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A METHODOLOGY FOR WIND POWER SERIES EXTENSION: DATA FOR INVESTMENTS, OPERATION AND EXPANSION PLANNING OF THE POWER SECTOR

Joaquim Garcia & Alexandre Street

Abstract

Wind power industry has grown a lot in the last few years and it will grow even faster in the next decade. Its participation in nowadays power systems is becoming more and more expressive every day, which brings difficulties for operation, certification and expansion planning, moreover investments in the area are growing in many countries. However this sector experiences a significant lack of data, because in most regions wind farms are very recent. Since this data is very important we propose a static methodology with physical background to extend existing short and medium term time series in order to obtain long term series.

Keywords

Wind power series; Long-term wind series; Multivariate regression; Reanalysis datasets; Time series extension.

I Introduction

Wind Energy Generation has been growing extremely fast in the last ten years, the global annual growth average is 22%. In 2012 this growth was represented by the installation of almost 45GW which correspond to 56 billion of euros. World´s installed capacity of about 282.5GW is mostly concentrated in Europe, United States and China, which together represent 86.5% of the global Total. Nevertheless some countries have shown significant growth in 2012, Brazil led Latin America in this developing industry with the installation of more than 1GW in 2012, which represented about 31% of regional installed capacity at the end that year [1].

Moreover, Brazilian government foresaw that by 2021 the installed capacity will reach 16GW, which is very significant compared to nowadays' capacity of 2.5GW [1][2]. Although this source is clean and has a great potential, it is highly seasonal and intermittent, which brings lots of difficulties to its commercialization and operation. Thus it is essential to study and understand it´s behavior in order to simulate and forecast wind power.

This understanding is made necessary because Brazilian´s energy market has been growing consistently after the crisis in 2001. In the last 12 years that market have been modified and restructured in order to attract private investment and grow sustainably [4]. This was when long-term contracts became the main responsible by the effective expansion of the energy offer and by the attractive prices for private industry. Two negotiation environments were created, the free trade environment (ACL) and the regulated environment (ACR). In the free trade environment private dealer and consumers can trade energy via bilateral contracts. In the regulated environment, energy is sold in public auctions [5] and in this second environment renewable energy has been stimulated since Brazilian government launched PROINFA in 2004 [6]. Wind energy was really shown as competitive in 2009 when the first auction for this kind of resource took place [7], and nowadays this is the second cheaper energy source in Brazil. In a market such as this, simulation and forecasting wind power are almost necessary for the private investor. In the regulated market wind energy contracts commonly last for 20 years that is why the owner of the plant has to have a great knowledge of his plant behavior in order to be able to offer competitive prices for his energy in the regulated market. In the free trade environment this knowledge is also vital because here the dealer is exposed to rules, in which a farm that isn't producing the contracted energy have to buy it on the highly volatile spot market [8].

Besides all those changes in energy regulation and commercialization, after the crisis the operation of the electrical system has changed a lot. Since then the system was interconnected creating one of the biggest power systems worldwide, what makes the system more efficient, however, harder to operate. To solve this issue, operation was centralized and is planned in short-term, mid-term and long-term by the National Operator of the System ONS [9]. Brazilian energy matrix is mostly composed of hydro plants and only complemented by thermo plants and recently by wind plants, consequently planning the operation in Brazil is quite challenging. In the wet period is important to save water for the dry period, which makes long term planning so important and difficult. Taking into account most plants connected to the system is important to control demand and load. As said before, wind energy is seasonal and intermittent, thus studies, simulations and forecasting of this resource are made necessary.

Future simulations in large resolutions such as weeks and months are the ones needed for most investment planning, for instance [3], as well as for long term-planning. Most contracts are in weekly monthly basis and the spot price is only changed weekly though the mean production in these resolutions is extremely important for investment analysis. The operation of the electrical system is also planned in many resolutions, although hourly operation is important, it is important to remember that long term operation is essential in Brazil for that reason great effort has been directed to this long-term planning, finally monthly and weekly resolution information are necessary for Brazilian system operation models such as NEWAVE [9].

Wind power stochastic behavior and seasonal characteristics vary from plant to plant, and may have long-term effects. The wide comprehension of those phenomena relies on the existence of long-term wind power series. However, Brazilian wind farms have started operating recently, most of the oldest large wind farms have been operating for no more than 2 years. This article proposes a methodology for extending this short wind time series applying statistics techniques with physical background. This history extension is a way to solve the problem of the lack of long term wind power data, which is extremely valuable for both public and private sectors.

It is worth emphasizing that a history extension like the proposed one is also useful for certification purposes. Every wind farm operating and commercializing in Brazilian market have to be certificated and must possess a firm energy certification (FEC) [10], the extended history can be used for this purpose once it represents the way the farm would have been operating for the past decades.

The development of this methodology was made possible by the existence of international weather databases, also known as Global Reanalysis datasets [11] [12] [13] [14]. Those datasets provide meteorological information about wind which is essential for the proposed methodology. On the other hand the is no impediment of using real data collect from weather stations, they are not used in the study cases simply because we are going to use wind information of wind farm site, and sites very close to weather stations are rare in Brazil.

This work is organized as follows: In section II a brief explanation of the model inputs will be made, these inputs may be global reanalysis datasets or measured wind series from meteorological stations. Section III outlines wind power characteristics that will be incorporated to the statistical model. Section IV describes the model. Section V illustrates the application of the model in case studies of 5 Brazilian wind farms. Finally, conclusions are presented in Section VI.

II Model Inputs

The model proposed is generic enough to have/receive as input any wind series to extend the power series. It is possible to feed the model with long wind series measured "in locus" or in meteorological stations nearby. The main requirement is that the wind series must include one of the following couples: a wind absolute speed series and a wind direction series, or series of wind speed in two orthogonal directions (both parallel to the floor).

It is common in wind resource assessment to use global reanalysis datasets. These datasets are generated by applying physical models to satellite observations. Some of the most famous datasets are NNRP, the NCAR/NCEP Reanalysis Project produced in the mid 90´s[15]; CFSR[16], produced by NOAA, National Weather Service and NCEP; ERA-Interi[17] produced by European Centre for Medium Range Weather Forecasts; and MERRA[18] produced by NASA. These last three were produced in the 2000´s with 34 years of satellite data and their latitude and longitude discretization is less than 0.5 degrees. Due to the possibility of obtaining data from these datasets for almost everywhere in the world, they were chosen to be used in this work.

