ENCIT 2018

ABCM Associação Brasileira de Engenharia e Ciências Mecânicas

17th Brazilian Congress of Thermal Sciences and Engineering
November 25th-28th, 2018, Águas de Lindóia, SP, Brazil

ENCIT-2018-0744
MIGRATORY BIRDS OPTIMIZATION APPLIED TO WIND ENERGY FOR PETROLINA, BRAZIL

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Abstract. *Due to the lack of rainfall, which directly impacts the electricity generation in Brazil, wind energy is becoming increasingly important, especially for the country northeast region, that is constantly suffering from drought. The wind speed variation description is a very important aspect for wind industry operators. Therefore, this paper aims to estimate, for the region of Petrolina-PE, using the heuristic method called Migratory Birds, the Weibull curve parameters, more used to predict the wind behavior. The method was implemented and the results were compared, by statistical tests, with the results presented by deterministic methods usually used for this purpose. The statistical tests showed that the Migratory Birds Method is efficient to estimate the Weibull curve parameters for the analyzed region, resulting in k = 3.2924 and c = 5.4774 m/s.*

Keywords: *Wind energy, Weibull Distribution, Migratory Birds Optimization, Heuristic, Deterministic*

1. INTRODUCTION

According to Brazilian Wind Energy Association, ABEEólica, in 2017, at the Northeast of Brazil, for example, the wind power source was the salvation in a year of hydroelectric reservoirs droughts, reaching more than 60% of the region's energy. In total, wind power production in 2017 was 26.5% higher than 2016, and for the first time the source reached double digits in the production matrix, representing 10% of the country's energy in August and 11% in September, months that are recognized by the large amount of winds in the region.

Wind speed variation description is a very important aspect for wind industry operators. In fact, wind turbine designers need to use this information in order to optimize turbine design and thereby minimize production costs Wais (2017).

This paper aims to estimate *k* e *c* parameters by the application of Migratory Birds Optimization, and to compare them with those already obtained by the following deterministic methods: Least Squares Method (LSM), Moment Method (MM), Maximum Likelihood Method (MLM), Energy pattern factor method (EPFM), Modified Maximum Likelihood Method (MMLM), Equivalent Energy Method (EEM), Empirical Method (EM) and Chi-Square Method (χ^2).

2. NUMERICAL METHODS FOR DETERMINING THE WEIBULL PARAMETERS

As the wind speed is a random variable, it is useful to use statistical analysis to determine the wind potential of a region Wais (2017), Celik (2003) and Akpinar and Akpinar (2004). Commonly, the two parameters Weibull distribution is the one that presents the best fit and is therefore the most used to estimate this potential Burton *et al.* (2001) and Manwell *et al.* (2009).

The Weibull distribution for the velocity v is expressed by the probability density function, wind velocity frequency curve, shown in Equation 1. Equation 2 expresses its cumulative probability function Ohunakin *et al.* (2011) and Chang (2011).

$$f(v) = (\frac{k}{c}) \cdot (\frac{v}{c})^{(k-1)} \cdot e^{-(\frac{v}{c})^k} \tag{1}$$

$$F(v) = \int_0^v f(v)\mathrm{d}v = 1 - e^{-(\frac{v}{c})^k} \quad v,\ k\, and\, c > 0 \tag{2}$$

Where c is the scaling factor with unit $m \cdot s^{-1}$, k is the shape factor (dimensionless) and $F(v)$ denotes the probability of velocities smaller than or equal to v.

2.1 Maximum Likelihood Method (MLM)

In the Maximum Likelihood Method, numerical iterations are required to determine the Weibull distribution parameters Fisher (1915). In this method Rocha *et al.* (2012), the parameters k and c are determined according to the Equations 3 and 4.

$$k = \left[\frac{\sum_{i=1}^{n} v_i^k ln(v_i)}{\sum_{i=1}^{n} v_i^k} - \frac{\sum_{i=1}^{n} ln(v_i)}{n}\right]^{-1} \tag{3}$$

$$c = \left(\frac{1}{n}\sum_{i=1}^{n} v_i^k\right)^{\frac{1}{k}} \tag{4}$$

Where n is the number of observed data and v_i is the wind speed measured in the interval i.

