SHORT TERM WIND GENERATION FORECAST AND OPTIMAL WIND FARM MAINTENANCE SCHEDULES MODEL - ELAEE

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Abstract

Wind farms must periodically take their turbines offline in order to perform scheduled maintenance repairs. This interruption impacts the energy generation of the wind farm, so ideally, maintenance should be scheduled for periods with the lowest wind speeds, which for the Brazilian NE region, occurs between March and May. In addition, in order to fulfill contractual obligations, any shortfall in energy production must still be covered by purchasing energy in the spot market, which is volatile. Thus, determining the optimal time to begin maintenance work in a wind farm is a function of both the expected wind speeds and electricity spot prices.

In this article we develop a model to determine the optimal maintenance schedule in a wind farm based of forecasted wind speeds and energy prices. We analyze a window of 15 weeks in the most likely period of the year, and perform weekly updates of expected wind speeds and energy price forecasts. Wind speeds are forecasted an (ARMAX) model, where monthly dummies are used as exogenous variables to capture the seasonality of wind speeds. Spot prices are simulated under the Newave dual stochastic programing model for a 15 week period beginning in March.

The optimal stopping decision is modeled as an American type real option in a modified ABM binomial lattice. We use actual data from a wind farm in the Brazilian NE, and will compare our results with the current practice and also with maintenance scheduling with perfect information, in order to determine the efficiency of the model.

Keywords: Wind farm, Wind forecasting, Maintenance, Real Options

1 - Introduction

Wind energy production in Brazil has grown substantially in recent years and has been gaining importance in the Brazilian energy matrix. By 2015, wind power ranked third in the matrix, representing 6.2% of the total energy produced. An increase of 1,700 MW in wind power generation was expected for the year 2016, and an additional 5,959 MW by 2018 (ANEEL, 2016). Under this scenario, more precise power generation forecasting have become increasingly important for the system operator and also for planning purposes and applications of private power companies.

One such application is the determination of the optimal moment for the maintenance stops of the wind farm equipment, considering the opportunity cost of the park´s energy generation. Wind farms must periodically take their turbines offline in order to perform scheduled maintenance repairs, which negatively affects the energy generation of the wind farm. All other thing equal, the cost of going offline when the park is producing high volumes of energy is greater than when the park is undergoing low winds periods. Rainfall is also negatively correlated with wind speeds, so ideally, interruptions should be planned for periods of high precipitation and low wind speeds, which for the Brazilian NE region, occurs between March and May. But in order to do so, a wind forecasting model is necessary.

In addition, wind farms must deliver the amount of energy stated in their sales contract, so any shortfall must be purchased in the short-term spot market, which adds an additional uncertainty to the scheduling decision. Thus, the optimal maintenance schedule will be the one that minimizes stoppage costs, which are a function of future wind speeds and electricity spot prices. Given that the flexibility of choosing the optimal stop time has the option characteristics, option pricing methods will be used to determine the decision trigger curve.

We develop a model to determine the optimal maintenance scheduling in a wind farm based of forecasted wind speeds and future energy spot prices. We analyze a window of 15 weeks in the most promising months of the year, and perform weekly updates of the wind and price forecasts. Wind speeds are forecasted an (ARMAX) model, where monthly dummies are used as exogenous variables to capture the seasonality of wind speeds. Spot prices are simulated under the Newave dual stochastic programing model for a 15 week period beginning in March. The optimal stopping decision is modeled as an American type real option in a modified ABM binomial lattice. We use actual data from a wind farm in the Brazilian NE, and compare our results with current practice and with maintenance scheduling with perfect information.

This paper is organized as follows. After this introduction we provide a brief review of the relevant literature in real options and wind and energy forecasting models. In section 3 we develop the wind forecasting model, and in section 4 we show how the optimal scheduling stop problem can be modeled under the real options approach. In section 5 we apply the model to the case of a wind farm in the NE region of Brazil using actual wind farm and regional weather data, and show the results. Finally we conclude.

2 – Literature Review

Wind Energy

The generation of energy worldwide through wind farms has grown significantly in the last decade, reaching 456,486 MW as of June 2016 (WWEA, 2016) China, United States, Germany, India and Spain are the largest wind power producers in the world (Table 1) and together represent 67% of this source of energy.

Country	2013	2014	2015	June 2016
China	91,324	114,763	148,000	158,000
United States	61,108	65,754	73,867	74,696
Germany	34,660	40,468	45,192	47,420
India	20,150	22,465	24,759	27,151
Spain	22,959	22,987	22,987	22,987
United Kingdom	10,711	12,440	13,614	13,940
Canada	7,698	9,694	11,205	11,298
France	8,254	9,296	10,293	10,861
Brazil	3,466	5,962	8,715	9,810
Italy	8,551	8,663	8,958	9,101
Sweden	4,470	5,425	6,029	6,338
Poland	3,390	3,834	5,100	5,300
Turkey	2,959	3,763	4,718	5,146
Denmark	4,772	4,883	5,064	5,089
Portugal	4,724	4,953	5,034	5,040
Rest of the World	29,718	35,968	41,409	44,309
Total	**318,914**	**371,317**	**434,944**	**456,486**

Table 1: Wind Energy Capacity (MW): June 2016. Source: WWEA, 2016

In Brazil, in 2016, there was an increase in installed capacity of 2,564 MW, reaching a total of 10,092 MW by year end. The states of Rio Grande do Norte and Ceará, in the Northeast Region, contributed most to the increase, adding 1,520 MW (ANEEL, 2016). The Northeast Region represents the greatest wind potential in the country due to the quantity and constancy of the winds.

