These optimization methods do not ensure that the solution is the best one, but that the solution can quickly converge to the best existing one [9].

Particle Swarm Optimization (PSO) is an evolutionary optimization technique developed by Dr. Eberhart and Dr. Kennedy in 1995, inspired by the social behavior of a set of birds in flight with its random movement locally, but globally determined [10]. In the algorithm, the particles are initially launched into the search space, each having the following characteristics:

- A position and a velocity;
- Knowledge of their position and the value of the objective function for this position;
- Knowledge of the neighborhood: the best position found and the value of its objective function;
- Storage of the best position found.

In each period of time the particle behavior is determined from three available choices:

a) go its own way;
b) heading out to its best position found;
c) follow to the best position found by some of its neighbors.

The stop condition is determined by two conditions: a pre-set number of iterations or when no further improvement is possible (stagnation). Three terms determine the next particle movement:

- the inertia term $(w^* v(t))$, which forces the particle to move in the same direction,
- the cognitive term $(c1^* r1^* (p(t) - x(t))$, which forces the particle to return to a previous position that is better than the present and
- the social learning term $(c2^* r2^*(g(t) - x(t))$, which forces the particle to follow the direction of his best neighbors.

Table 1
Statistical parameters of the wind speed data.

Wind speed (m/s)	Maracanaú			Parnaíba			Petrolina		
	1st S	2nd S	Annual	1st S	2nd S	Annual	1st S	2nd S	Annual
Minimum	0.40	0.40	0.40	0.40	0.40	0.40	0.40	0.40	0.40
Maximum	14.60	14.80	14.80	16.80	15.90	16.80	13.40	14.30	14.30
Average	4.87	6.39	5.63	6.57	8.54	7.55	6.40	6.96	6.71
Median	4.80	6.40	5.60	6.60	8.70	7.60	6.60	7.10	6.90
Standard deviation	2.17	2.08	2.26	2.19	2.09	2.36	1.79	1.79	1.81
Variance	4.73	4.31	5.10	4.78	4.37	5.55	3.22	3.20	3.19
Number of measurements	52,686			52,302			47,424		

After finding the two best values, the particle updates its velocity and position according to:

$$v(t+1) = (w^*\, v(t)) + (c1^*r1^*\,(p(t)-x(t)) + (c2^*\,r2^*(g(t)-x(t)) \quad (1)$$

$$x(t+1) = x(t) + v(t+1) \quad (2)$$

$v(t)$ is the particle velocity, $x(t)$ is the particle position, $c1$ e $c2$ are social and cognitive parameters, $r1$ e $r2$ are random numbers between 0 and 1, $p(t)$ is the best position reached by each particle, $g(t)$ is the best solution of all available in the entire population of particles and w is the inertia weight.

Eq. (1) is used to calculate the new speed of the particle according to its previous speed and the distance between its current position, its best position and the best of the group. Its new position is then given according to Eq. (2).

Based on the observed wind speed data, the Weibull distribution can be described as

$$f_{Weibull}(v) = \frac{k}{c}\cdot\left(\frac{v}{c}\right)^{k-1}\cdot e^{-\left(\frac{v}{c}\right)^{k}} \quad (3)$$

k and ***c*** are the shape and scale parameters of the Weibull distribution and ***v*** is the wind speed. To improve the fit capability of the Weibull distribution, the difference between the Weibull function and the wind speed histograms should be minimized. Thus, the objective function to be minimized is given by:

$$\varepsilon(v_i) = \frac{1}{2}\sum_{i=0}^{n}\left(f_{real}(v_i) - f_{Weibull}(v_i)\right)^2 \quad (4)$$

$f_{real}(v_i)$ is the frequency of each wind speed class, $f_{Weibull}(v_i)$ is the Weibull probability density function (Eq. (3)) and n is the total number of wind speed classes.