III Wind and Wind Power Characteristics

The conversion from wind data to Wind Power is highly non-linear. A simplification of steady-state the response of a single wind turbine, similar to the one used in [19], is given by *Figure 1*. The figure is divided in four main segments; in the first no power is produced at all due to inertia, those low wind speeds are not enough to move the turbine; the following segment is the hardest to model because is where wind to power conversion is mostly non-linear and is the region in which the generator is operating most time; the third region of the curve is where the turbine is operating at full power; finally, in the last part of the curve, the generator does not produce any energy at all, because the elevated wind speeds can damage the generator. Multi-Turbines response is even more complex, Norgaard and Holtinen show that in [20].

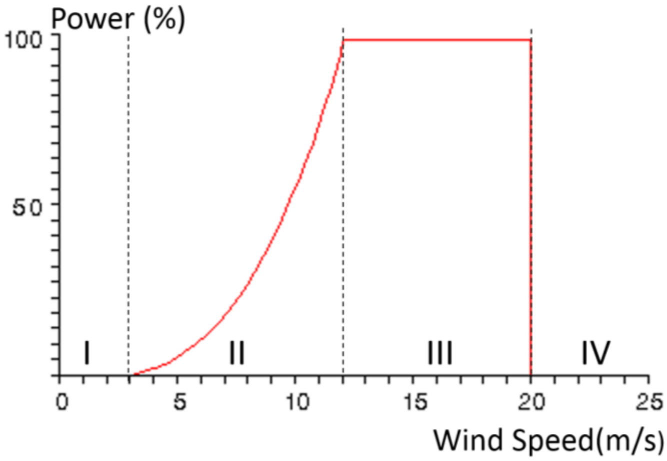

Figure 1 - Wind power transfer function

III.1 The Energy of Fluids

It is common to model the second segment of the wind power curve, see Figure *1*, as a linear function due to its huge simplicity. However we are going to use another approach to improve the model´s accuracy.

For a physically correct approach we ought to begin with the kinetic energy equation:

$$E = \frac{1}{2} m v^2 \qquad (1)$$

As said in [21] this equation is based in the fact that the mass of a moving solid is constant, wind as the motion of a fluid (air) has it density and speed varying in time, but considering the mass constant, for now, is a good approximation. Deriving equation (1) we obtain the power of moving particles:

$$P = \frac{dE}{dt} = \frac{1}{2} \frac{dm}{dt} v^2 \qquad (2)$$

The mass m of the fluid is equal to ρV, where ρ is the air density and V is the volume occupied by the fluid, on the other hand, V can be seen as the product of area(A) and length(l): $V = Al$, which can be derived in time, considering the area and density as constants:

$$\frac{dm}{dt} = \frac{d(\rho A l)}{dt} = \rho A \frac{dl}{dt} = \rho A v \qquad (3)$$

Finally, substituting (3) in (2) we obtain:

$$P = \frac{1}{2} \rho A v^3 \qquad (4)$$

This is a good simplification of the power of a moving fluid with density ρ and speed v, passing through an area A. This cubic relation between wind speed and power, which is also used in [22] and [23] [24], will be applied in the model proposed.

III.2 Wind Direction

Wind turbines are of two main types horizontal axis wind turbines (HAWT) and vertical axis wind turbines (VAWT), the second one has the interesting characteristic that wind direction is theoretically irrelevant due to its cylindrical symmetry, the power production of the first kind of turbine is affected by wind direction since wind flow facing the blades generates much more power than parallel flows. Horizontal axis turbines are the most widely used, mainly in Brazil, which is the first reason for considering wind in the model. It is true that most HAWT can move, allowing them to face wind and improve their power generation efficiency, even so this movement cost energy and is not very fast consequently this mechanism does not solve the problem.

Furthermore, empirical studies have shown that wind direction affects wind power generation. In [25] and [26], wind data is separated in eight groups of directions and then one independent curve is fitted separately for each. The approach here will take into account the direction of wind, however, we are going to consider two variables, which together represent both wind speed and wind direction, these variables will be two orthogonal values of wind speed.

III.3 Wind at different heights

Wind turbines can be installed at various heights, however wind series do not provide information for every single mast height and not rarely only provide wind data for one single height, it is usual to apply the following formula, also used in [19] and [24].

$$v = v_0 \left(\frac{h}{h_0}\right)^{\alpha} \qquad (5)$$

Where v_0 is wind speed at the original altitude, h is the new altitude, h_0 is the original altitude and α is a constant that depends on the terrain and localization, values are obtained empirically such as in [27].

III.4 Wind Power Cycles

Wind is caused by differences of pressure, which is mainly caused by the incidence of sun radiation onto earth, global winds are also affected by earth motion and these variations of wind speed and direction affect directly wind power production. Therefore, many patterns can be observed, the two most easy to observe are daily and monthly patterns. The first is mainly caused by the difference of insolation during the hours of the day, and can be enhanced or smoothed by the proximity or distance from the sea, which can conserve heat due to water's high thermic capacity. The second pattern is due to the different sun radiation in each month and season of the year. This two patterns have been studied in [28] [29] [30].

These patterns are outlined in *Figure 2*, which shows that generation in each month has significant differences, and for each hour of the day it is also possible to see wind speed variations.

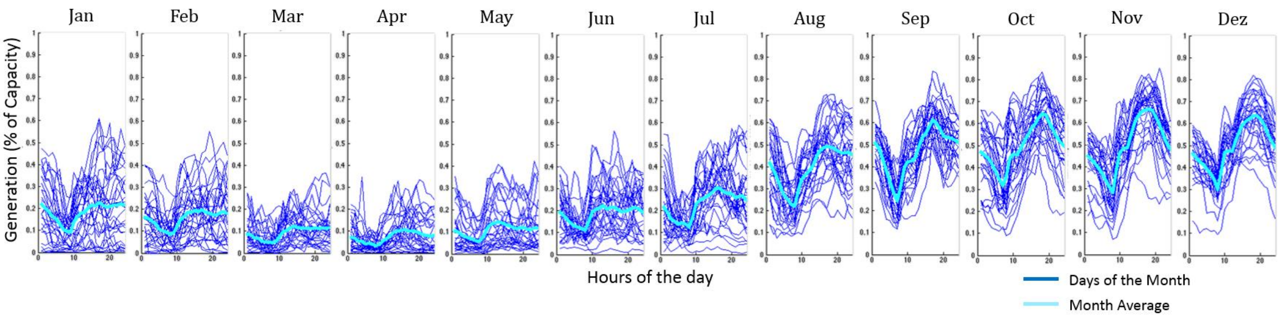

Figure 2 - Wind generation patterns for year 2011

IV The Model

After this review the model shall be presented. The extension model will be a multivariable regression [32] whose variables will be based on the previous discussion.