2.2 Moment Method (MM)

The Moment Method maybe used as an alternative to the Maximum Likelihood Method and it is recommended when the mean and standard deviation of the elements are known and are initially on an appropriate scale Justus *et al.* (1978). In this case Rocha *et al.* (2012), the k and c parameters are determined by the Equations 5 and 6.

$$\sigma = c \cdot \sqrt{\Gamma(1 + \frac{2}{k}) - \Gamma^2(1 + \frac{2}{k})} \tag{5}$$

$$\overline{v} = c \cdot \Gamma(1 + \frac{1}{k}) \tag{6}$$

Where $\overline{v}$, σ, Γ are, respectively, the average wind speed, the standard deviation of the observed wind speed data, and the gamma function.

2.3 Empirical Method (EM)

The empirical method Rocha *et al.* (2012) and Chang (2011) is considered a simplified form of the Moment Method, in which the determination of the k parameter follows Equation 7 and the c parameter Equation 8.

$$k = (\frac{\sigma}{\overline{v}})^{-1,086} \tag{7}$$

$$\overline{v} = c \cdot \Gamma(1 + \frac{1}{k}) \tag{8}$$

Where $\overline{v}$ and σ are respectively the mean wind speed and the standard deviation of the observed wind speed data.

2.4 Equivalent Energy Method (EEM)

The Equivalent Energy Method seeks the equivalence between the energy density of the observations and the theoretical Weibull curve. For this, the k parameter is estimated from the third moment of the velocity, by minimizing the square error related to the adjustment, represented by Equation 9 and the c parameter is adjusted by using Equation 10 Silva (2003) and Andrade *et al.* (2014).

$$\epsilon^2 = \sum_{i=1}^{n}\left\{W_i - e^{-\left[\frac{(v_i-1)(\Gamma(1+\frac{3}{k}))^{1/3}}{(\overline{v^3})^{1/3}}\right]^k} + e^{-\left[\frac{(v_i)(\Gamma(1+\frac{3}{k}))^{1/3}}{(\overline{v^3})^{1/3}}\right]^k}\right\}^2 \tag{9}$$

$$c = \left[\frac{\overline{v^3}}{\Gamma(1 + \frac{3}{k})}\right]^{1/3} \tag{10}$$

2.5 Energy Pattern Factor Method (EPFM)

The energy pattern factor, E_{pf}, method is related to the averaged data of wind speed and is defined by the following equations 11 until 13 Akdag and Dinler (2009):

$$E_{pf} = \frac{\overline{v^3}}{\overline{v}^3} \tag{11}$$

$$k = 1 + \frac{3.69}{(E_{pf})^2} \tag{12}$$

$$\overline{v} = c \cdot \Gamma\left(1 + \frac{1}{k}\right) \tag{13}$$

2.6 Modified Maximum Likelihood Method (MMLM)

The modified maximum likelihood method can only be considered if the available data of wind speed are already in the shape of the Weibull distribution and, as in the maximum likelihood method, it requires numerical iterations for the solution of the equations:

$$k = \left[\frac{\sum_{i=1}^{n} v_i^k ln(v_i) f(v_i)}{\sum_{i=1}^{n} v_i^k f(v_i)} - \frac{\sum_{i=1}^{n} ln(v_i) f(v_i)}{f(v \geq 0)}\right]^{-1} \tag{14}$$

$$c = \left(\frac{1}{f(v \geq 0)} \sum_{i=1}^{n} v_i^k f(v_i)\right)^{\frac{1}{k}} \tag{15}$$

where $f(v_i)$ represents the Weibull frequency and $f(v \geq 0)$ is the probability of wind speed ≥ 0.

