OPTIMAL TIMING FOR WIND FARM MAINTENANCE: AN APPLICATION AND EMPIRICAL EVIDENCE

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Abstract

Wind farms must periodically take their turbines offline in order to perform scheduled maintenance repairs. Since this interruption impacts the generation of energy and any shortfall in production must be covered by energy purchases in the spot market, 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 on forecasted wind speeds and energy prices. We analyze a window of opportunity in the most likely period of the year, and perform weekly updates of expected wind speeds and energy price forecasts. Wind speeds are forecasted with an (ARMAX) model, where monthly dummies are used as exogenous variables to capture the seasonality of wind speeds, while spot prices are simulated under the Newave dual stochastic programing model. The decision to defer maintenance to a future date is modeled as an American real option. We test the model with actual data from a wind farm in the Brazilian Northeast, and compare our results with current practice and with maintenance scheduling considering perfect information in order to determine the benefits of the model. The results suggest that this model may provide significant advantages over a stopping decision that randomly chooses a week to begin maintenance within the opportunity window and is close to the optimal stopping date considering perfect information on future wind speeds and electricity prices.

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. With only 27.1 MW in 2005, by 2016 the installed capacity had increased to 10,747 MW, ranking third in total energy produced in the matrix, and is expected to reach 17,257 MW by 2020 (ABEEólica, 2017; ANEEL, 2016). Under this scenario, more accurate forecasting models 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 affect the energy production of the wind farm. All things 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.

In addition, wind farms must deliver the amount of energy agreed upon 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 stopping time has option like characteristics, option pricing methods will be used to determine the decision trigger curve.

We develop a model to determine the optimal maintenance scheduling for a wind farm based on forecasted wind speeds and future energy spot prices during the most likely period of the year, and perform weekly updates of wind speed and price forecasts. Wind speeds are forecasted as an (ARMAX) model, where monthly dummies are used as exogenous variables to capture the seasonality of wind speeds and spot prices are simulated under the Newave dual stochastic programing model. The optimal stopping decision is modeled as an American type real option using a Monte Carlo simulation model. We use actual data from a wind farm in the Brazilian Northeast and compare our results with current practice and considering perfect information. The results suggest that the model may provide significant advantages over a stopping decision that randomly chooses a week to begin maintenance, and is close to the optimal stopping date considering perfect information on future wind speeds and electricity prices.

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 problem can be modeled under the real options approach. In section 5 we apply the model to the case of an actual wind farm using 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), with China, United States, Germany, India and Spain being the largest wind power producers in the world (Table 1), accounting for 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
Rest of the World	50,033	58,826	67,354	71,222
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, with states of Rio Grande do Norte and Ceará, in the Northeast region, which has the greatest wind energy potential in the country due to the quantity and constancy of the winds, contributing with 1,520 MW (ANEEL, 2016).

On the other hand, one of the problems with wind energy is the difficulty in predicting wind speeds, and consequently, power generation, which makes wind farm valuation and maintenance scheduling a challenge. Therefore, models that can more accurately forecast future wind speeds can be useful for optimal wind farm management.

Reliability and Maintenance

The purpose of maintenance is to extend equipment life and increase the medium time between faults. Reliability and maintenance are connected, and the numerical relationship between these two concepts has been shown by Patra, Mitra, and Earla (2006).Wind farm equipment requires maintenance and when a wind turbine is taken offline there is a loss of generation an opportunity cost involved. Thus, ideally, equipment shut down for maintenance should be done in such a way as to minimize any financial losses.

Maintenance programs must be able to ensure good reliability indexes for the system and its component, but this only one of the tools required to ensure the high reliability of a system and its components. The observed time between intrinsic device failures can be controlled by internal maintenance programs directed to the device (Endrenyi, Anders, Bertling, & Kalinowski, 2004). Endrenyi et al. (2001) describe maintenance management by 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 Forecasting