Firstly, the understanding of wind direction effect on wind power generation outlined in section III.2 induces us to consider somehow this variable in the model. Since wind direction is a circular variable it is hard to use it directly as a variable in a linear regression model. For instance, it is easy to see that the value 1 degree and 364 degrees are almost the same, however with a single coefficient multiplying wind direction the output would be significantly different these numbers. What is more, the probability distribution of wind direction is not rarely multimodal another effect that a linear regression cannot capture. There are two evident ways for solving this problem, the first is to make multiple regressions, one for each group of wind directions as it is done in [25][26], the second is to decompose the wind speed in two variables:

$$v_{c_i} = v_{0_i}\, cos(\phi) \quad (6a)$$
$$v_{s_i} = v_{0_i}\, sin(\phi) \quad (6b)$$

Where v_0 is the original wind is speed and ϕ is the wind direction. Now we have to orthogonal wind speeds that together represent both wind speed and wind direction.

From section III.1 we found evidence that a model to capture wind proportionality to wind power should consider the cube of the wind speed. The speed to power curve of a generator can be modeled in many ways with polynomials, piecewise linear or piecewise polynomials [19]. [22] shows that the power curve in a single generator can be modeled with high accuracy with a third degree polynomial, thus we are going to use this approach here, even though we are trying to model an entire farm.
By now we have the following model:

$$Power_i = \beta_0 + \beta_1 v_{s_i} + \beta_2 v_{s_i}^2 + \beta_3 v_{s_i}^3 + \beta_4 v_{c_i} + \beta_5 v_{c_i}^2 + \beta_6 v_{c_i}^3 + \varepsilon_i \quad (7)$$

Where ε_i is a random error for period i.

One might say that the transformation of wind from its original altitude to wind in the altitude of the generators should be done, but the widely used model, presented in section III.3 consists in simply multiplying the wind by a constant, thus this operation is not necessary because this constant will be "included" in the variable multipliers decided by the regression model.

The last step is to take into account the knowledge of wind cycles evidenced in section III.4. In order to consider these seasonal and diurnal cycles' dummy variables will be added to the model. The model can be applied for datasets in many different time resolutions. Depending on the discretization daily dummies we are possible to be used or not. The usually series like these have hourly resolution, so the model will include on dummy for each hour of the day and a dummy for each month of the year, consequently the average generation of each hour at each month will be considered in the proposed model. Dummy variables for day hour are very good for enhancing the model accuracy, but they can be discarded or changed by other dummy if the data is in a different resolution.

The model now is:

$$Power_i = \beta_0 + \beta_1 v_{s_i} + \beta_2 v_{s_i}^2 + \beta_3 v_{s_i}^3 + \beta_4 v_{c_i} + \beta_5 v_{c_i}^2 + \beta_6 v_{c_i}^3 + \varepsilon_i + hour(i)_{dummy} + month(i)_{dummy} \quad (8)$$

Where $month(i)_{dummy}$ is the month to which period i belong, for $hour(i)_{dummy}$ the idea is the same. The whole process is shown in *Figure 3*.

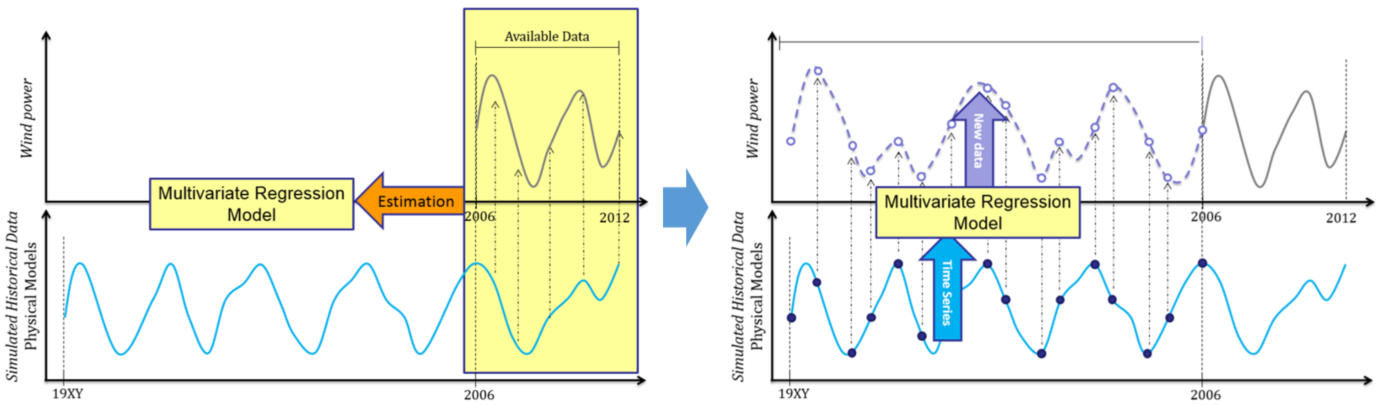

Figure 3 - Wind power series extension process

IV.1 A first enhancement

Different data sets usually contain different information, which can be seen in Figure *4* where a scatterplot of wind speed from NNRP dataset and ERA-Interim is shown. Although there is an evident linear relation between the sets, but the data spread is significant and the intercept is not in the origin, these characteristics evidence the difference of the sets.

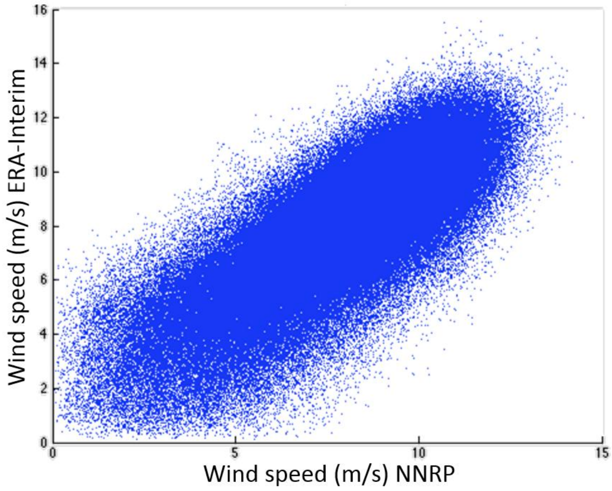

Figure 4 - Comparisson between different datasets

Therefore it is possible to include multiple datasets in the regression model giving rise to the following model:

$$Power_i = \beta_0 + \sum_{k \in DS} \beta_{1,k} v_{s_{i,k}} + \beta_{2,k} v_{s_{i,k}}^2 + \beta_{3,k} v_{s_{i,k}}^3 + \beta_{4,k} v_{c_{i,k}} + \beta_{5,k} v_{c_{i,k}}^2 + \beta_{6,k} v_{c_{i,k}}^3 + \varepsilon_i + hour(i)_{dummy} + month(i)_{dummy} \qquad (9)$$

Where *DS* the set of wind data sets.