One of the problems regarding wind energy is the difficulty to predict wind speeds, and consequently, power generation, which makes it difficult both to make the wind farm valuation and to plan maintenance interruptions. Therefore, it is important for this sector the development of models that can more accurately provide the forecast of the winds / generation and indicate the optimal times of equipment stops.

Reliability and Maintenance

The purpose of maintenance is to extend the life of equipment and increase the time between two faults. Reliability and maintenance are connected, and the numerical relationship between these two concepts has been proved by (Patra, Mitra, & Earla, 2006).Wind farm equipment needs maintenance and when a wind turbine is taken offline for maintenance purposes there is a loss of generation, so there is an opportunity cost involved in maintenance routines. This way, the shutdown of the equipment must be done in such a way as to minimize any financial losses.

The maintenance program must be able to ensure good reliability indexes for the system and its components, however, it should be noted that the maintenance program is only one of the tools to ensure the high reliability of the system and its components. The times observed between intrinsic device failures can be controlled by maintenance programs directed to the device. These actions are classified as internal maintenance (Endrenyi et al., 2004). Endrenyi et al. (2001) describe the handling of maintenance by showing and comparing the maintenance program's impact on system reliability through the deterministic and probabilistic approaches.

Optimal maintenance policies should minimize downtime but also unsure lower costs. Both loving care and emergency replacement lead to higher costs and excessive breakdowns. Complex systems, higher costs of labor and materials and increased quality requirements made the need of proper maintenance techniques been emphasized by many authors (Sherif & Smith, 1981)

Dynamic programming has been the primary method for maintenance models, where the stochastic element is time-to-failure. Maintenance models may be divided into two categories: the class in which the equipment fails stochastically and its actual state is not known and the class of preventive maintenance models in which the state of the equipment is always known (McCall, 1965).

Wind Forecast

The nature of wind energy is different from the more traditional means we know. Energy is generated through the passage of air flow through the blades of wind turbines. This airflow varies widely and is influenced by different factors such as weather conditions, seasonality, terrain and nearby turbines (Ahlstrom et al., 2005).

Wind forecasting is challenging for two reasons: generation variation over the time horizon and low wind predictability. Even advanced forecasting models can generate vastly different forecasts due to the non-linear characteristics of the atmospheric system (Archer et al., 2017). Pinto et al. (2014) emphasize that both speed and wind direction are variables that are difficult to accurately simulate due to their large variability in time and space, due to the effects of surface ruggedness, type of landscape, vegetation and soil cover throughout the year. Several other meteorological phenomena also influence the atmospheric dynamics in northeastern Brazil, such as the location of the Area of Intertropical Convergence (ZCIT), which impacts the direction and intensity of the winds, anomalies in the temperatures of the Pacific Ocean.

The operating strategies of the systems are based on generation forecasts. Sophisticated algorithms are used to provide this prediction and when there is a divergence between the predicted value and the actual value, the costs to provide the energy to the consumer are likely to grow compared to the optimized plan (Ahlstrom, et al., 2005).

Real Options

Financial options are contracts that provide the holder the right, but not the obligation, to buy or sell an asset for a pre-established price at a certain future date. A wind farm has the flexibility to delay the start of maintenance if it deems this is not the best time to do so. This flexibility has option like characteristics, and thus, can be modeled as a problem of real options, as it involves real, rather than financial assets.

The real options methodology derives from the financial options pricing methodology developed in the 1970s by (Black & Scholes, 1973) and (Merton, 1973) (BSM) which developed an analytical formula for valuing European options. Tourinho (1979) extended the work of BSM to the valuation of a natural resource reserve which had a perpetual extraction option, and was the pioneer in the application of these methods to the valuation of real assets.

A real option is the flexibility a manager has to make decisions on real assets. As new information emerges and uncertainties about the future cash flows are revealed, the manager can make decisions that will positively influence the final value of the project. An investment decision that can be deferred is analogous to an American type purchase option, which is one that can be exercised at any time up to maturity, and where the underlying asset is the present value of the project and the strike price is the investment cost (McDonald & Siegel, 1986).

The option to temporary shutdown an investment is calculated in a way analogous to the European option purchase option and the asset is the cash flow produced by the operating income and the exercise price is the variable cost of production (McDonald & Siegel, 1985). The option to permanently shut down a project was evaluated by Myers and Majd (1983). A model in which the expansion option is exercised continuously was developed by Majd and Pindyck (1987). The interactions between options and value creation and destruction are evaluated by Trigeorgis (1993). Dixit and Pindyck (1994) makes a general and quite complete overview of the development of the Real Options Theory in continuous time. Discrete-time models are widely discussed in Trigeorgis (1995).