2.7 Least Squares Method (LSM)

The purpose of the method is to define a line where the values of a sample are contained by minimizing the square root of the discrepancy between the value of the sample and the value predicted by the line (objective function) according to Equations 16 until 22 Justus *et al.* (1978):

$$y_i = ax_i + b \tag{16}$$

$$\epsilon_i = y_i - (ax_i + b) \tag{17}$$

$$\epsilon^2 = \sum_{i=1}^{n} [y_i - (ax_i + b)]^2 \tag{18}$$

$$a = \frac{\sum_{i=1}^{n} x_i(y_i - \overline{y})}{\sum_{i-1}^{n} x_i(x_i - \overline{x})} \tag{19}$$

$$b = \overline{y} - a\overline{x} \tag{20}$$

$$k = a \tag{21}$$

$$c = e^{-\frac{b}{k}} = e^{[\overline{x} - (\frac{\overline{y}}{k})]} \tag{22}$$

2.8 Chi-Square Method (χ^2)

Similarly to the adjustment by the equivalent energy method, the Chi-Square method seeks to minimize the error of the Chi-Square test between measured data and the expected data, according to Equations 23 and 24 Dorvlo (2002).

$$\chi^2 = \sum_{i=1}^{n} \left\{ \frac{[F(v_i) - (1 + exp(\frac{v_i}{k})^k)]^2}{1 + exp(\frac{v_i}{k})^k} \right\} \tag{23}$$

$$\overline{v} = c \cdot \Gamma(1 + \frac{1}{k}) \tag{24}$$

It is worth mentioning that for all methods that use frequency distribution values (histogram), the value v_i represents the central value of the speed *(bin)*.

3. HEURISTIC METHODS

Heuristics encompasses a set of methods where, to solve a problem, the variables in question use the experience gained over the iterations. Heuristic methods combine different concepts intelligently to explore the search space, so that learning strategies are used to structure information and find efficient and almost optimal solutions Osman and Laporte (1996). Many of the heuristic approaches depend on probabilistic decisions made during the algorithm run. The main difference against pure random search is that in heuristic algorithms randomness is not used blindly but intelligently and biased Stutzle (1999). It is valid to emphasize that every optimization procedure searches for the best result of a function for the desired scenario. This function is called the Objective Function. In this paper, the objective function is the one presented in Equation 25, which represents the minimization of the square error sum applied to the frequency of occurrence values found by the curve adjusted by the method and the observed frequency of occurrence in the histogram of the data.

$$\epsilon^2 = \sum_{i=1}^{n} (f_{adjustment} - f_{observed})^2 \quad (25)$$

Where n is the number of histogram velocity intervals and $f_{adjustment}$ and $f_{observed}$ are the occurrence frequencies by the adjusted curve and observed in the histogram, respectively.

3.1 Migratory Birds Optimization (MBO)

The "V" formation is the most famous formation that migratory birds use to fly long distances. The name is due to the form similarity that the birds make with the letter "V", in which there is a leader who guides the flock and two other lines of birds following it. There are other formations such as in column, arc shape and formation in "J", among others. It is believed that this training is very efficient for migratory birds.

Two hypotheses were proposed in order to explain the use of this "V" formation by birds. The first hypothesis points out that in this way it is possible to save energy during the flight, because when the leading bird gets tired, its place is occupied by one of the birds that remain in the later positions. The second hypothesis is that the "V" formation may reflect a mechanism by which birds avoid collisions with each other and remain in visual contact as shown in Figure 1, showing the formation angle α, the distance *d* between one bird and another, and the WTS, spacing between the bird wing tip and the subsequent bird wing tip Duman *et al.* (2012).