IV.2 A Non-Linear Adjustment

Since the model is based on a regression with wind and dummies variables it can have as output some physically impossible information. There is nothing in the model that prevents it from outputting negative generation and generation larger than a hundred percent of the installed capacity of the farm. Empirical tests have shown that these cases do not occur with significant frequency, to the following procedure of does not insert much non-linearity in the model.

$$\begin{aligned} &if\ Power_i > 1\ then \\ &\quad Power_i \coloneqq 1 \end{aligned}$$

$$\begin{aligned} &if\ Power_i < 0\ then \\ &\quad Power_i \coloneqq 0 \end{aligned}$$

With this procedure the model is completely determined and it is physically consistent.

V Case Studies

The developed model was applied in five wind farms in Brazil: Icaraizinho, Bons Ventos, Enacel and Canoa Quebrada in the north-east and Sangradouro in the south. The hourly power production time series and basic information such as their localization, installed power capacity and the date of beginning of commercial operation was obtained from ONS and MME (Brazilian Energy Secretary). That information is disposed in Table *1*.

Name	**Beginning of Operation**	**Localization**		**Capacity (MW)**
Icaraizinho	October 2009	03º21’56’’S	39º49’58’’W	54.6
Bons Ventos	February 2010	04º27’19’’S	37º45’14’’W	57.0
Canoa Qubrada	January 2010	04º32’02’’S	37º41’28’’W	50.0
Enacel	March 2012	04º33’05’’S	37º44’43’’W	31.5
Sangradouro	September 2006	29º55’30’’S	50º18’00’’W	50.0

Table 1 - Brazilian wind farms in the case study

The plants localization was used to obtain reanalyzed wind series from NNRP, ERA-Interim datasets. The reanalyzed wind series have hourly resolution beginning at January first 1981 and ending at September thirtieth 2012. Some of the series have wind polar representation, speed and direction are separated, other have wind in Cartesian representation, two orthogonal wind speed series. The model needs the wind series in the second form, so whether they are disposed in the first form they are converted following the methodology proposed in equations 6a and 6b from section IV.

In order to compare easily the results of the extension of different power plants their hourly generation was normalized, by simply dividing their generation by their nominal power, thus the generation in the case studies will be in percentage of generation.

Firstly we will present the detailed results of the application of the methodology for one of the plants, Icaraizinho, and then the results for the remaining plants will be presented in a simplified way.

The Described Model was applied to the corresponding data for the plant of Icaraizinho. The regression was done in hour resolution. The data was extended in sample to check the accuracy of the model, which means that after the regression coefficients were obtained via ordinary least squares we the model was applied in sample. The result is displayed in Figure *5*, which show in blue the original data from the power plant generation, and in red is the in sample modeled data, the modeled data.

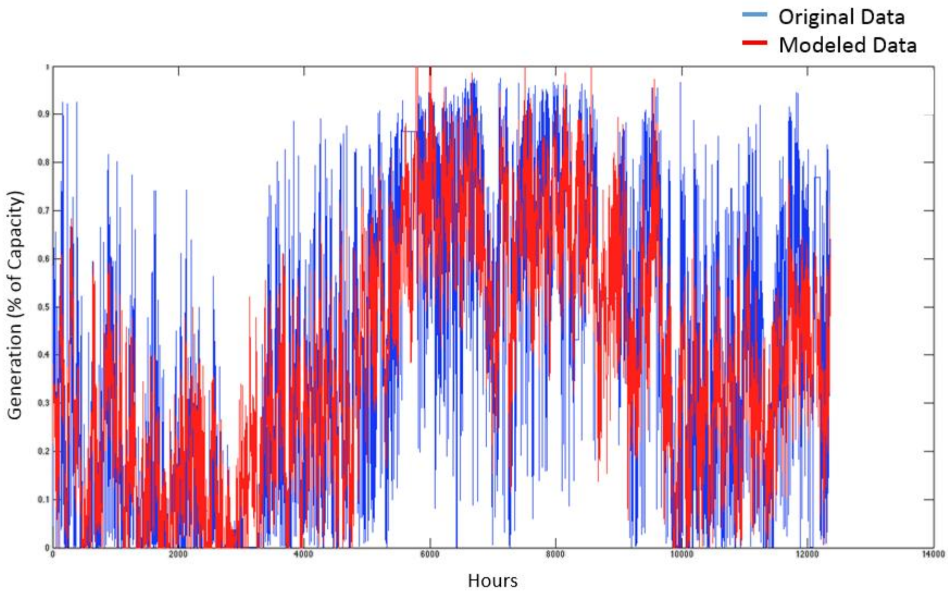

Figure 5 - Icaraizinho hourly generation time-series

It is possible to see that many patterns were caught by the model since the red line is following the blue one. However, one can note that generation spikes, up spikes or down spikes, are hardly caught by the model, that is due to the fact that in this study, it was used meteorological data from reanalysis datasets, therefore the wind data is not the exact verified wind in that spot. [22] and [26] for instance use on site measured data, in such case it would be possible to caught more spikes.

More statistical tests were performed to provide us a wider understanding of the model behavior. Figure *6* is the histogram of the model error, i.e., the difference between the original data and the modeled data. Figure *8* is a QQ-Plots that contrasts de original and the modeled data if shows once more that extreme generation either very high or very low are hardly captured, though as said before this fact is mostly due to the input series. Finally, Figure *7* is the error plot, i.e., the series originated from the difference between original and modeled data most of the time the absolute difference is smaller than 20% however many spikes cross this error margin.