In the present research, PSO was implemented with a random population of 50 particles, being assigned zero speed for each particle. Seeking to avoid premature convergence in the initial search and enhance convergence to the global optimum solution in the final phase, the inertia weight and acceleration coefficients (cognitive and social parameters) vary nonlinearly during the search, as proposed by Ref. [11], following Eqs. (5)–(7). For the inertia weight (w) were set the maximum and minimum values of 0.9 and 0.4, respectively. For the cognitive and social parameters (c_1 and c_2) were set the maximum and minimum values of 2.5 and 0, respectively. The power coefficients α, β, γ have been assigned with the values 0.5, 1.5 and 1.0, respectively. $iter_{max}$ represents the maximum number of iterations.

$$w(j) = \left(1 - \frac{j}{iter_{max}}\right)^{\alpha}(w_{max} - w_{min}) + w_{min} \quad (5)$$

$$c_1(j) = \left(1 - \frac{j}{iter_{max}}\right)^{\beta}(c_{1max} - c_{1min}) + c_{1min} \quad (6)$$

$$c_2(j) = \left(1 - \frac{j}{iter_{max}}\right)^{\gamma}(c_{2min} - c_{2max}) + c_{2max} \quad (7)$$

Due to the good performance obtained with Intelligent Optimization Algorithms in solving nonlinear optimization problems, some papers have reported in the last years the use of PSO applied to the wind sector.

PSO is applied in Ref. [12] to effectively solve a wind turbine control problem for fixed and variable speed wind turbines, determining the maximum power coefficient that maximizes electricity yield. Three methods are used in Ref. [13] for wind speed prediction at three different sites in Saudi Arabia. PSO is one of the methods used to train neural networks to predict hourly mean wind speeds, presenting a better performance when compared to the others methods.

An application of PSO and Artificial Bee Colony (ABC) algorithms to optimize the design parameters of variable-speed wind turbines for electricity production at minimum cost is found in Ref. [14]. It was found that PSO outperformed the ABC algorithm for this optimization problem. The wind potential in Taiwan is analyzed in Ref. [11], combining PSO and a numerical method (maximum likelihood - ML) to calculate the Weibull parameters. The results show that the combination PSO-ML has a good performance for wind energy applications and a rapid convergence in estimating Weibull parameters.

A modified PSO algorithm to optimize wind farm turbines position for electricity production is found in Ref. [15]. Simulation results demonstrate the efficiency of the proposed algorithm for the micro-siting problem, considering a greater electricity production, and the reduction of the algorithm computational time.

A study about power flow in wind energy systems applying a hybrid Fuzzy – PSO method is found in Ref. [16]. The results reveal that the method has good performance and is very effective in reaching an optimal setting for real power generation levels, voltage magnitudes and LTC (Load Tap Changer) tap positions, when uncertainties in load demand and wind speed are considered.

An improved PSO algorithm is proposed in Ref. [17] to control the maximum power point tracking of a wind power generation system. According to the proposed algorithm, the particle location depends only on its speed and dynamic change in the best position neighborhood. The results obtained indicate that the proposed PSO reduces the algorithm dependence on parameters and improves global search capability, demonstrating more effectiveness compared to the traditional PSO.

A combination of PSO and Ant Colony Optimization (ACO) to predict the electricity production of a wind farm in Binaloud, Iran, is presented in Ref. [18]. The wind farm output power for 364 days are used for training and testing of the proposed model. The proposed hybridization profits from the advantages of both algorithms, leading to a high quality prediction with a fast convergence capability.

Table 2 summarizes the different mentioned PSO applications.

2.3. Investigation of numerical methods for estimation of Weibull parameters

The wind energy potential in a period may be evaluated by a probability density function, such as the Weibull distribution. As mentioned before, this distribution is characterized by two variables: k, the dimensionless shape parameter and c, the scale parameter, having the same unit with the wind speed [19]. The distribution is named Rayleigh distribution if k is equal to 2. Several numerical methods for the calculation of the Weibull parameters from an observed wind speed set are found in the literature; in this way, investigations into the accuracy of the numerical methods for a specific site should be considered.

Six kinds of numerical methods for estimating Weibull parameters are reviewed in Ref. [20]: moment (M), empirical (E), graphical (G), maximum likelihood (ML), modified maximum likelihood (MML) and energy pattern factor (EPF) method. From analysis of actual wind speed data observed at three stations experiencing different weather conditions, it is found that if wind speed distribution matches well with Weibull function, the six methods are applicable; but if not, the ML method performs best followed by the MML and M methods; the G method gets the worst performance.

A new method for the estimation of Weibull parameters, called equivalent energy (EE) method, is considered in Ref. [6]: the method is based on the energy content of the distribution and aims to improve the accuracy of the parameters estimation mainly for wind data sets with relatively high shape factor values. According to the authors, the Weibull distributions of the Brazilian sites exhibit relatively high shape factor values and reduced wind direction variations; it was found that errors between 2% and 7% in the energy content could happen on half of the tested sites. In this way, the research goal was to develop a method that should present a mean error of 1% in the energy content of the wind.

