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Atmospheric stability in wind resource assessment: Development of a new tool for an accurate wind profile estimate

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ABSTRACT

The main objective of this paper is to investigate some key issues related to the atmospheric stability for the development of wind power projects, aiming to contribute to increase the reliability of this source and its safe insertion into the energy matrix. It is also important to note that the techniques and methodologies to be described were conceived taking into consideration one main premise: using information and data that is already available for a standard wind power project. The methodology presented here consists of solving an inverse problem using the Bayesian Inference in order to estimate the Monin Obukhov's length. The only input required for the aforementioned methodology is one mean horizontal wind speed time series – this requirement is highly cost-efficient and can be widely used. Therefore, the proposed solution will require a very low additional investment for the project developer and it will improve the quality of the wind resource assessment designed by the wind power project developers.

Keywords: *Wind Resource Assessment, Wind Profile Estimate, Atmospheric Stability, Monin Obukhov's length, Bayesian Inference, Reliability and Risks Mitigation.*

INTRODUCTION

The treatment of atmospheric stability conditions in the wind resource analysis of a region of interest in wind power projects is very rare. The available commercial computational programs that are widely used by the wind power project developers around the world are not ready to take into proper account the influence of this phenomenon. These pieces of software usually have a modeling that require users to inform *a priori* parameters such as the Monin Obukhov's length, which is not easily (or directly) obtained during wind measurement campaigns.

This paper presents a Bayesian estimate methodology that expresses the conditions of atmospheric stability of a given region, considering a wind measurement campaign following the rule established by the Brazilian Energy Research Company (EPE) - a three year measurement campaign is mandatory for the registration of a wind power project in the energy auctions in Brazil.

This methodology is validated through the use of measured horizontal wind speed time series from several different sites and heights. Very promising results are presented.

THEORETICAL BACKGROUND

The objective of this section is to present a brief theoretical review of the technique known as "Monte Carlo Markov Chain Integration" or MCMC (Monte Carlo Markov Chain) and its application to the study of atmospheric stability of a region of interest.

The Bayesian Inference as well as any statistical inference is related to the process of drawing conclusions or making predictions based on limited information. A Bayesian approach to a real problem is a powerful tool for describing an inverse problem and there are many techniques for solving these problems. The more general ones are usually the minimization of an objective function of the difference between the measured and the calculated parameters from the mathematical model.

For the solution of inverse problems within the Bayesian structure all variables included in the mathematical formulation of the problem from a physics point of view (direct problem) are modeled as random variables. Every Bayesian approach is based on the Bayes' theorem that shows the relationship between a conditional probability and its inverse. Mathematically, this can be stated as follows:

$$\pi_{\text{posterior}}(P) = \pi(P|Y) = \frac{\pi(Y|P)\pi(P)}{\pi(Y)} \qquad (1)$$

in which: P is the parameter; Y is the measurement; $\pi_{posterior}(P)$ is the probability density *a posteriori* of P conditioned to Y; $\pi(P)$ is the probability density *a priori* of P; $\pi(Y|P)$ is the probability density *a posteriori* of Y conditioned to P (likelihood function); and $\pi(Y)$ is the marginal probability density of the measurements, which plays the role of a normalization constant.

Monte Carlo Markov Chain

The method known as Markov Chain Monte Carlo is the estimate parameter technique used in this study of atmospheric stability. The method that follows – as its name suggests – is part of an integration of a stochastic and random process. The MCMC technique is a good alternative to simulate priors without known statistical formulation. Although, this technique can have a very high computational demand.

Markov chains can be defined as stochastic processes where the future depends only on the present, that is, it does not depend on the past. The formulation expressed by Eq. (2) mathematicises this concept:

$$q(P_t = y | P_t = x_t, P_{t-1} = x_{t-1}, \ldots, P_0 = x_0) = q(P_{t+1} = y | P_t = x) \qquad (2)$$

in which: $q(P_{t+1}|P_t)$ represents the probabilistic distribution of the states of the chain.

Some properties such as reversibility, ergodicity, homogeneity are associated with the cited stochastic process among others. Each property of the Markov chain is linked to a condition that must be satisfied. Some of these properties are used in our method.