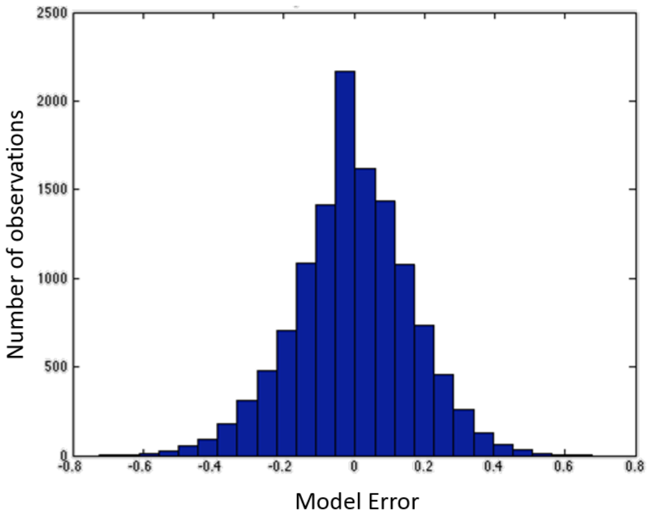

Figure 6 - Histogram of the model error in hour resolution

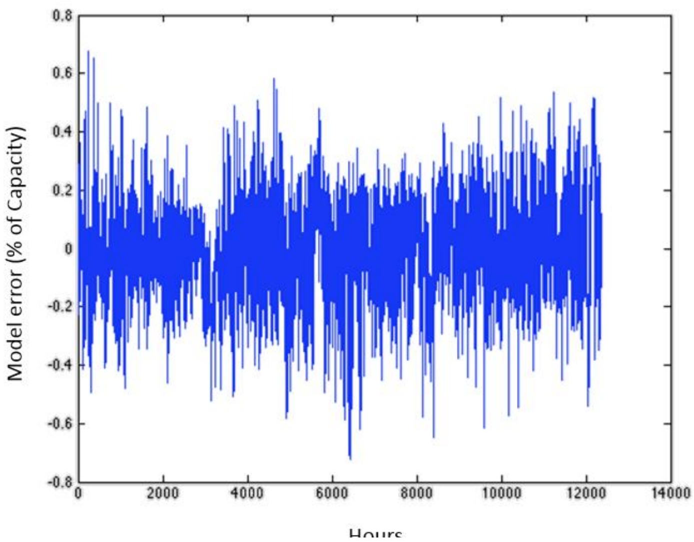

Figure 7 – Model’s Error plot in hour resolution

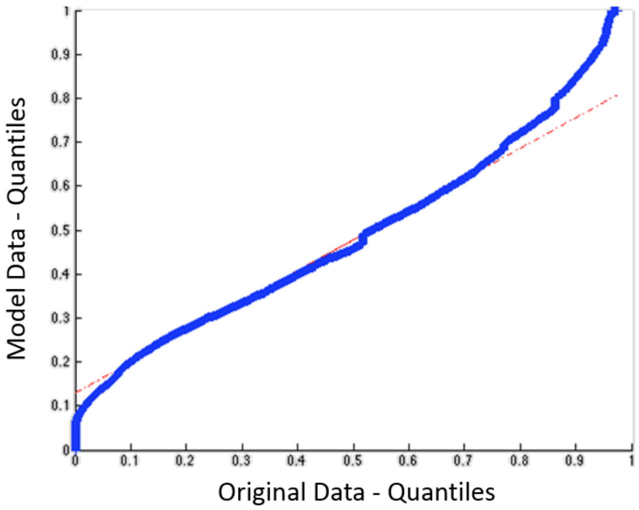

Figure 8 - QQ-plot in hour resolution

As said before, results in other resolutions such as days, weeks and months are extremely valuable and in many occasions they are the exact kind of data needed, for instance, week and month data used by Brazilian investors since the contracts in Brazil are settled in monthly or weekly basis. Thus we go further in this study to present results for this other resolutions.

The results that follow were obtained by averaging the model output presented above. Firstly, Figure *9*, Figure *10* and Figure *11* show the analogous results for daily resolution.