An analysis and comparison of the seven mentioned numerical methods for the assessment of effectiveness in determining the Weibull parameters, using wind speed data collected in two sites in the coastline of Ceará, Brazil, is found in Ref. [21]. As a result, the EE method is considered fully adequate to estimate the k and c parameters for the wind speed data from the coastal area of Ceará; the G and the EPF methods are the least effective methods.

Five numerical methods for the calculation of Weibull parameters are used in Ref. [22]: Mean Wind Speed (MWS), G, ML, MML and Power Density (PD). These methods aim to fit the wind speed distributions found in Zafarana, a wind farm in Suez Gulf, Egypt. The best performances are found for MWS and ML methods.

Aiming to compare with PSO, five numerical methods are used in this study for estimation of Weibull parameters: Moment Method (M), Empirical Method (E), Energy Pattern Factor Method (EPF), Energy Equivalent Method (EE) and Maximum Likelihood (ML).

The M method determines the k and c parameters with the use of Eqs. (8) and (9) [20].

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

$$\sigma = c\left[\Gamma\left(1+\frac{2}{k}\right) - \Gamma^2\left(1+\frac{2}{k}\right)\right]^{1/2} \tag{9}$$

$\bar{v}$ and σ are the mean wind speed and the standard deviation of the observed data, respectively; Γ represents the gamma function.

The E method is considered a special case of the M method, determined using Eqs. (10) and (11) [15].

$$k = \left(\frac{\sigma}{\bar{v}}\right)^{-1,086} \tag{10}$$

$$\bar{v} = c\Gamma\left(1+\frac{1}{k}\right) \tag{11}$$

The EPF Method is related to the mean wind speed and is defined by Eqs. (12)–(14) [23].

$$E_{pf} = \frac{v^3}{(\bar{v})^3} \tag{12}$$

$$k = 1 + \frac{3,69}{\left(E_{pf}\right)^2} \tag{13}$$

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

E_{pf} is the Energy Pattern Factor.

The EE method was developed by Ref. [3], aiming to identify a methodology for estimation of Weibull parameters with an adequate adjustment to the wind resource found in the BRNER (wind data with relatively high shape factor values). The name comes from the fact that it is based on the equivalence between the energy density of the Weibull curve and the energy density of the observed data. The Weibull parameters are determined with the use of Eqs. (15) and (16).

Table 2
Main PSO applications in the wind sector.

Authors	Application	Strategy
Kongnam and Nuchprayoon [12]	Wind turbine control	PSO
Mohandes and Rehman [13]	Wind speed prediction	PSO
Eminoglu and Ayasun [14]	Wind turbine design optimization	PSO and ABC
Chang [11]	Wind energy potential assessment in Taiwan	PSO-ML
Wan et al. [15]	Optimization of the turbines positions	PSO
Liang et al. [16]	Power flow in wind energy systems	Hybrid Fuzzy – PSO
Tianpei and Wei [17]	Maximum power point tracking	PSO
Rahmani et al. [18]	Wind farm power prediction	PSO – Ant Colony Optimization (ACO)

$$\sum_{i=1}^{n}\left[W_{v_i} - e^{-\left\{\frac{(v_i-1)\left[\Gamma\left(1+\frac{3}{k}\right)\right]^{1/3}}{\overline{v^3}^{1/3}}\right\}^k} + e^{-\left\{\frac{(v_i)\left[\Gamma\left(1+\frac{3}{k}\right)\right]^{1/3}}{\overline{v^3}^{1/3}}\right\}^k}\right]^2 = \sum_{i=1}^{n}\varepsilon_{v_i^2} \tag{15}$$

$$c = \frac{(\overline{v})^3}{\Gamma\left(1+\frac{3}{k}\right)} \tag{16}$$

W_{v_i} is the frequency of occurrence of each interval, $\overline{v^3}$ the mean of the cubic wind speed and ε_{v_i} the approximation error.

The ML method requires extensive numerical iterations for solution of Eq (17) e (18):

$$k = \left[\frac{\sum_{i=1}^{n} v_i^k \ln(v_i)}{\sum_{i=1}^{n} v_i^k} - \frac{\sum_{i=1}^{n}\ln(v_i)}{n}\right]^{-1} \tag{17}$$

$$c = \left(\frac{1}{n}\sum_{i=1}^{n} v_i^k\right)^{1/k} \tag{18}$$

v_i is the wind speed n the number of measurements.