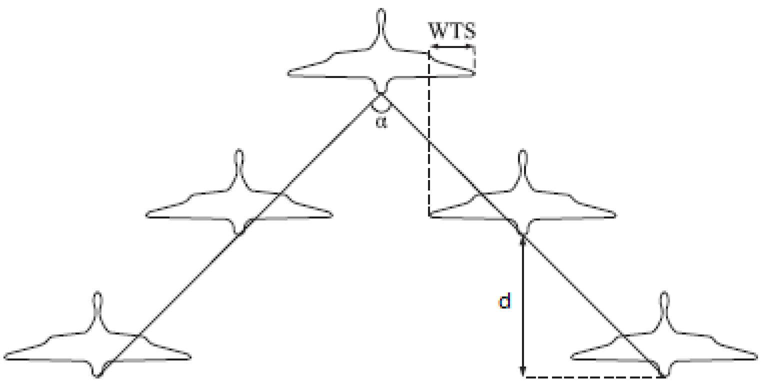

Figure 1. Adapted from Duman *et al.* (2012) by the author

3.1.1 Migratory Birds Optimization Algorithm

The MBO algorithm is a search technique that takes into account the neighborhood. Each birds formation in "V" represents a possible solution, starts with the first solution, bird leader, proceeding through all the other individuals until reaching the last bird at the tip of the formation. Each solution must be developed by the solutions of its neighbors and if a neighboring bird brings a better solution, it is automatically replaced by the solution initially registered. There is another efficiency mechanism in the algorithm. This mechanism transfers the best neighbor not used solutions to the next solution. In the algorithm, this situation is called neighbors sharing. In this way, the existing solution is enhanced by using not only its own produced solutions, but also neighboring solutions that come from other solutions. This sharing of neighbors is completed by sharing the solution by all birds except the last two birds located on the two lines. This process continues until the total number of iterations is reached Duman *et al.* (2012).

Makas and Yumusak (2016) suggested that due to the diversity of the initial population directly affect the performance of the algorithm, the initialization of the position of the birds, representing the possible solutions, is an important point to improve the optimization. The initial positions are assigned through Equation 26:

$$x_{ij} = x_j^{min} + rand \cdot (x_j^{max} - x_j^{min}) \tag{26}$$

Where:

(a) x_{ij} is the position of the i-th solution in dimension j;

(b) x_j^{min} e x_j^{max} are limit values for dimension j;

(c) rand is a random number ranging from 0 to 1.

After initialization, one of the solutions is chosen as the leader and all generated solutions are placed arbitrarily in a hypothetical "V" formation. Starting with the first solution, which corresponds to the leading bird, and progressing along the lines to the tails, the MBO algorithm aims to improve each solution using its neighboring solutions.

Makas and Yumusak (2016) generated neighbors "k" by equation 27.

$$\hat{x}_{ij} = x_{ij} + \varphi \cdot (x_{ij} - x_{kj}) \tag{27}$$

Where:

(a) $\hat{x}_{ij}$ is the new neighbor position generated in the j-th dimension for the i-th solution;

(b) x_{ij} is the position of the i-th solution in dimension j;

(c) k is a randomly selected index value, different from i;

(d) x_{kj} is the position of the k-th solution in dimension j;

(e) φ is a random number that varies from (-1, 1).

Equation 27 calculates neighborhood creation while comparing two bird positions in parentheses. That is, the smaller the difference between x_{ij} and x_{kj}, the closer are the solutions.

After these neighbors creation, if the Objective Function of the neighboring solution has a better result than the leader, the neighboring solution position is assigned to the solution, and then twice the parameter *x* solutions that are not shared are shared with the two birds in the second line.

An iteration ends after implementing the improvement for all birds. In summary, the leading bird spends more energy creating "k" neighbors in iterations. However, birds in other positions benefit from the birds in front and spend less energy creating neighbors (k-x) in iterations.

The algorithm simulates the fatigue of the leading bird after performing a number of previous (m) iterations. The leading solution is then shifted to the one-sided end in the hypothetical "V" formation, and the second solution on that side is shifted to the leading position.

The parameters *k* and *x* must be properly chosen because they directly affect the performance of the algorithm. The parameter *k* is inversely proportional to the flight speed of the birds. If small values are chosen, birds are assumed to fly at high speeds. Higher speeds allow the MBO algorithm to reduce overall execution time. However, the search depth of the algorithm increases if the parameter *k* increases. The parameter *x* represents the benefit of the vortex generated by the birds wings after the leader (WTS). Since the neighbor sharing of the MBO algorithm is defined as the number of good neighbors solutions obtained from the predecessor solution, high values of *x* make the solutions similar to each other. Thus, premature convergence can happen Duman *et al.* (2012).