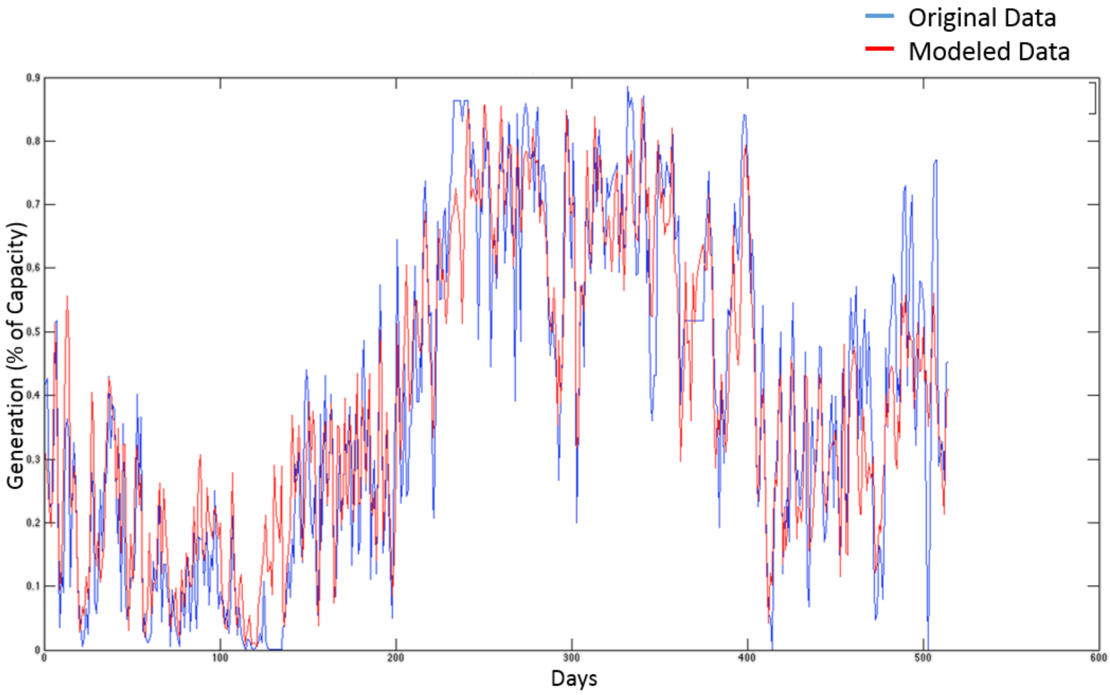

Figure 9 - Icaraizinho daily generation time-series

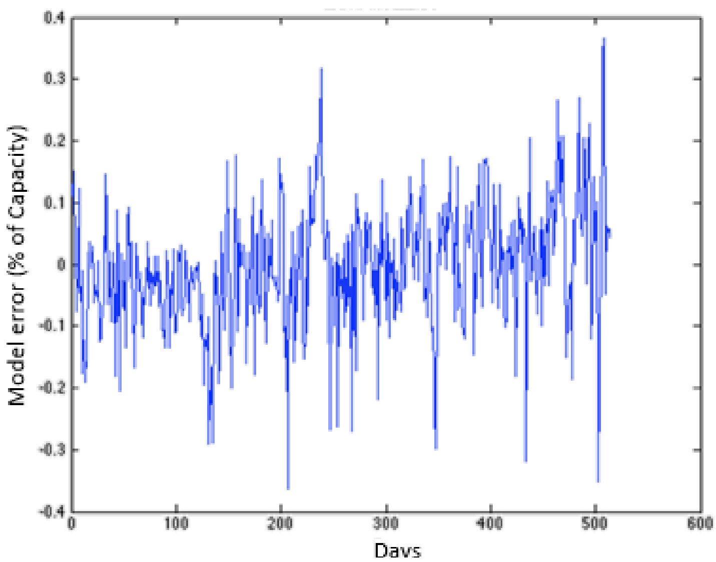

Figure 10 - Model’s Error plot in day resolution

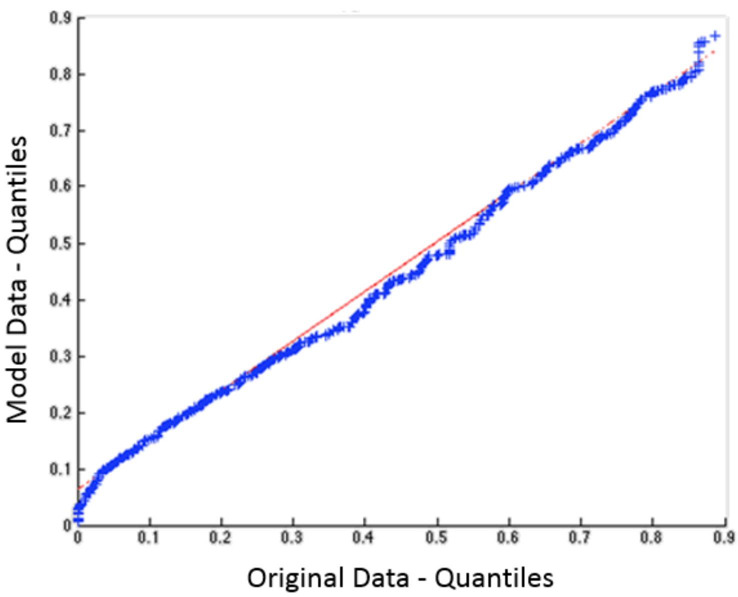

Figure 11 - QQ-plot in day resolution

Now, one can see that even extreme value were well modeled, the quantiles of modeled and original data coincide a lot and the error is now mostly contained in 10% margin. Daily averages are more well behaved than hourly values and do not have lots of up and down spikes, so the reanalyzed data from the datasets make it possible to have this far better fit.

Figure *12*, Figure 13 and Figure *14* show the results for weekly resolution:

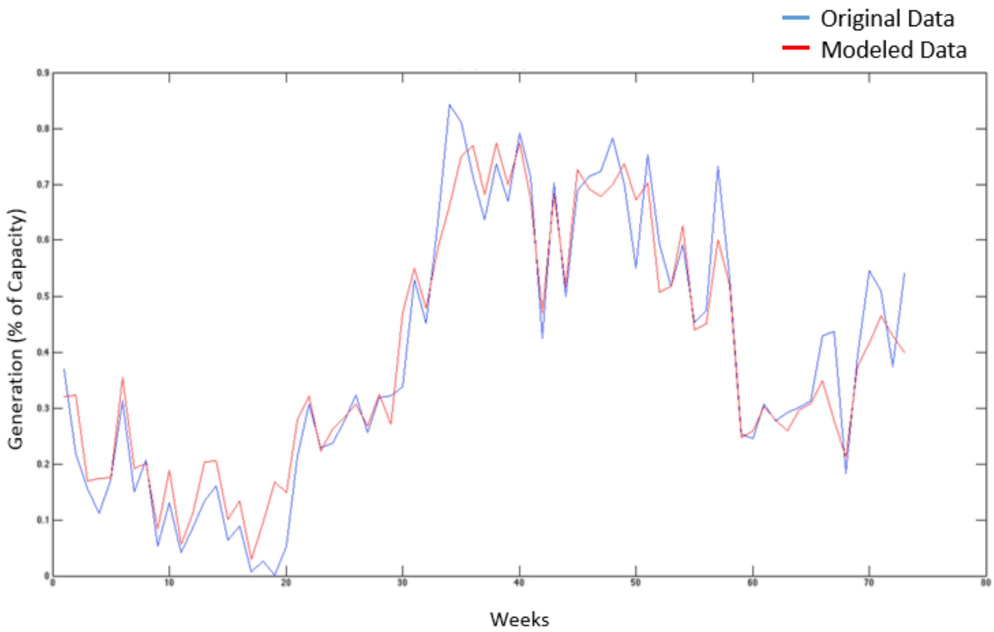

Figure 12 - Icaraizinho weekly generation time-series

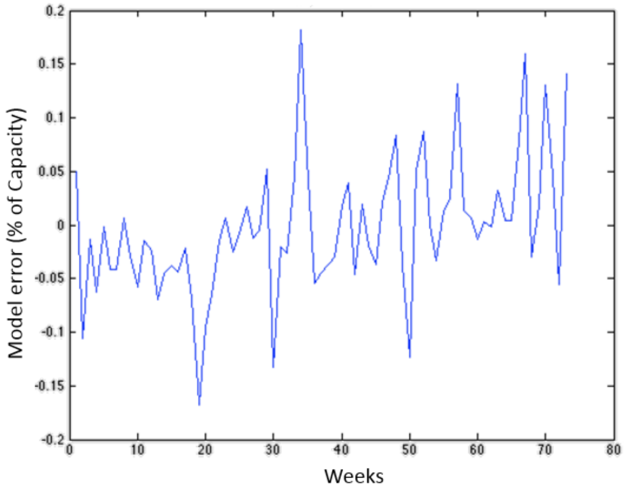

Figure 13 - Model's Error plot in week resolution

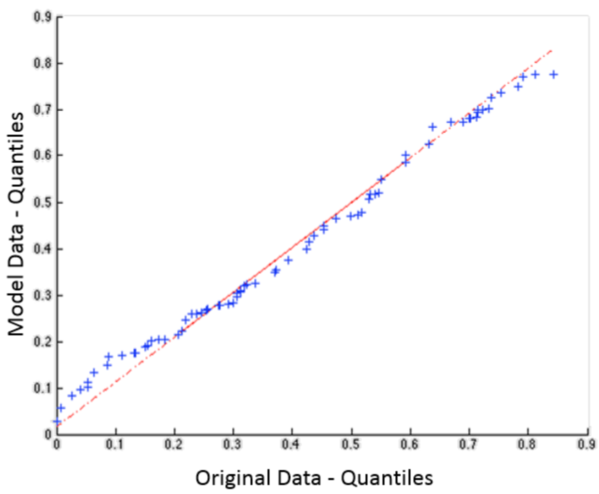

Figure 14 - QQ-plot in week resolution

At this point the model output is capturing almost all the information contained in the power generation series, the adherence statistics shown in table are extremely satisfactory, figure shows that extreme values are being modeled and figure shows that the absolute error is almost never more than 15% and most of the time it is smaller than 5%.