Wind energy is generated through the passage of air flow through the blades of wind turbines. This airflow varies widely and is influenced by factors such as weather conditions, seasonality, terrain and nearby turbines (Ahlstrom, Jones, Zavadil, & Grant, 2005). Wind forecasting is challenging due to generation variation over the time horizon and low predictability of wind speeds. Even advanced forecasting models can generate vastly different forecasts due to the non-linear characteristics of the atmospheric system (Archer, Simão, Kempton, Powell, & Dvorak, 2017). Pinto, Martins, Pereira, Fisch, and Lyra (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 (R. 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 (R. L. 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 no existent in the early 1980s, but has been steadily gaining importance, and is expected to reach 2,600 GW of installed capacity by the year 2050, out of a total potential of 70,000 GW (MME, 2016). Wind energy, as other renewable energies, has also been gaining importance in Brazil. The 2024 Ten Year Energy Expansion Plan (MME, 2015) indicates that wind power generation is expected to reach 24 GW/year by 2024, mostly concentrated in the northeast region of Brazil due to high incidence of winds, which should generate 90% (21.6 GW) of this total. In this context, wind power generation models become increasingly necessary for the industry, in order to schedule maintenance activities and manage their generation portfolio.

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: Rainfall levels and timing, and the South Atlantic Convergence Zone (ZCAS). The exogenous variable ZCAS has greater influence in the months of December and January, while rain influences the series with greater intensity in the months of March to 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.

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 eventual 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 prior 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 2010.

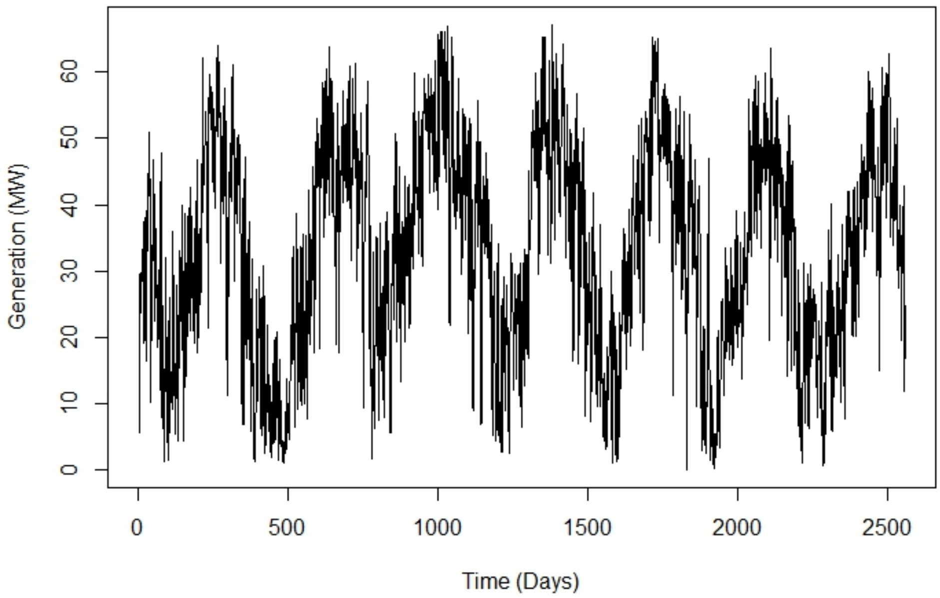


Figure 1: Wind farm energy generation

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 can be observed that in periods of higher rainfall, the wind and, consequently, the power generation of the park, decreases. 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. 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 levels. 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.