3 – Wind Forecasting Model

The share of wind sources in the energy matrix worldwide was practically nil in the early 1980s. By 2015, wind energy accounted for 3.5% of the world total. (MME, 2014) Wind energy, like other renewable energies, has been gaining importance in the energy matrix in Brazil and in the world. The 2024 Ten Year Energy Expansion Plan (MME, 2015) indicates that wind power generation is expected to reach 24 GW/year by 2024. The northeast region is the most representative in the generation because it is an area with a high incidence of winds and should generate 90% (21.6 GW) of this total.

The Ministry of Mines and Energy (MME) forecasts that there will be a significant expansion in wind energy worldwide, reaching 2600 GW capacity by 2050 (MME, 2016). The MME also estimates that wind energy has a total potential above 70,000 GW worldwide. In this context, wind power generation models become increasingly necessary for industry. Activities such as scheduling maintenance are heavily dependent on wind farm generation forecasting and more accurate forecasting models generate returns relevant to companies.

For the construction of the forecasting and testing model, generation data from January 2010 to December 2016 was selected for a wind farm in operation in the state of Ceará, in the Northeast of Brazil. The selected period is long enough to capture the typical seasonality of this type of series and econometric models that have been tested. The following exogenous climatic variables were also considered: Rain and South Atlantic Convergence Zone (ZCAS). The exogenous variable ZCAS has greater influence in the months of January to December, while rain influences the series with greater intensity in the months of March and June. For this work will model the of the generation series from the months of March to June, and also the influence of the exogenous rain variable.

To set up the historical series for the application and validation of the generation forecast model, we use as base the generation data of a wind farm located in the state of Ceará. The wind farm has turbine power metering equipment in place since November 2014, with the operating data updated daily. For forecasting purposes, generation data was adjusted to disregard the effects of the unavailability of the equipment.

To capture the effects of seasonality, a longer historical series is needed, but as the wind farm was not in operation before 2014, no data is available. However, it was possible to construct a synthetic series based on wind data measured at a local measuring station. Figure 1 shows the wind farm energy generation in the period since 2014.

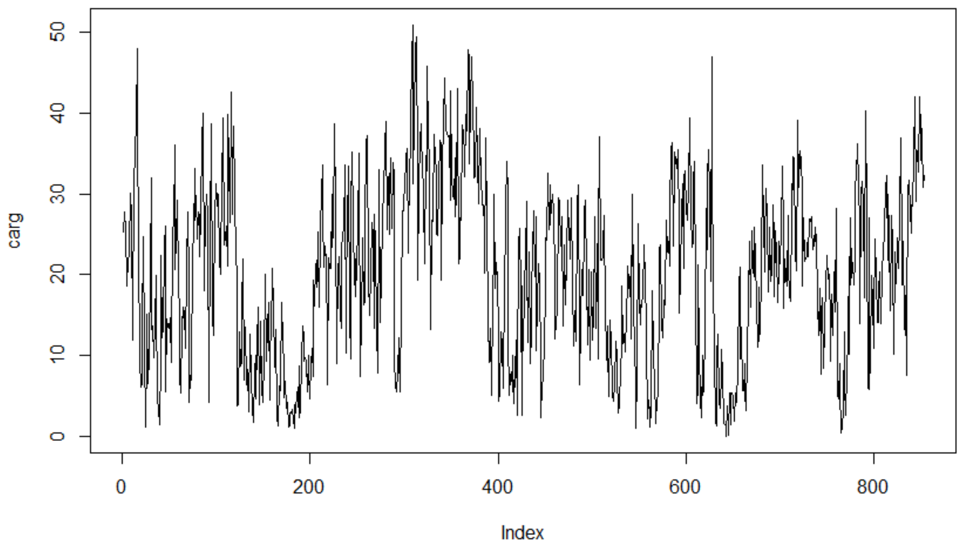

Figure 1

Rainfall data were obtained from the Cearense Foundation for Meteorology and Water Resources (FUNCEME). The foundation has several measurement stations in the Northeast and the stations with the closest proximity to the wind park were selected for analysis. It is observed that in periods of higher rainfall, the wind and, consequently, the generation of the park, decrease. In order to determine the best stations for the collection of rainfall data for the study, a correlation analysis was performed between stations with greater proximity to the wind farm and the energy generation of the farm. Four stations were considered in the analysis, located in the following municipalities, as shown in Table 1:

Station	Municipality	Distance (Km)
Pici	Fortaleza	135
Santo Amaro	São Gonçalo do Amarante	90
Fortaleza	Fortaleza	135
Arapari	Itapipoca	45

Table 1: Stations Vs Distances

The correlation between the rain and energy generation series is shown in table 2:

Stations / Stations	Fortaleza	Pici	Santo Amaro	Arapari	Geração
Fortaleza	100,00%	73,04%	47,69%	32,28%	-36,95%
Pici	73,04%	100,00%	55,03%	38,05%	-35,79%
Santo Amaro	47,69%	55,03%	100,00%	40,52%	-37,83%
Arapari	32,28%	38,05%	40,52%	100,00%	-38,80%
Geração	-36,95%	-35,79%	-37,83%	-38,80%	100,00%