At last *Figure 15*, *Figure 16* and *Figure 17* show the results for monthly resolution. One can observe that the model is even better than the already good results from weekly resolution, the absolute error is always smaller than 8% and it is usually smaller than 4%.

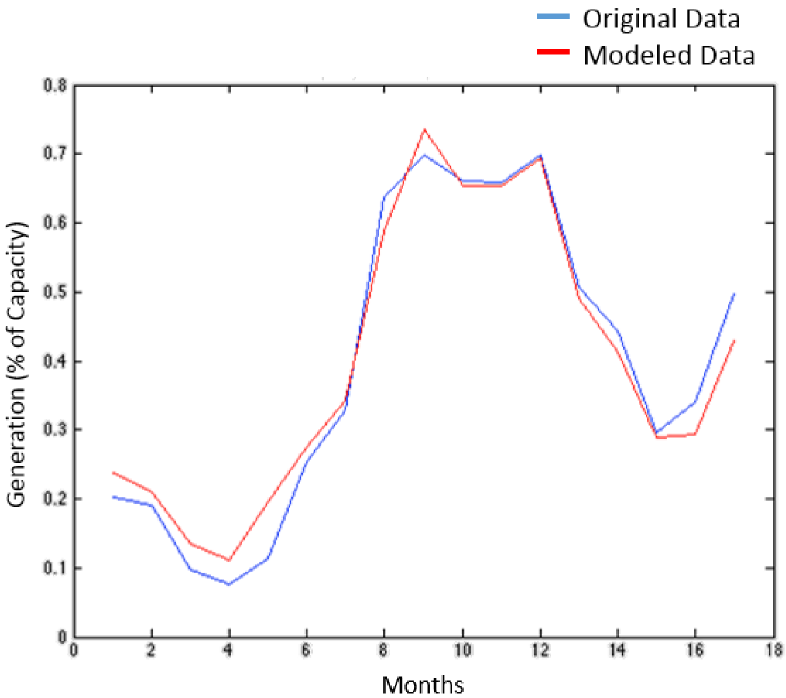

Figure 15 - Icaraizinho monthly generation time-series

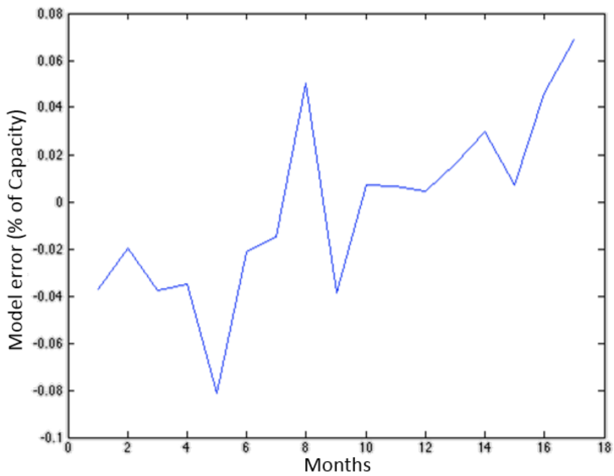

Figure 16 - Model’s Error plot in month resolution

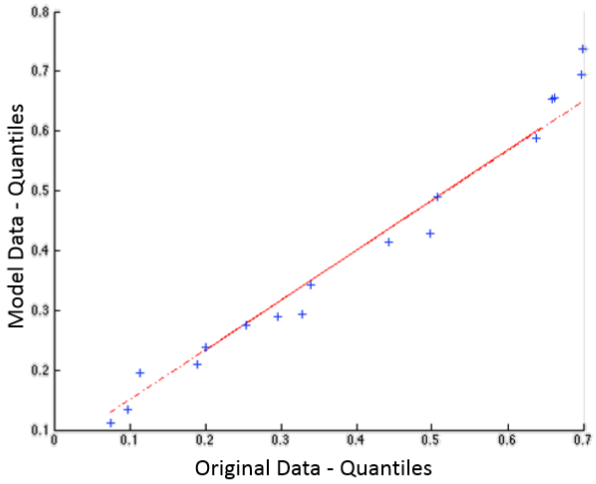

Figure 17 - QQ-plot in month resolution

Completing the case study, the adherence statistics of the remaining wind farms are presented in Table *2*, R2 is the r-square, MAE is the mean absolute error and MSE stands for mean square error. NE and S stand for North-east and South of Brazil respectively.

Name	Region		Hourly	Daily	Weekly	Monthly
Icaraizinho	NE	R2	0.705	0.8517	0.9285	0.9699
		MAE	0.1264	0.0753	0.0467	0.0307
		MSE	0.0272	0.01	0.004	0.0014
Bons Ventos	NE	R2	0.6881	0.8472	0.9452	0.9805
		MAE	0.1229	0.0647	0.0337	0.0193
		MSE	0.0266	0.0069	0.0018	0.0005
Enacel	NE	R2	0.6833	0.8457	0.9421	0.9725
		MAE	0.1245	0.0645	0.0351	0.0241
		MSE	0.0264	0.0068	0.002	0.0008
Canoa Quebrada	NE	R2	0.6825	0.8444	0.9374	0.9728
		MAE	0.128	0.0685	0.0366	0.0203
		MSE	0.0286	0.0076	0.0023	0.0008
Sangradouro	S	R2	0.6489	0.8057	0.8735	0.9753
		MAE	0.142	0.0828	0.0352	0.0114
		MSE	0.0372	0.0123	0.0018	0.0002

Table 2 - Statistical tests for case study

This table is a simplified way of showing the results for many plants, the pattern is the same as the observed in Icaraizinho case. Hourly extension works well and are satisfactory approximations of reality, daily averaging are capturing plenty of information and weekly and monthly extensions exhibit outstanding approximations.

VI Conclusions

The results presented in the last section illustrate how accurate the model behaves in each time resolution, the extension of all the plants in the case study turned to be statically satisfactory approximations of reality with improving results as we obtain larger resolutions. Hourly and daily series are useful for primary studies since they are good approximation, final studies in these resolutions would require on site measurements. Weekly and monthly series show excellent results, thus they can be widely used by agents of the sector for purposes of certification, expansion planning, operation in countries like Brazil in which the system is operated in resolution such as weekly and monthly, this data can also be used by the private sector for investment planning.

Future developments include the application of the developed methodology to wind power series extension with on-site data.

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References

[1] S. Sawyer, K. Rave, "Global Wind Report – Annual Market Update 2012," GWEC,Global Wind Energy Council.