After defining the concept of a Markovian process, the next point to be discussed - and the key point of the MCMC algorithm - is the 'sampler' of the Markov chain. In the literature there are two traditional algorithms to perform such a function: the Gibbs sampler and the Metropolis-Hastings algorithm - for this work the second of these two techniques will be utilized.

The Metropolis-Hastings algorithm is a method to obtain a sequence of random samples from a probability distribution for which direct sampling is difficult. Such algorithm extracts samples of a candidate density, and then an acceptance-rejection method is used to generate samples for the chains of the parameters to be estimated.

The Metropolis-Hastings' implementation begins with the selection of proposals or candidates distribution $q(P^*|P^{(t)})$. The Markov Chain's current state $P^{(t)}$ is utilized in order to create a new candidate state P^*. A restrictive condition – the need of a reversible property – is applied as a filter for new candidates. The acceptance algorithm is formulated as:

$$\begin{cases} \pi_{posterior}\left(P^{(t)}\right)q\left(P^*|P^{(t)}\right)\alpha\left(P^*|P^{(t)}\right) = \pi_{posterior}\left(P^*\right)q\left(P^{(t)}|P^*\right) & (3) \\ \alpha\left(P^*|P^{(t)}\right) = \min\left[1, \frac{\pi_{posterior}\left(P^*\right)q\left(P^{(t)}|P^*\right)}{\pi_{posterior}\left(P^{(t)}\right)q\left(P^*|P^{(t)}\right)}\right] & (4) \end{cases}$$

DIRECT PROBLEM

The physical-mathematical model used for the estimate of the atmospheric stability conditions in this article is the logarithmic profile of the mean wind velocity in the lower layers of the atmosphere - region of interest for the calculation of the energy production of wind farms.

In order to obtain an approximate profile of the mean velocity U of the flow near the earth's surface in function of the height z, the logarithmic profile updated with stability concept is modeled by Eq. (3).

$$U = \left(\frac{u_*}{\kappa}\right)\left[\ln\left(\frac{z}{z_0}\right) + \psi_M\right] \qquad (3)$$

in which: κ is the Von Karman constant; u_* is the friction velocity; z_0 is the roughness; ψ_M is the functional that represents the effect of the stability of the atmosphere.

Usually, in wind power projects, the functional ψ_M is assumed to be zero – it corresponds to neutral condition –, due to the practical difficulty of estimating it. It can be seen in Figure 1, different wind profiles due to the three different atmospheric stability conditions (stable, neutral, unstable) plotted on a semi log graph.

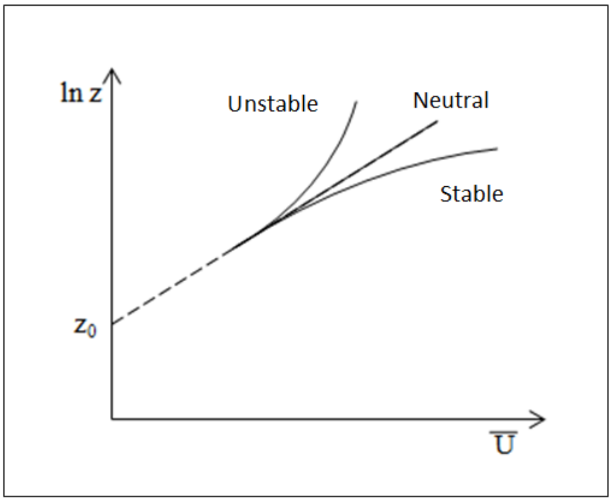

Figure 1 - Different wind profiles due to the three main different atmospheric stability conditions.

The functional ψ_M is the parameter to be estimated in this work. It depends on the height of the measurement and the Monin Obukhov's length (L) – a variable that, even for simplified representations, is not very feasible to be directly obtained. Equation (4) shows a simplified representation of the Monin Obukhov's length [2], considering the similarity of the velocity and temperature profiles in the statistically stable atmospheric condition.

$$L \cong \frac{u_* \bar{\theta} \Delta \bar{U}}{k\, g\, \Delta \bar{\theta}} \qquad (4)$$

in which: g is the acceleration of gravity; and $\bar{\theta}$ is the average temperature of the measurement height.