Table 2: Rain and Generation Correlations

As expected, the station closest to the wind farm (Arapari) is the one with the highest correlation with generation (-38.80%). The negative result is also consistent with expectations, indicating that rainy periods are correlated to lower generation. We also analyzed the correlations of the series together to verify if it would be more appropriate to consider the Arapari station, which presented a higher correlation with the generation, or another set. The result of the analysis is presented in table 3:

Stations	Generation
Fortaleza	-36,95%
Pici	-35,79%
Santo Amaro	-37,83%
Arapari	-38,80%
Arapari +Santo Amaro	-45,60%
Arapari + Pici	-44,08%
Pici + Santo Amaro	-41,72%
Arapari + Pici + Santo Amaro	-46,50%

Table 3: Aggregate Rain and Generation Correlations

As can be observed, the rainfall of the Arapari, Pici and Santo Amaro stations together show a higher correlation with generation. In this way, the sum of rainfall in these three locations was selected as the exogenous variable. Figure 2 shows simultaneously the generation and rainfall curve. We can observe that there is a strong decrease in generation in the periods of greater rainfall.

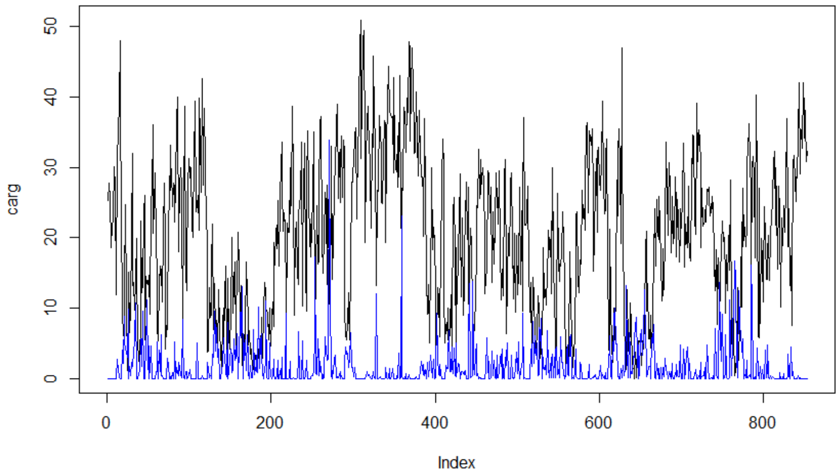

Figure 2

The Augmented Dickey Fuller (ADF) Test was performed to both Generation and Rainfall series to ensure that we can use these series without any problems or conversions to build the forecast model. The test suggests that the series Generation and Rainfall are stationary. Figures 3 and 4 shows the test results for the lags from 1 to 20:

Augmented Dickey-Fuller Test for Generation Series (carg):

Dickey-Fuller = -4.8376, Lag order = 9, p-value = 0.01

Alternative hypothesis: stationary

Conclusion: The result suggests that Generation Series is stationary.

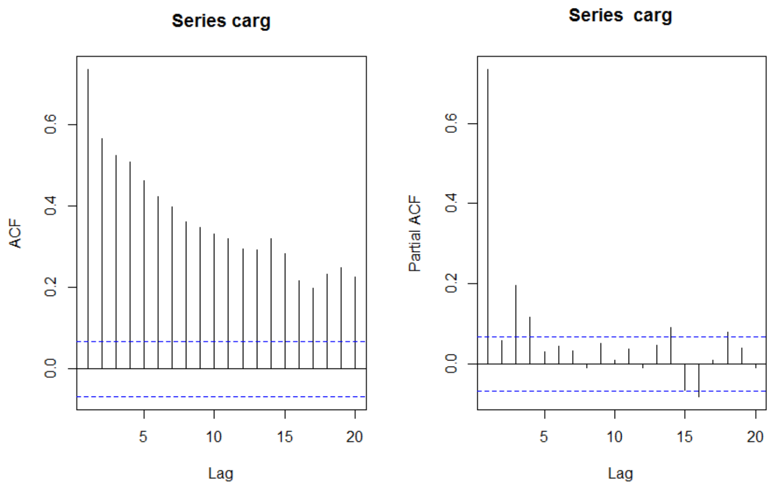

Figure 3

Augmented Dickey-Fuller Test for Rainfall Series (carg)

Dickey-Fuller = -72154, Lag order Rainfall = 9, p-value = 0.01

Alternative hypothesis: stationary

Conclusion: The result suggests that Rainfall Series is stationary.