The efficiency of the five numerical methods and PSO are determined using the following statistical tests: correlation (r), relative bias (RB) and root mean square error (RMSE), described in Eqs. (19)–(21).

$$r = \frac{\sum_{i}^{N}(X_i - X_{med})\cdot(Y_i - Y_{med})}{\sqrt{\sum_{i}^{N}(X_i - X_{med})^2\cdot(Y_i - Y_{med})^2}} \tag{19}$$

$$RB = \frac{X_{med} - Y_{med}}{Y_{med}} \tag{20}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(X_i - Y_i)^2}{N}} \tag{21}$$

N is the number of observations, Y_i the frequency of observations, X_i the Weibull frequency, X_{med} the mean of X_i and Y_{med} the mean of Y_i.

3. Results and discussion

Figs. 5–7 show Weibull curves for each of the five used numerical methods and for PSO method and wind speed data histograms for Maracanaú, Parnaíba and Petrolina.

According to Figs. 5–7, Weibull curves for each of the five numerical methods considered and for PSO method have different coincidence levels with the histograms. Considering only numerical methods, the best adjustments are found in Figs. 5 and 6, representing Weibull adjustment to the wind data obtained in coastal sites; lower adjustments are found in Fig. 7, representing wind data from a site far from the coast.

Comparing the five used numerical methods and PSO, PSO method has a very good performance for the estimation of the Weibull parameters, followed by the EE numerical method. Among the numerical methods, this result confirms the expectations, since the EE numerical method was developed to optimize the application of the Weibull density function for the wind data found in the BRNER.

Tables 3–5 show the application of the statistical tests (r, RB e RMSE) for Maracanaú, Parnaíba e Petrolina, respectively, using a measurement height of 78 m. These tests are applied to the wind speed data obtained from February 2012 to January 2013 for Maracanaú, from August 2012 to July 2013 for Parnaíba and from May 2012 to March 2013 for Petrolina.

According to the statistical tests, PSO method shows the best fit in Tables 3–5. The high correlation and low relative bias and error values indicate that the method converges to the optimal solution in the three sites.

It is important to remember that the shape and scale parameters are calculated using an annual distribution of wind speed data and because of that these parameters lose in this case their representative characteristic due to the large seasonal difference observed in the analysis period (1 year).

According to [3] annual curve should represent all observed months, hence the estimates of k and c should represent both low speed data (first semester) as high speed data (second semester). Figs. 8–10 show k values obtained using E method for all considered months in the 3 sites. As it can be observed, k monthly values vary considerably throughout the year, with a peak occurring in the second semester of the year, showing a difference compared to the annual value.

Considering data from Maracanaú, Table 3 shows, for the used methods, a k annual value between 2.6 and 2.9; considering the monthly variation, Fig. 8 shows that for the second semester most of k values are found between 3 and 4. Table 4 (data from Parnaíba) shows a k annual value between 3.2 and 3.9; according to Fig. 9, most of k values in the second semester are higher than 6. Petrolina data (Table 5) shows a k annual value between 3.5 and 5.1; according to Fig. 10, k values vary between 5 and 7 in the second semester. For Parnaíba and Petrolina the k annual value shows a significant difference compared to the k parameters considering the monthly variation, especially in the dry semester.

Considering data from Maracanaú, Table 3 shows, for the used methods, a c annual value between 6.3 and 6.9 m/s; considering the monthly variation, Fig. 11 shows that for the second semester most of the c values are found between 7 and 8 m/s; Table 4 (data from Parnaíba) shows a c annual value between 8.3 and 8.9 m/s; according to Fig. 12, most of c values are found in the second semester between 8 and 10 m/s. Petrolina data (Table 5) shows a c annual value between 7.3 and 7.9 m/s; according to Fig. 13, most of c values vary between 7 and 8 m/s in the second semester.

4. Conclusions

Attempts to diversify the electricity matrix with the use of decentralized renewable energy plants have been increasingly implemented in the last decades worldwide. For the particularly case of Brazil, success has been obtained mainly with wind plants, achieving a share of 2.88% of the country total power generation in 2014.