Thus, the difficulty of determining the Monin Obukhov's length *a priori* defined the inverse problem of this work. That is, the Monin Obukhov's length (L) is obtained from the Bayesian inference of the functional ψ_M treated as a parameter and estimated for the height of the anemometer used.

Therefore, the proposal that will be presented is to estimate, via MCMC, a probabilistic distribution of ψ_M, using information from the measured time series of average horizontal wind speed available in a standard measurement campaign. Other parameters are simultaneously estimated in such process (u_*, κ e z_0).

After estimating all parameters of interest, the Businger (1971) formulation [3] is used to recover a value that represents the Monin Obukhov's length. This step is solved numerically via Newton-Rapson – for the unstable case. The Eqs. (5), (6) and (7) express the ψ_M as a function of z, z_0 and L.

$$\psi_M = -4.7\left(\frac{z}{L}-\frac{z_0}{L}\right),\ \text{se}\ \left(\frac{z}{L}>0\right) \quad (5)$$

$$\psi_M = 0,\ \text{se}\ \left(\frac{z}{L}=0\right) \quad (6)$$

$$\psi_M = 2\ln\left(\frac{1+x}{1+x_0}\right)+\ln\left(\frac{1+x^2}{1+x_0^{\,2}}\right)-2\arctan(x)+2\arctan(x_0),\ \text{se}\ \left(\frac{z}{L}<0\right) \quad (7)$$

where:

$$x = \left[1-\left(15\frac{z}{L}\right)\right]^{1/4} \quad (8)$$

$$x_0 = \left[1-\left(15\frac{z_0}{L}\right)\right]^{1/4} \quad (9)$$

Finally, as anticipated, the relationship between stability and instability of a profile is quantified by the magnitude of the Monin Obukhov's length. There are some references in the literature that express the qualitative classification of the possible values of L. Table 1 is one example of such classification.

Table 1 – Classification of the Monin Obukhov's length.

Range of Monin Obukhov's length	Classification
|L|>1000	Neutral
200 > L >1000	Stable
0 > L >200	Very Stable
0 > L >-200	Very Unstable
-200 > L >-1000	Unstable
Note: L is not defined for the zero value	

METHODOLOGY

MatLab® was the computational tool in which the MCMC code was developed. The wind profile estimate algorithm's inputs is one .csv file of horizontal mean wind speed time series

The model's parameters calibration required numerous numerical experiments which used the posterior convergence, the acceptance rate, the chain quality and the parameters estimate (u_*, κ, z_0, ψ_M) as the calibration metric. The Monte Carlo's computational demand was significantly reduced by the fact that the direct problem's model was an algebraic equation.

Figure 2 shows one well calibrated estimate case to illustrate the aforementioned successful code calibration work. The acceptance rate is close to 30 % and this indicates the estimate quality, as shown in Figure 2 (b). Figure 2 (a) shows that convergence and ergodicity were met in u_* Markov chain – all chains respected those rules and Figure 2 is merely illustrative – and figure 2 (c) shows the output statics quality.