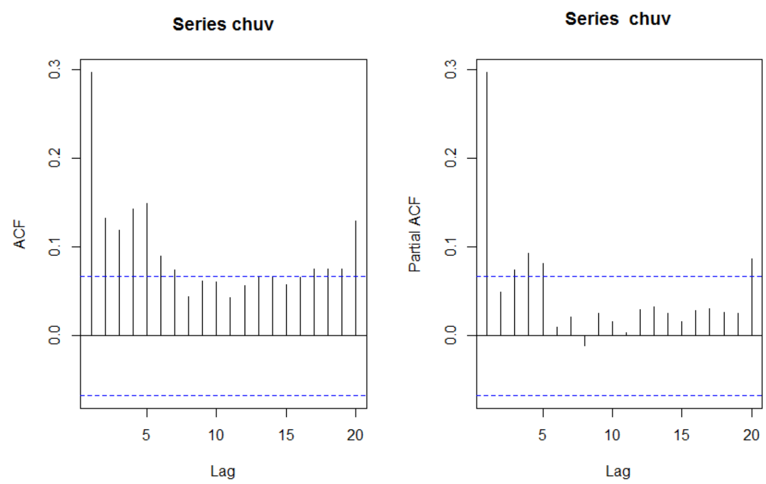

Figure 4

To select the best ARIMA model we use the AIC criteria and a maximum lag of 20. The function auto.arima of forecast model, on R, was used to select the best model and the results are shown on table 4:

MODEL	ZERO-MEAN	AIC
ARIMA(2,0,2)	NO	5772.049
ARIMA(0,0,0)	NO	6476.935
ARIMA(1,0,0)	NO	5816.971
ARIMA(0,0,1)	No	6043.214
ARIMA(0,0,0)	YES	7751.777
ARIMA(1,0,2)	**NO**	**5769.855**
ARIMA(1,0,1)	NO	5812.028
ARIMA(1,0,3)	NO	5770.825
ARIMA(2,0,3)	NO	5772.924
ARIMA(1,0,2)	YES	Infinite
ARIMA(0,0,2)	No	5930.969

Table 4: Selection of ARIMA Models

The best model selected is ARIMA(1,0,2) with non-zero mean, which presented the lower AIC indicator. The coefficients and estimators are shown on tables 5 and 6.

	AR1	MA1	MA2	Intercept
Values	0.9374	-0.2998	-0.2659	202.769
s.e.	0.0182	0.0397	0.0375	16.578

Table 5: ARIMA Coefficients

Estimators	Values
sigma^2 estimated	50.33
log likelihood	-2880.09
AIC	5770.19
AICc	5770.26
BIC	5793.93

Table 6: Estimators

To generate the errors indicators, the generation series was divided into 2 series: insample and outsample series. Insample series was delimited from 2010 to 2015. Data from 2016 was used for the outsample series. The results are shown on table 7:

Errors	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Trainning Set	-0.01243	7.0774	5.6507	-47.3168	68.5031	0.9231	0.0086

Table 7: Model Errors

Where:

- ME: Mean Error
- RMSE: Root Mean Squared Error
- MAE: Mean Absolute Error
- MPE: Mean Percentage Error
- MAPE: Mean Absolute Percentage Error
- MASE: Mean Absolute Scaled Error
- ACF1: Autocorrelation of errors at lag 1

The figures 5 and 6 show the graphic of ARIMA model errors, ACF and PACF with maximum lag of 30. The results suggest that the model have an acceptable pattern of errors.