[2] Plano Decenal de Expanção de Energia, EPE, empresa de pesquisa energética, and MME, ministério de Minas e Energia, disponible at: http://www.epe.gov.br/PDEE/Forms/EPEEstudo.aspx

[3] A. Street, L. Freire, and D. Lima, "Sharing Quotas of Renewable Energy Hedge Funds: a Cooperative Game Theory Approach." in Proc. IEEE PES General Meeting 2011, Trondheim, Norway.

[4] L. A. Barroso, J. Rosenblatt, B. Bezerra, A. Resende, and M. V. Pereira,"Auctions of contracts and energy call options to ensure supply adequacy in the second stage of the Brazilian power sector reform," in Proc. IEEE PES General Meeting, Montreal, QC, Canada, 2006.

[5] A. Street, L.A. Barroso, S. Granville, and M.V. Pereira "Offering Strategies and Simulation of Multi Item Dynamic Auctions of Energy Contracts," IEEE Trans. Power Syst., vol.26, no.4, pp.1917-1928, Nov. 2011.

[6] PROINFA – Programa de Incentivo às Fontes Alternativas de Energia Elétrica. [Online]. Disponível em: http://www.mme.gov.br/programas/proinfa/.

[7] F. Porrua, B. Bezerra, P. Lino, F. Ralston, M. Pereira, "Wind power insertion through energy auctions in Brazil," Power and Energy Society General Meeting, 2012 IEEE, Mineapolis, MN, United States

[8] M.V. Pereira, L.A. Barroso, and J. Rosenblatt, "Supply adequacy in the Brazilian power market," IEEE Power Engineering Society General Meeting 2004, vol. 1, pp. 1016-1021, June 2004

[9] M.V. Pereira and L.M. Pinto, "Multi-Stage stochastic optimization applied to energy planning," Mathematical Programming, vol. 52, no.1-3, pp. 359-375, 1991.

[10] E. Faria, L. A. Barroso, R. Kelman, S. Granville, and M. V. Pereira,"Allocation of Firme-energy rights among hydro plants: An Aumann-Shapley approach," IEEE Trans. Power Syst., vol. 24, no. 2, pp.541–551, May 2009.

[11] L. Liang, J. Zhong, J. Liu, P. Li, C. Zhan, Z. Meng, "An implementation of synthetic generation of wind data series," in Innovative Smart Grid Technologies (ISGT), 2013 IEEE PES, Washington, DC, United States.

[12] L. Wang, M. Goldberg, X. Liu, L. Zhou, "Assessment of reanalysis datasets using AIRS and IASI hyperspectral radiances," Geoscience and Remote Sensing Symposium (IGARSS), 2010 IEEE International, Hoholulu, United States.

[13] Kubik, M. L., Brayshaw, D. J., Coker, P. J. and Barlow, J. F. "Exploring the role of reanalysis data in simulating regional wind generation variability over Northern Ireland," Renewable Energy, vol.57, pp. 558-561, September 2013.

[14] C. W. Potter, H. A. Gil, J. McCaa, “Wind Power Data for Grid Integration Studies,” Power Engineering Society General Meeting, 2007. IEEE, Tampa, FL, United States.
[15] NNRP dataset webpage: http://www.esrl.noaa.gov/psd/data/gridded/data.ncep.reanalysis.html
[16] CFSR dataset webpage: http://cfs.ncep.noaa.gov/cfsr/
[17] ERA-Interim dataset webpage: http://www.ecmwf.int/research/era/do/get/index
[18] MERRA dataset webpage: http://gmao.gsfc.nasa.gov/merra/
[19] V. Thapar , G. Agnihotri , V. Krishna Sethi, “Critical analysis of methods for mathematical modelling of wind turbines,” Renewable Energy 36 (2011) 3166-3177- ALTITUDE, PIECEWISE
[20] P. Norgaard, H. Holttinen, “A Multi-Turbine Power Curve Approach,” Nordic Wind Power Conference March 2004.
[21] A. W. Manyonge, R. M. Ochieng, F. N. Onyango, J. M Shichikha, “Mathematical Modeling of Wind Turbine in a Wind Energy Conversion System: Power coefficient Analysis,” Applied Mathematical Sciences, Vol. 6, 2012, no. 91, 4527-4536
[22] S. Akdag, O. Guler. “Comparison of Wind Turbine Power Curve Models,” International Renewable Energy Congress, 2010, Sousse, Tunisia.
[23] Z. Olaofe, K. Folly, “Wind energy analysis based on turbine and developed site power curves: A case-study of Darling City,” Renewable Energy, vol.53, pp. 306-318, May 2013.
[24] M. Hasani-Marzooni, S. Hossein, “Dynamic model for market-based capacity investment decision considering stochastic characteristic of wind power,” Renewable Energy, vol.36, issue 8, pp.2205-2219, August 2011.
[25] Y. Wan, E. Ela, and K. Orwig, “Development of an Equivalent Wind Plant Power-Curve,” NREL, National Renewable Energy Laboratory. Presented at Wind Power 2010.
[26] IEC 61400-12-1 Ed.1: Wind turbines - Part 12-1: Power performance measurements of electricity producing wind turbines, International Electrotechnical Commission, 2005
[27] Z. Đurisic, J. Mikulovic, “A model for vertical wind speed data extrapolation for improving wind resource assessment using WAsP,” Technical Note, Renewable Energy 41 (2012) 407-411.
[28] C. W. Potter, A. Archambault, K. Westrick, “Building a smarter smart grid through better renewable energy information,” Power Systems Conference and Exposition, 2009. PSCE '09. IEEE/PES, Seattle, United States.
[29] A. Hasson, N. AL-Hamadani, A. AL-Karaghouli, “Comparison between measured and calculated diurnal variations of wind speeds in northeast Baghdad,” Solar & Wind Technology, Vol. 7, No. 4. Pp 481-487, 1990.
[30] R. Belu, D. Koracin, “Wind characteristics and wind energy potential in western Nevada,” Renewable Energy, Vol. 34, Issue 10, October 2009, Pages 2246-2251
[31] J. M. Wooldridge. “Introdutory Econometrics A Modern Approach,” 4.ed. South-Western Cengage Learning.
[32] W. Hines, D. Montgomery, D. Goldsman, C. Borror, “Probability and Statistics in Engineering” 4th.ed. Wiley, 2003.
[33] “Acompanhamento Mensal da Geração de Energia das Usinas Eolielétricas com Programação e Despacho Centralizados pelo ONS”, ONS, Operador Nacional do Sistema, Fevereiro 2012, Disponible at: http://www.ons.org.br/resultados_operacao/boletim_mensal_geracao_eolica