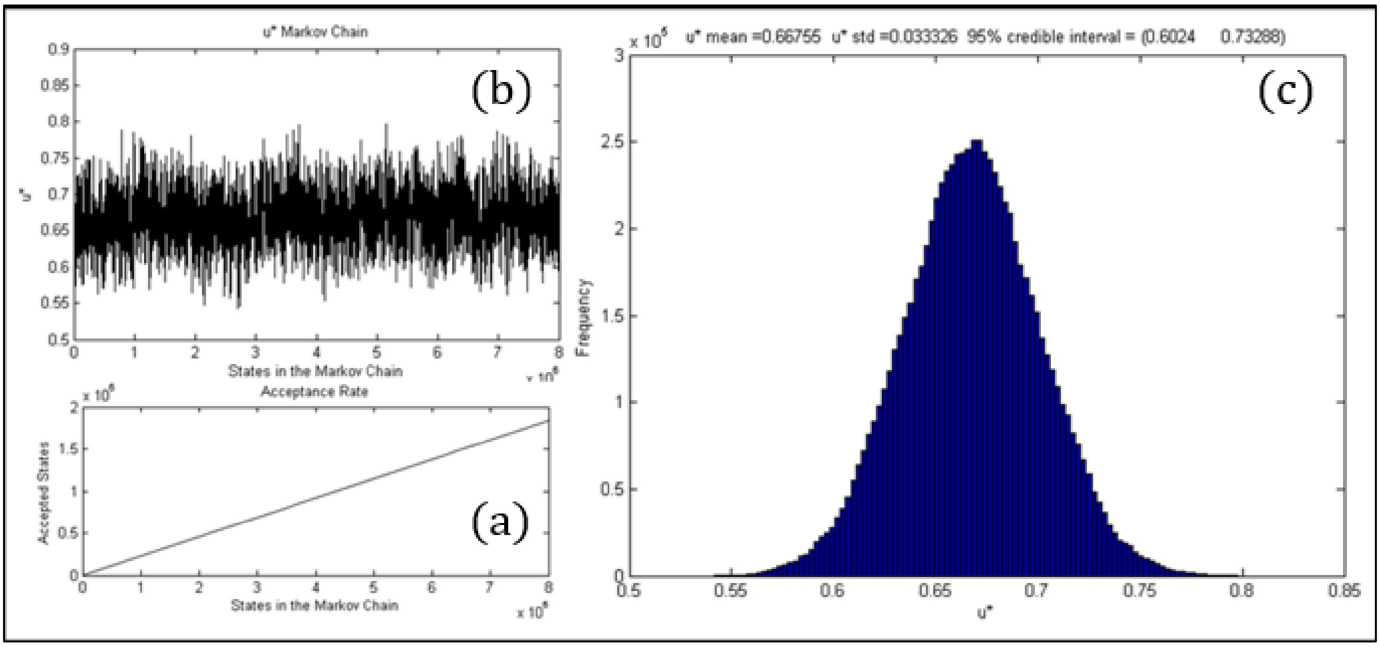

Figure 2: Calibrated estimate case (only u_* results are shown)

More concise results of this calibrated estimate case are presented in Table 2:

Table 2 – Classification of the length of Monin Obukhov.

Parameter	Average	Standard Deviation	Confidence Interval
u_*	0.67 m/s	0.03 m/s	0.60 m/s – 0.73 m/s
κ	0.40	0.02	0.37 – 0.44
z_0	0.35 m	0.02 m	0.32 m – 0.38 m
ψ_M	-0.51	0.15	-0.80 – -0.22

All average values are coherent with their magnitude orders. Thus, a good calibration can be assumed. The average Von Karman constant estimate (κ) – the most well-known prior parameter – is in accordance with 0.41 found in important fluid mechanics literature [1].

RESULTS

Several results showing the efficiency of the developed methodology are illustrated below. On Figures 3 to 5 wind profile estimates from different met masts – located in different sites and climatologies – and input time series are shown.