4. METHODOLOGY

The method application and data elaboration applied used the statistical tool called RStudio, integrated development environment of the R language. A wind data series was tested by combining a pair (*k*, *c*), composed by 52,560 speed values, number of values established according to the IEC 61400 PART 12-1(2005) standard that defines 1 (one) year of integrated data every 10 minutes, totaling 52,560 values.

The adjustment tests with real data were performed with public data from the Federal Government's SONDA project, referring to the PTR11 station, located in Petrolina, PE, at 50m at ground level and with one year of data for reasons of availability, the year 2010 was selected and the occurrence of inconsistent data was reviewed.

To analyze the efficiency of the aforementioned methods, the following tests are used: RMSE (Root Mean Square Error), Mean Absolute Error (MAE), R^2 (analysis of variance or efficiency of the method) and the percentage value of the production deviation between the obtained curve and the histogram was also evaluated. These tests are defined by Equation 28 until Equation 31 respectively.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(y_i^{calculated} - y_i^{measured})^2}{n}} \tag{28}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|y_i^{calculated} - y_i^{measured}\right| \tag{29}$$

$$R^2 = \frac{\sum_{i=1}^{n}(y_i^{measured} - \bar{y}^{measured})^2 - \sum_{i=1}^{n}(y_i^{measured} - y_i^{calculated})^2}{\sum_{i=1}^{n}(y_i^{measured} - \bar{y}^{measured})^2} \tag{30}$$

$$WPD = \left(\frac{WPD_{estimated} - WPD_{measured}}{WPD_{measured}}\right) \cdot 100 \tag{31}$$

Where, according to (Jamil *et al.*, 1995), WPD$_{measured}$ and WPD$_{estimated}$ are calculated respectively by Equations 32 and 33

$$WPD_{medido} = \frac{1}{2} \cdot \rho \cdot c^3 \cdot \Gamma\left(1 + \frac{3}{k}\right) \tag{32}$$

$$WPD_{estimado} = \frac{1}{2} \cdot \rho \cdot v^3 \tag{33}$$

Where ρ is the specific mass of the air.

5. RESULTS AND DISCUSSION

Figures 2 present the Weibull distribution curves, described by its probability function $f(v)$, versus wind speed. The MBO method was calculated based on the parameters, birds number to 51, "k" neighbors to 3, "x" number to 1 and and "m" iterations number to 1. Figure 2 compares eight deterministic methods and the heuristic method, MBO.