Motivated by the increasing relevance of wind power generation in Brazil, the study here reported investigated the PSO technique as a method to estimate the Weibull parameters adjusted for the particular wind conditions found in the BRNER. To characterize the wind resource of that Brazilian region, wind speed data were collected in 80 m high measurement towers installed in three sites. Two of the towers are at the coastal towns of Parnaíba and

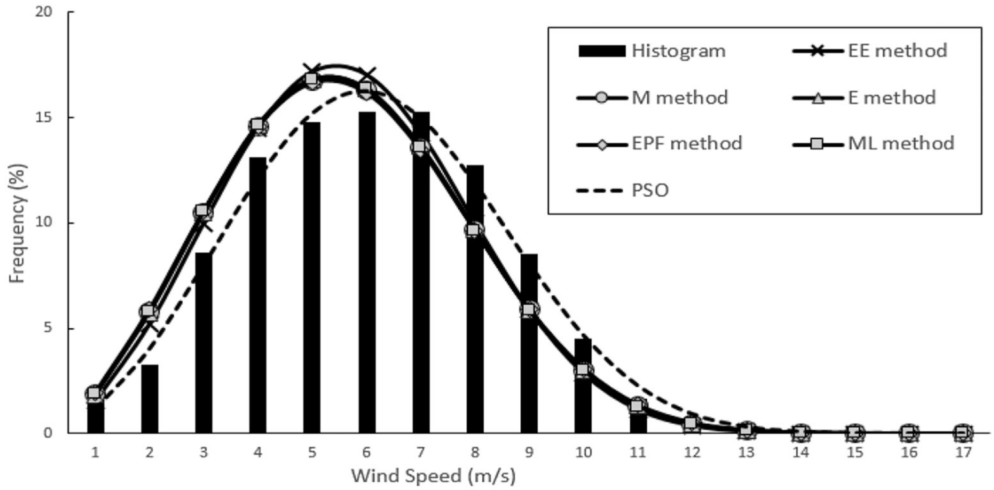

Fig. 5. Weibull distribution curves and histogram - Maracanaú (February 2012–January 2013).

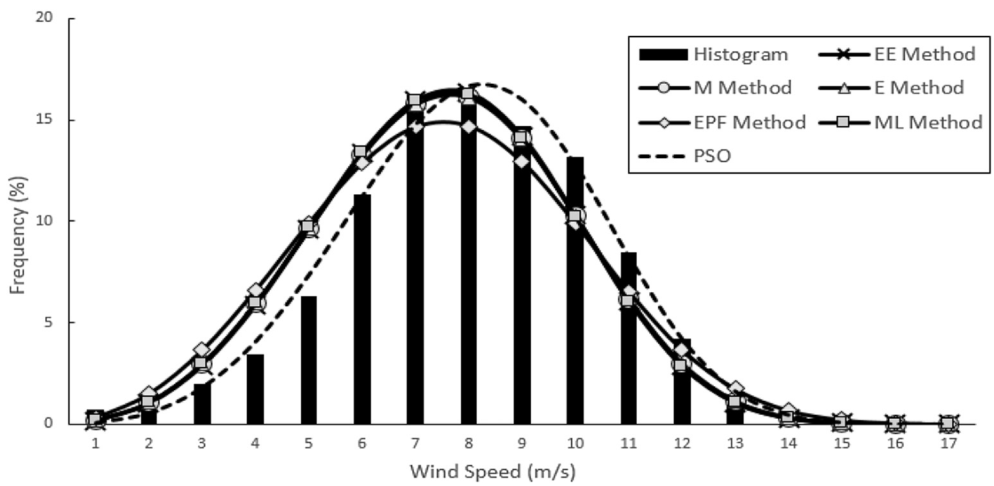

Fig. 6. Weibull distribution curves and histogram - Parnaíba (August 2012–July 2013).