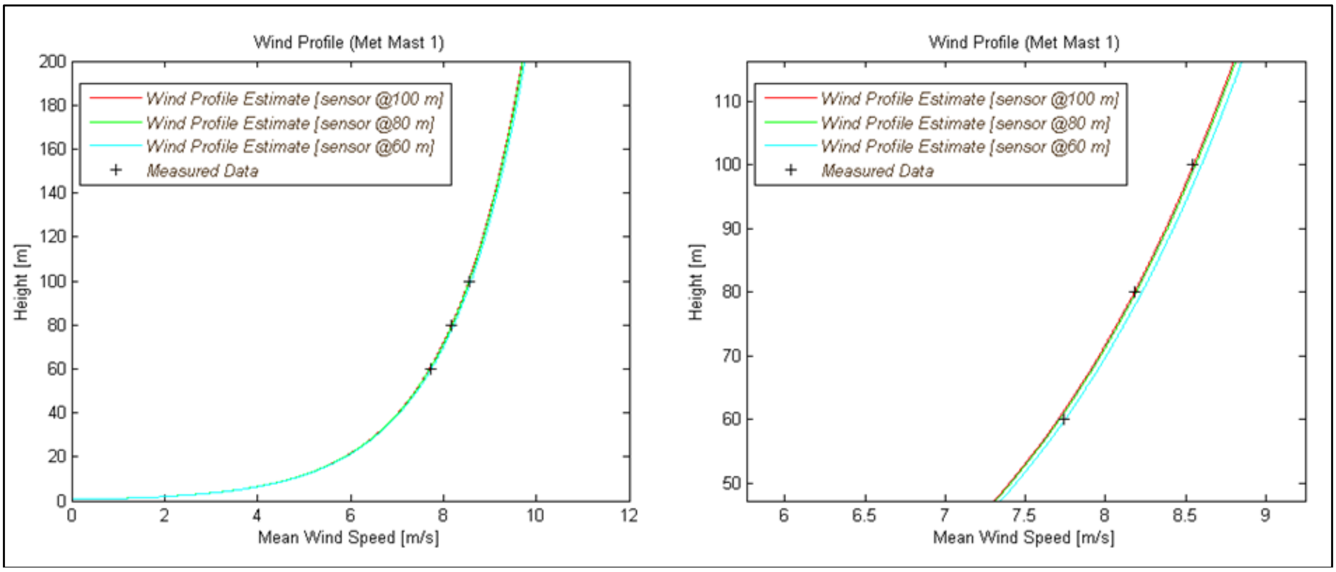

Figure 3: Wind profile estimates (Met Mast 1)

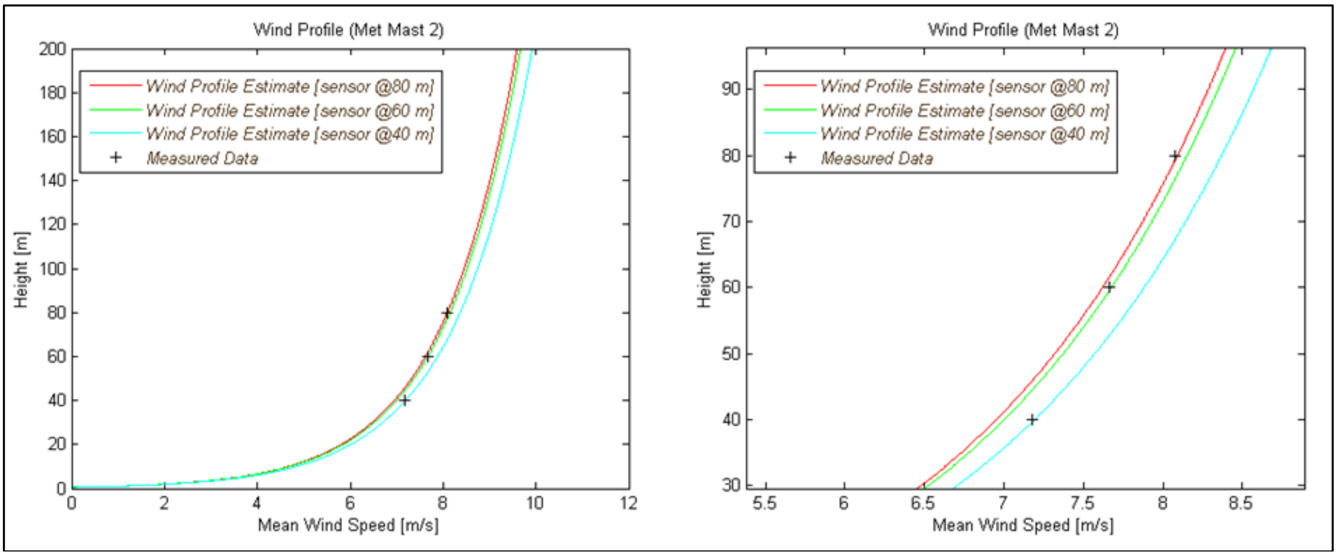

Figure 4: Wind profile estimates (Met Mast 2)