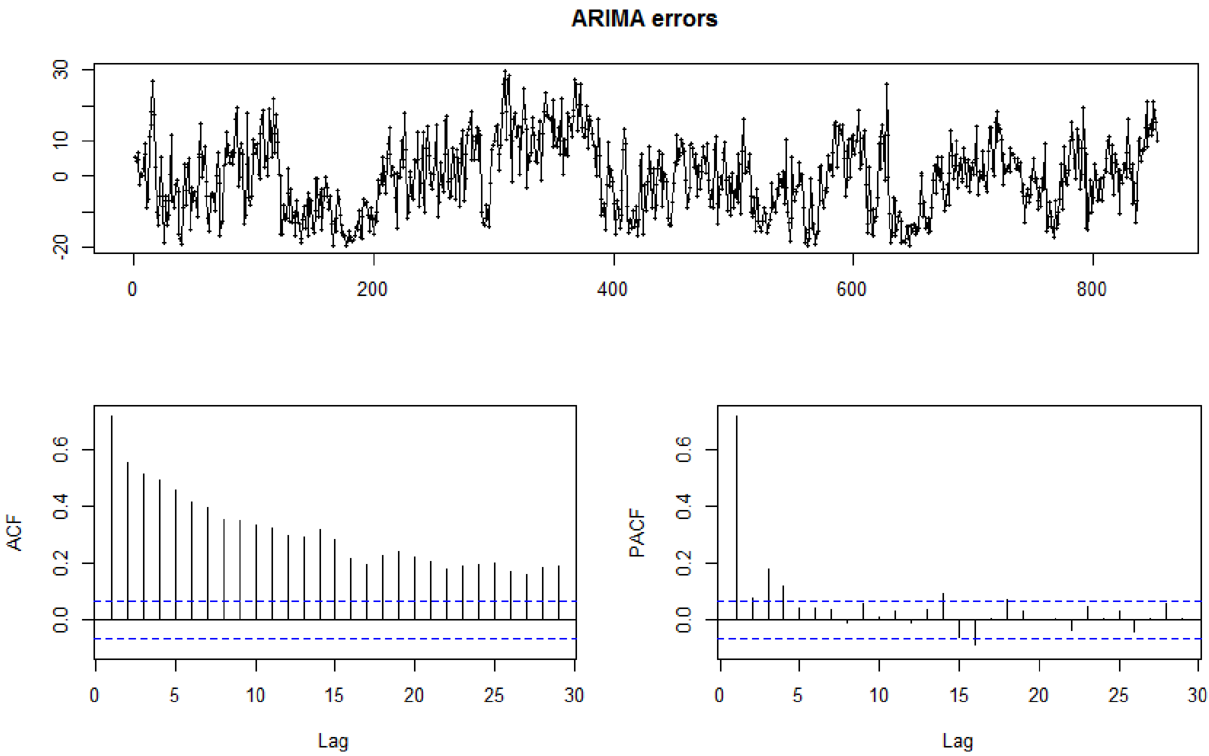

Figure 5: ARIMA Errors

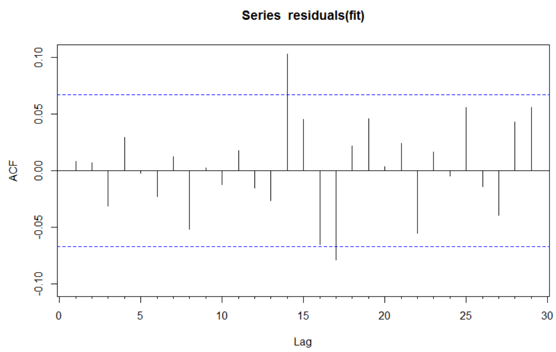

Figure 6: Series Residuals – ACF

For the construction of Optimal Scheduling Model it was used the ARIMA(1,0,2) with rainfall as external variable. The forecast was performed every week with horizon of 10 days and the new actual data was incorporated to the model every week to increase accuracy.

The figures 7, 8 and 9 bellow shows the forecast for the weeks 1, 2 and 15 (the last one). The blue line shows the forecast and the black line represents the actual measures values.