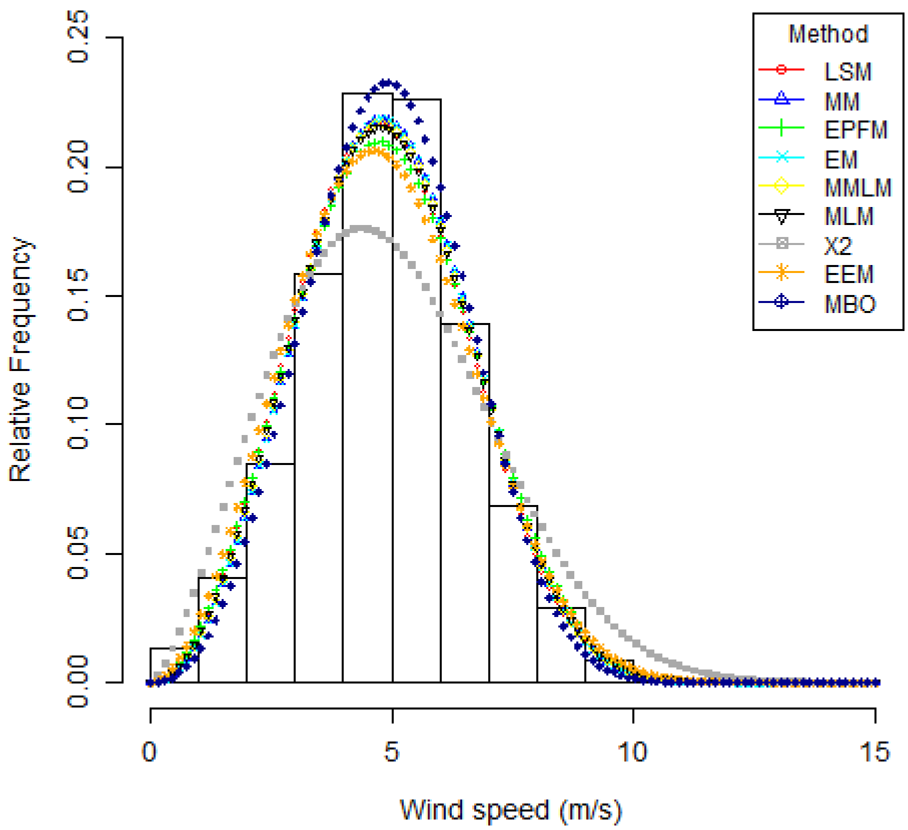

Figure 2. MBO and eight deterministic methods Comparison

The results of the statistical tests for the PTR11 station located in Petrolina are presented in Tab.1.

Table 1. Statistical Analysis of Petrolina, year 2010.

Method	k	c	RMSE	MAE	R^2	WPD (%)
LSM	2.9883	5.3996	0.002714	0.006299	0.980309	-2.440258
MM	3.0593	5.4665	0.002282	0.005948	0.986070	0.252696
EPFM	2.9212	5.4776	0.002958	0.007336	0.976597	2.870922
EM	3.0595	5.4665	0.002281	0.005946	0.986081	0.249014
MMLM	3.0258	5.4536	0.002439	0.006081	0.984086	-0.009484
MLM	2.9980	5.4560	0.002569	0.006266	0.982346	0.512640
χ^2	2.3840	5.5121	0.006426	0.016840	0.889589	17.962000
EEM	2.8169	5.3952	0.003639	0.008796	0.964585	$-5.551115 \cdot 10^{-14}$
MBO	3.2924	5.4774	0.001727	0.004988	0.992025	-1.823873

According to the Table 1, it can be observed that MBO method presented the lowest RMSE test value, 0.001727. The heuristic method also presented the best performance when it was analyzed the MAE and R^2 tests with values of 0.004988 and 0.992025, respectively. The WPD results showed a superiority of the EEM among all methods tested with value of $5.55 \cdot 10^{-14}\%$. MBO performed well, since the value obtained, 1.823873%, less than 2%,which was below the acceptable limit for the deviation of Wind Power Density.

The MBO method obtained a better fit to the histogram when compared to deterministic methods. It is noticed that the curve suffers a slight shift to the right, in addition, the velocity peak becomes better represented.

6. CONCLUSION

In this paper, eight deterministic and one heuristic optimization methods namely Migratory Birds Optimization were used to estimate the parameters, *k* and *c*, of the Weibull distribution for Petrolina, a city with good conditions, climate and geomorphology, for wind energy generation. The results were compared to each other. The deterministic methods were compared with the MBO method, using as a selection criteria the statistical tests. The following conclusions can be drawn based on the results presented in the previous sections:

1. For Petrolina, Equivalent Energy Method stood out, presenting the best performance among all methods tested for the cubic velocity energy production (WPD), obtained the best performance with value of $5.55 \cdot 10^{-14}\%$.

2. Migratory Birds Optimization was an efficient method, for determining the Weibull distribution, *k* and *c* parameters, for Petrolina, PE, Brazil.

7. ACKNOWLEDGEMENTS

This research was jointly supported by the Coordenação de Aperfeiçoamento de Pessoal de Nível Superior (CAPES), and the Conselho Nacional de Desenvolvimento Científico e Tecnológico (CNPq), Brazilian governmental agencies.

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