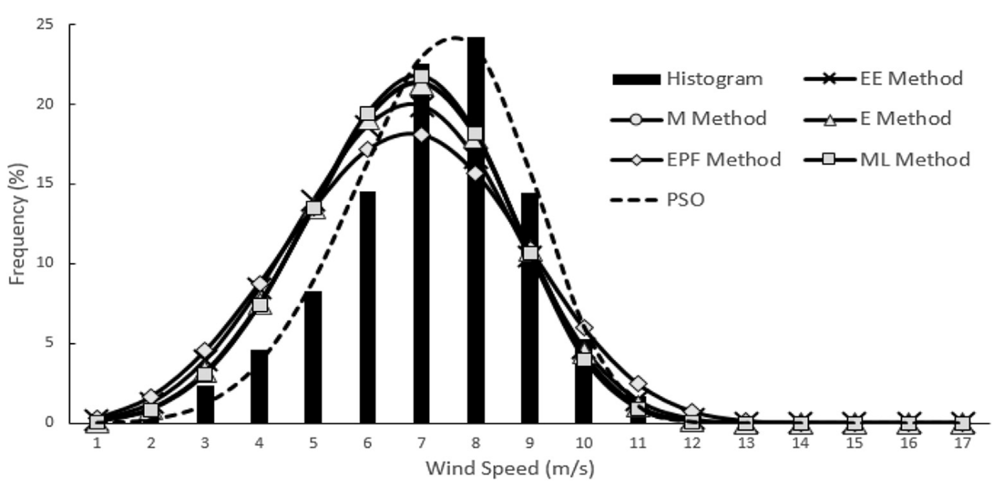

Fig. 7. Weibull distribution curves and histogram - Petrolina (May 2012–March 2013).

Maracanaú, distant 365 Km from each other. The third tower is located at Petrolina, ca. 650 Km far from the coastline.

Aiming to compare with PSO, five numerical methods are chosen for estimation of Weibull parameters: Moment Method (M), Empirical Method (E), Energy Pattern Factor Method (EPF), Energy Equivalent Method (EE) and Maximum Likelihood (ML).

Table 3
Application of statistical tests for Maracanaú — CE.

Numerical methods	Weibull parameters		Statistical tests		
	K	c	r	RMSE	RB
Equivalent energy method	2.8170	6.3709	0.9744	0.0143	0.0001031
Moment method	2.6900	6.3362	0.9694	0.0151	0.0002445
Empirical method	2.6988	6.3355	0.9696	0.0151	0.0002325
Energy pattern factor method	2.6660	6.3381	0.9689	0.0152	0.0002795
Maximum likelihood	2.6920	6.3267	0.9687	0.0153	0.0002427
Particle Swarm Optimization	2.8546	6.9167	0.9959	0.0055	0.0000594

Table 4
Application of statistical tests for Parnaíba — PI.

Numerical methods	Weibull parameters		Statistical tests		
	K	c	r	RMSE	RB
Equivalent energy method	3.5970	8.3802	0.9686	0.0150	0.0000148
Moment method	3.5590	8.3891	0.9683	0.0150	0.0000153
Empirical method	3.5462	8.3907	0.9681	0.0150	0.0000155
Energy pattern factor method	3.2376	8.4301	0.9585	0.0175	0.0000024
Maximum likelihood	3.5740	8.3654	0.9667	0.0154	0.0000154
Particle Swarm Optimization	3.9143	8.9013	0.9949	0.0061	0.0000060

Table 5
Application of statistical tests for Petrolina — PE.

Numerical methods	Weibull parameters		Statistical tests		
	K	c	r	RMSE	RB
Equivalent energy method	3.8470	7.3377	0.9281	0.0294	0.0000161
Moment method	4.1720	7.3877	0.9460	0.0255	0.0000071
Empirical method	4.1438	7.3905	0.9456	0.0256	0.0000077
Energy pattern factor method	3.5207	7.4579	0.9248	0.0309	0.0000257
Maximum likelihood	4.2320	7.3667	0.9448	0.0258	0.0000061
Particle Swarm Optimization	5.1171	7.9010	0.9962	0.0077	0.0000001

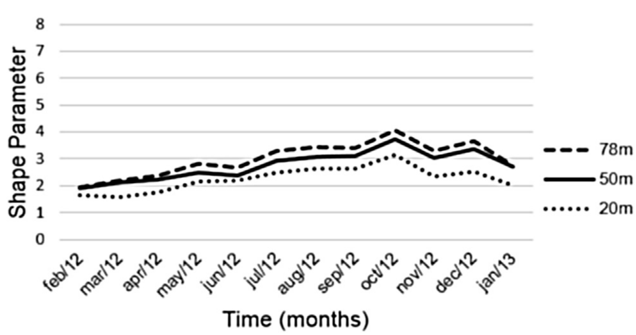

Fig. 8. Shape parameter monthly variation - Maracanaú.