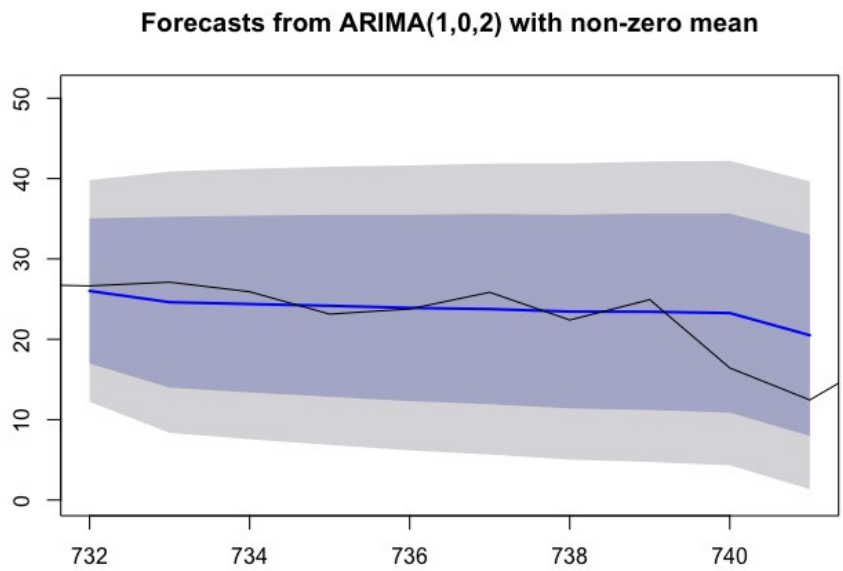

Figure 7 : Forecast week 1

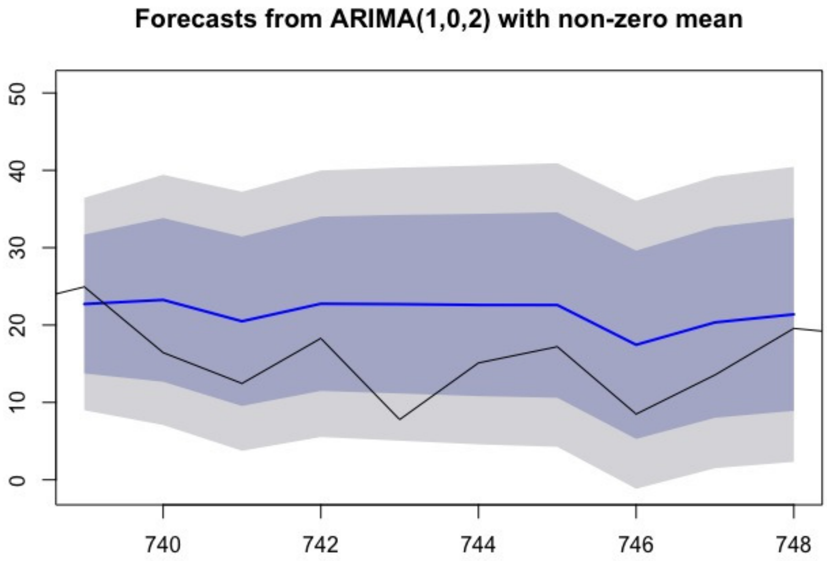

Figure 8: Forecast Week 2

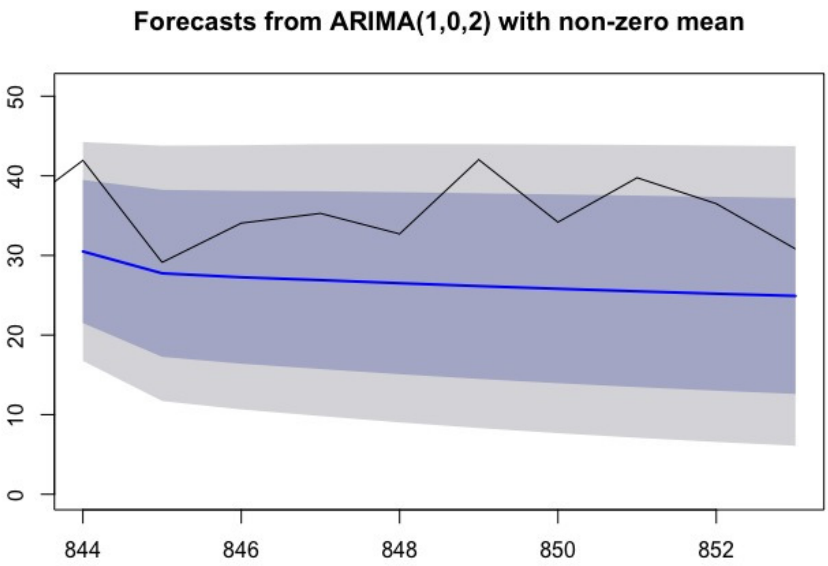

Figure 9: Forecast week 15

The proxy for spot market energy price is assumed to be the PLD - Preço de Liquidação de Diferenças determined by the Electrical Energy Clearing Chamber (CCEE). We use the monthly simulation made by the National System Operator (ONS) for the year of 2016 for the Brazilian northeast energy market where the wind farm is located.

4 – Optimal Scheduling Model

We assume the maintenance of wind turbines will be done within a period of 15 weeks between March and May of each year, with 4 maintenance teams working simultaneously. Each of these teams maintenance works on a single wind turbine at a time, and takes 2 full days. Since the wind farm has a total of 28 wind turbines, maintenance is carried out in 14 days. When there is maintenance, four of the 28 wind turbines are taken off line for two days, reducing production by 4/28, or 1/7 of the total.

Maintenance can begin at any time between March and May, and once started, the maintenances are carried out uninterruptedly during the 14 days until all work is completed. We also assume that there is no additional cost to postpone the allocation of maintenance teams and that the loss of generation must be returned to the customer through free market purchases at PLD plus an premium. Ideally, this interruption occurs in periods of low generation and low PLD.

The generation forecast is divided into 2 horizons: short term and long term. The short-term forecast is considered in the model as deterministic while the long-term forecast is considered stochastic. Every 7 days a new forecast is performed and if the optimal maintenance start moment occurs in the next 7 days, maintenance is scheduled, otherwise, on the next week a new forecast is made and the optimization model is reapplied.

The objective is to minimize downtime costs due to scheduled maintenance interruptions. We assume the wind farm has some discretion, within bounds, to decide when this interruption will occur. Given that the months of March, April and May are historically the periods with the lowest wind speeds of the year, we focus on a 15 week maintenance scheduling window beginning on March 1st, as shown in Figure 3.

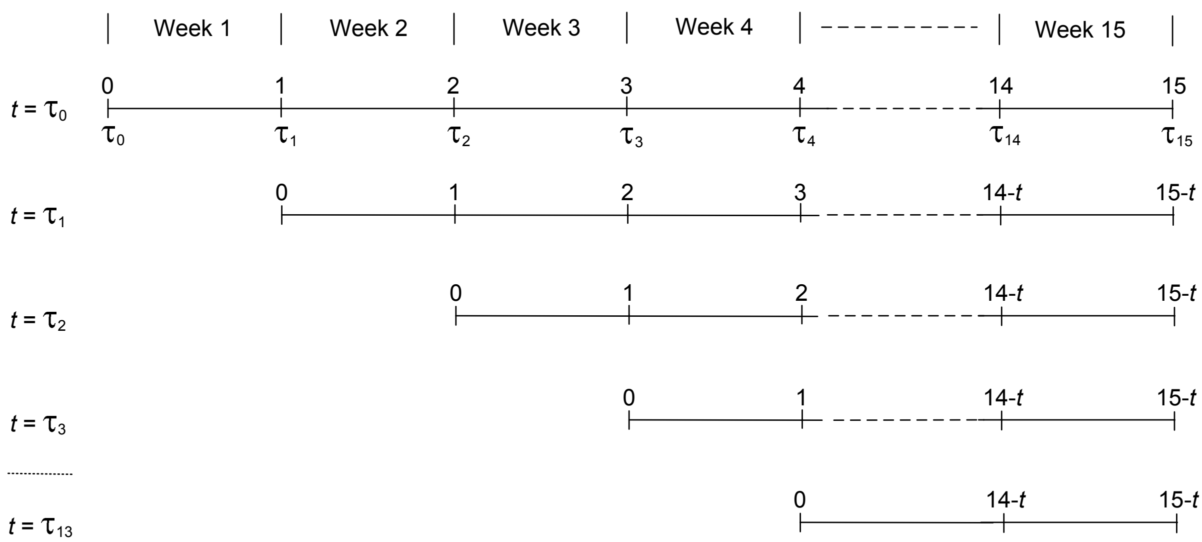

Figure 10 – Maintenance Model

We assume that all operating costs are fixed, independent of whether the wind farm is operating or not. Thus, maintenance interruptions impact only the cost (Π) of spot market purchases, which is a function of the energy shortfall (q) and the PLD spot price (ω), such that $\Pi = q \times \omega$.