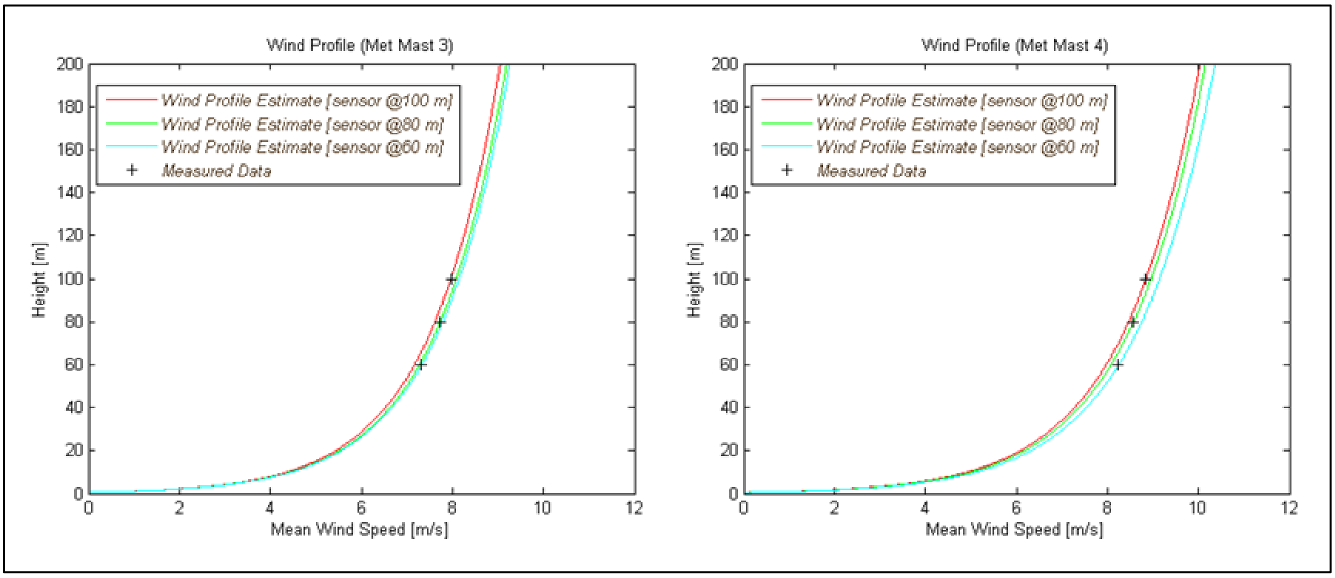

Figure 5: Wind profile estimates (Met Mast 3 & Met Mast 4)

CONCLUSION

Considering the results obtained during the long process of experimentation and validation of the method described above, we have a fairly strong reason to believe that this method is able to competently provide an accurate wind profile estimate and also a cost efficient atmospheric stability assessment.

Regarding the graphs presented – they represent only a small sample of the entire data examined –, one can see that the distance between the estimated curves and the measured data was insignificant for estimates with sensors above 60 m of height.

Deeper studies are being carried out by our team and improvements in accuracy are being actively pursued so that lower sensor heights can be successfully used in a very near future to estimate accurate wind profiles – this feature will certainly help prospectors to evaluate wind resource without the need of high investments.

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BIOGRAPHIES

Daniel A. Ramos – Born in the city of Rio de Janeiro on July 15th, 1993. He graduated in mechanical engineering at the Federal University of Rio de Janeiro in the middle of 2016, with emphasis in aerodynamics and numerical simulations of turbulent flows.

Eng. Daniel had internships in some energy companies, acquiring knowledge and experience in wind energy projects. Nowadays he is concluding his master's degree in Aerodynamics at PEM / COPPE-UFRJ (June 2017) and he is also fellow research at CEPEL with a few published articles related to wind energy applications.

Vanessa Gonçalves Guedes – Born in the city of Rio de Janeiro on 31 October. She graduated in mechanical engineering at the Federal University of Rio de Janeiro in 1995. Her master’s and doctor’s degrees at PEM / COPPE-UFRJ, were completed in 1996 and 2003, respectively, with specialization in aerodynamics and numerical simulations of turbulent flows.

Dr Guedes has worked in the wind energy sector over the past 14 years at Cepel - Electrical Energy Research Center. Her performance in the area consists of several projects for the Eletrobras System companies and publications and contributions for final course projects and master thesis for institutions such as IME, INPE and UFRJ.

Rodrigo R. S. Pereira – Born in the city of Rio de Janeiro on April 26th. He is a mechanical engineer student at Federal University of Rio de Janeiro(UFRJ), with interest in aerodynamics and numerical simulations of turbulent flows.

Rodrigo is currently an engineering intern at Electrical Energy Research Centre (CEPEL). He has been working on wind projects, the development of numerical analysis of flows and optimisation algorithms.