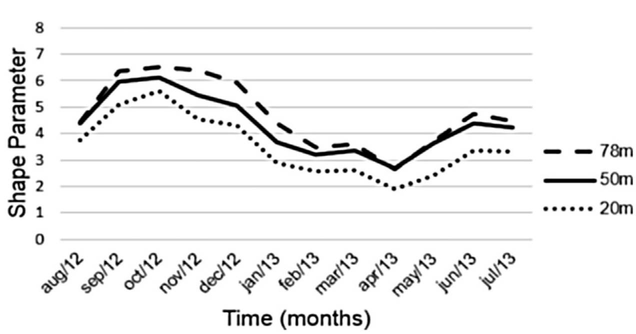

Fig. 9. Shape parameter monthly variation - Parnaíba.

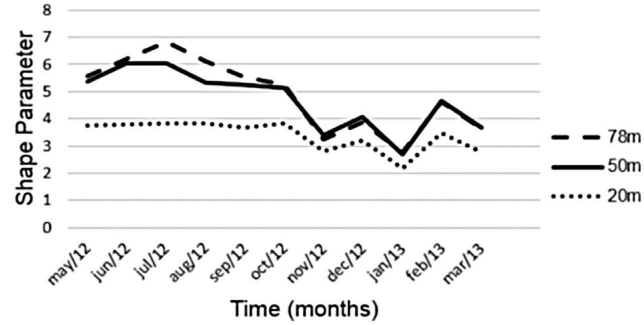

Fig. 10. Shape parameter monthly variation — Petrolina.

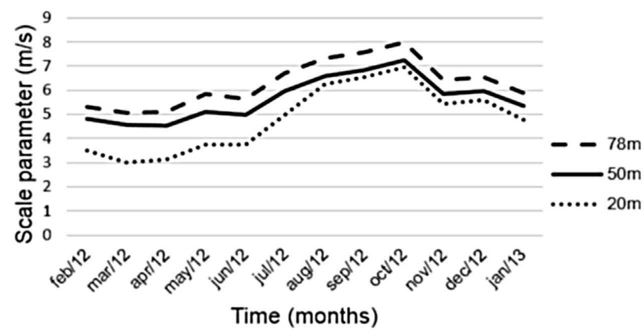

Fig. 11. Scale parameter monthly variation — Maracanaú.

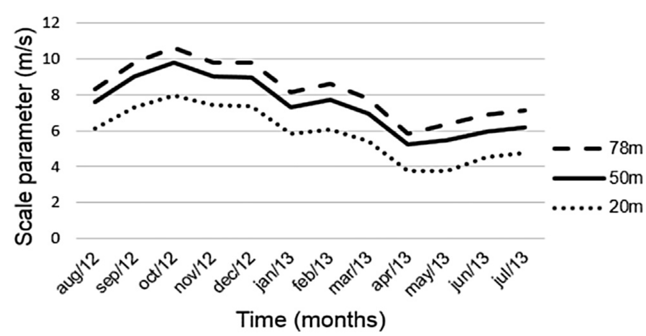

Fig. 12. Scale parameter monthly variation — Parnaíba.

Considering only the numerical methods, EE Method shows the best results for the near the coast sites. EE produced a high correlation value of 96%, almost zero relative bias and an error of 0.015. For Petrolina, far from the coast, M and E Method show the best results. M and E produced correlation values above 94%, low

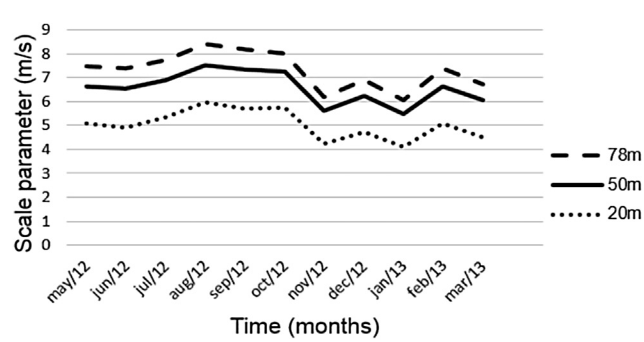

Fig. 13. Scale parameter monthly variation — Petrolina.

relative bias and error 0.0255 and 0.0256, respectively. The best performance for the EE Method for coastal areas agrees with other paper, using two sites in the coastline of Ceará, Brazil [20].

Compared with the five used numerical methods, PSO shows the best performance in the three sites under investigation. Correlation values higher than 99%, relative bias almost zero and an error lower than 0.0044 are found. Therefore, PSO proves to be a valuable technique for characterization of the particular wind conditions found in the BRNER.