At the beginning of the period ($t = \tau_0$) the managers receive a 1 week ahead wind forecast, from which the quantity of energy that will be forgone (q_1) can the determined. The spot price for the upcoming week (ω_1) is also know at this time, so the opportunity cost for the first week is know with certainty. For the second, and all the remaining 14 weeks, expected weekly revenues are derived from simulated wind speeds and energy spot prices. Thus, the opportunity cost of immediate maintenance stoppage at $t = \tau_0$ is equivalent to the costs of the energy deficit of the first two weeks, as shown in Eq. (1).

$$t = \tau_0 \qquad \Pi_{\tau_0,0} = \bar{q}_1\bar{\omega}_1 + \tilde{q}_2\tilde{\omega}_2 \tag{1}$$

Similarly, the cost of stopping in one week´s time is:

$$\Pi_{\tau_0,1} = \tilde{q}_2\tilde{\omega}_2 + \tilde{q}_3\tilde{\omega}_3$$

The cost of stopping in two weeks is

$$\Pi_{\tau_0,2} = \tilde{q}_3\tilde{\omega}_3 + \tilde{q}_4\tilde{\omega}_4 \quad \text{and so on.}$$

The cost of the last opportunity to stop as forecasted at time $t = \tau_0$ occurs at time 13.

$$\Pi_{\tau_0,13} = \tilde{q}_{14}\tilde{\omega}_{14} + \tilde{q}_{15}\tilde{\omega}_{15}$$

Once the cost of stopping in all the possible 14 two week periods is calculated, the period with the lowest opportunity cost can be determined as

$$\min \Pi_{\tau_0,\mathrm{j}} \quad \tau_0 = 0; \quad j = 0,1,2,....13$$

If the lowest cost is $\Pi_{\min} = \Pi_{\tau_0,0}$, then it is optimal to stop now and begin the maintenance immediately. Otherwise, if $\Pi_{\min} \in \Pi_{\tau_0,\mathrm{j}} \quad j = 1,2,3,...13$ the firm waits another week to decide and moves to $t = \tau_1$. There are now 14 weeks left in the season to perform the maintenance. The cost of stoppage for the first week is:

$$\Pi_{\tau_1,0} = \bar{q}_1\bar{\omega}_1 + \tilde{q}_2\tilde{\omega}_2$$

And for subsequent weeks until week 12

$$\Pi_{\tau_1,1} = \tilde{q}_2\tilde{\omega}_2 + \tilde{q}_3\tilde{\omega}_3$$

$$\Pi_{\tau_1,2} = \tilde{q}_3\tilde{\omega}_3 + \tilde{q}_4\tilde{\omega}_4$$

……………………..

$$\Pi_{\tau_1,12} = \tilde{q}_{13}\tilde{\omega}_{13} + \tilde{q}_{14}\tilde{\omega}_{14}$$

Or

$$\Pi_{\tau_1,\mathrm{j}} = \tilde{q}_{j+1}\tilde{\omega}_{j+1} + \tilde{q}_{j+2}\tilde{\omega}_{j+2} \qquad j = 1,2,3,...13-\tau_1$$

Once the cost of stopping in all the possible 13 two week periods is calculated, the period with the lowest opportunity cost can be determined as

$$\min \Pi_{\tau_1,\mathrm{j}} \qquad j = 0,1,2,....13-\tau_1,$$

where:

$$\text{If} \begin{cases} \Pi_{\min} = \Pi_{\tau_1,0} & \text{stop immediately} \\ \Pi_{\min} \in \Pi_{\tau_1,\mathrm{j}} \quad j = 1,2,3,...13-\tau_1 & \text{wait} \end{cases}$$

In case it is not optimal to stop immediately, then the firm waits for an additional week to time τ_3 and repeats the procedure. The final opportunity to stop is in period τ_{13}, when there are only two weeks left for the end of the maintenance opportunity window, so the wind farm must necessarily stop then, as this is the last opportunity to do so.

$$\Pi_{\tau_{13},0} = \overline{q}_1\overline{\omega}_1 + \tilde{q}_2\tilde{\omega}_2 \quad \text{and} \quad \Pi \min = \Pi_{\tau_{13},0}$$

The proposed model will be compared with the current practice and also with the ideal hypothetical model considering perfect information. This will be done by comparing our results with the ideal maintenance schedule for the year 2016, assuming that all the actual wind and energy price data for the year were known at the beginning of the year.

5 – Application and results

A wind farm in the northeast region was selected for the study because of its great importance for the Brazilian energy matrix.

6 – Conclusions

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