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References

[1] ASSOCIAÇÃO NACIONAL DE ENERGIA ELÉTRICA – ANEEL: http://www.aneel.gov.br. Accessed in: 07 de Dezembro de 2014.
[2] T.C. Carneiro, Caracterização de Potencial Eólico para Fins de Geração Eolioelétrica: Estudo de Caso para Maracanaú (CE), Parnaíba (PI) e Petrolina (PE), Fortaleza, Diss. Mestr. Eng. Elétrica. Univ. Fed. Ceará (2014) 24–86.
[3] G.R. Silva, Características de vento da Região Nordeste, análise, modelagem e aplicações para projetos de centrais eólicas, Master's thesis, 2003. Recife-PE.
[4] Secretary of Infrastructure of Ceará – SEINFRA: Wind Resource Atlas of State of Ceará, 2000.
[5] M.E.P. Maceira, D.D.J. Penna, J.F.M. Pessanha, A.C.G. Melo, Modelagem estatística de ventos para utilização nos modelos de planejamento e operação. Florianópolis – Santa Catarina. XXI SNPTEE – Seminário Nacional de Produção e Transmissão de Energia Elétrica, 2011.
[6] G. Silva, A. Pereira, D. Faro, E. Feitosa, On the accuracy of the Weibull parameters estimators, in: Proceedings of the European Wind Energy Conference, London, 2004.
[7] Instituto Brasileiro de Geografia e Estatística: www.ibge.gov.br. Accessed in: 18 de Novembro de 2013.
[8] F. Antunes, Algoritmo de sistema de formigas aplicado ao planejamento da operação de sistemas hidrotérmicos de potência. 2011, Dissertação. (Mestrado em Energia), Universidade Federal do ABC, Santo André – SP, 2011.
[9] G.F. Medeiros, M. Kripka, Algumas Aplicações de Métodos Heurísticos na Otimização de Estruturas, Rev. CIATEC – UPF 4 (1) (2012) 19–32.
[10] X. Hu, Particle Swarm Optimization, 2006. Accessed in: 20 de Setembro de 2014, http://www.swarmintelligence.org/.
[11] T.P. Chang, Wind energy assessment incorporating particle swarm optimization method, Energy Convers. Manag. 52 (2010) 1630–1637.
[12] C. Kongnam, S. Nuchprayoon, A particle swarm optimization for wind energy control problem, Renew. Energy (2010) 2431–2438.
[13] M.A. Mohandes, S. Rehman, Short term wind speed estimation in Saudi Arabia, J. Wind Eng. Ind. Aerodyn. (2014) 37–53.
[14] U. Eminoglu, S. Ayasun, Modeling and design optimization of variable-speed wind turbine systems, Energies (2014) 402–419.
[15] C. Wan, J. Wang, G. Yang, H. Gu, X. Zhang, Wind farm micro-siting by Gaussian particle swarm optimization with local search strategy, Renew. Energy (2012) 276–286.
[16] R. Liang, S. Tsai, Y. Chen, W. Tseng, Optimal power flow by a fuzzy based hybrid particle swarm optimization approach, Electr. Power Syst. Res. (2011) 1466–1474.
[17] Z. Tianpei, S. Wei, MPPT method of wind power based on improved Particle Swarm Optimization, Telkomnika 11 (No. 6) (2013).
[18] R. Rahmani, R. Yusof, M. Seyedmahmoudian, S. Mekhilef, Hybrid technique of ant colony and particle swarm optimization for short term wind energy forecasting, J. Wind Eng. Ind. Aerodyn. (2013) 163–170.
[19] P.C.M. Carvalho, Geração Eólica, first edição, Editora Imprensa Universitária, Fortaleza – CE, 2003, p. 146.
[20] T.P. Chang, Performance comparison of six numerical methods in estimating Weibull parameters for wind energy application, Appl. Energy 88 (2011) 272–282.
[21] P.A.C. Rocha, R.C. Sousa, C.F. Andrade, M.E.V. Silva, Comparison of seven numerical methods for determining Weibull parameters for wind energy generation in the northeast region of Brazil, Appl. Energy 89 (2012) 395–400.
[22] S. Abdel-Hady, A. Abou El-Azm Aly, H. Saleh, Assessment of different methods used to estimate Weibull distribution parameters for wind speed in Zafarana wind farm, Suez Gulf, Egypt, Energy 44 (2012) 710–719.
[23] S.A. Akdag, A. Dinler, A new method to estimate Weibull parameters for wind energy applications, Energy Convers. Manag. (2009) 1761–1766.