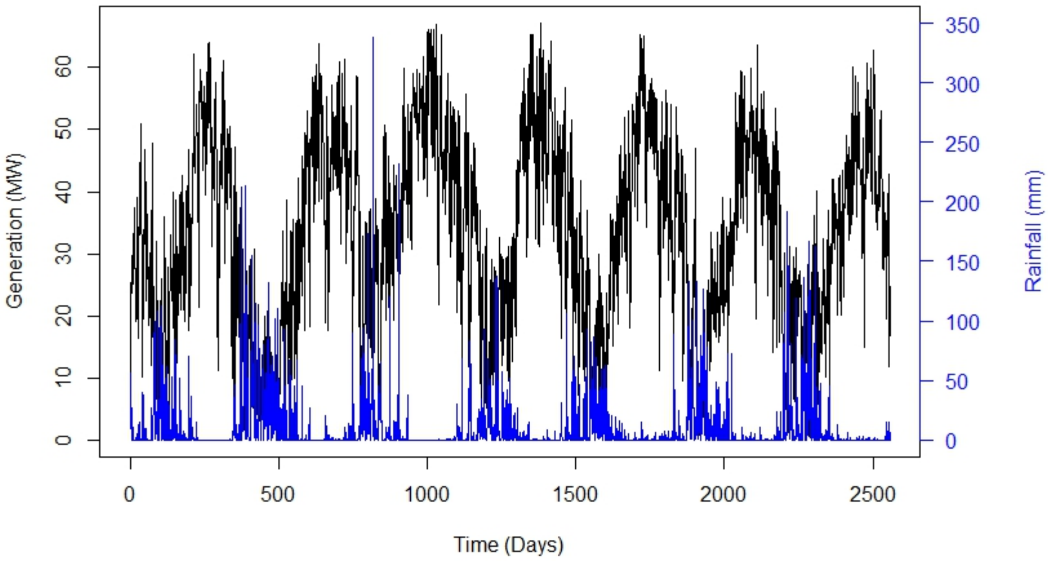


Figure 2: Wind farm energy generation and rainfall

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.

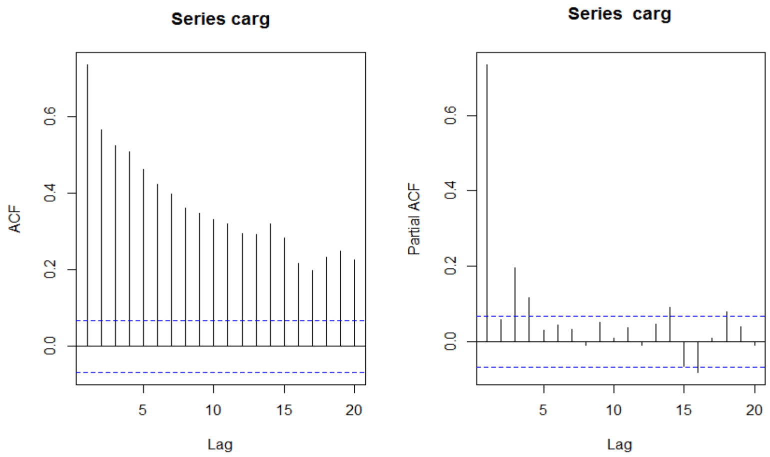


Figure 3: ADF and Partial ADF test for Generation (Carg)

Augmented Dickey-Fuller Test for Rainfall Series (chuv)

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

Alternative hypothesis: stationary

Conclusion: The result suggests that Rainfall Series is stationary.

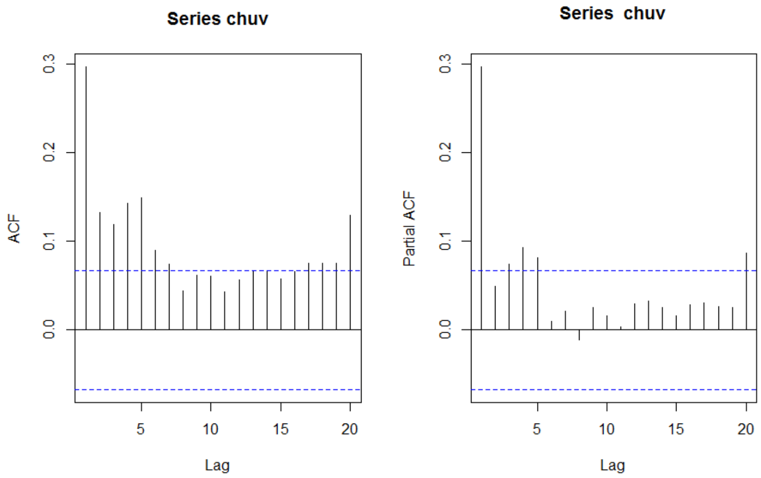


Figure 4: ADF and Partial ADF test for Rainfall (chuv)

To select the best ARIMA model we used 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 best ARIMA Model

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
σ^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 graph of ARIMA model errors, ACF and PACF with maximum lag of 30. The results suggest that the model has an acceptable pattern of errors.

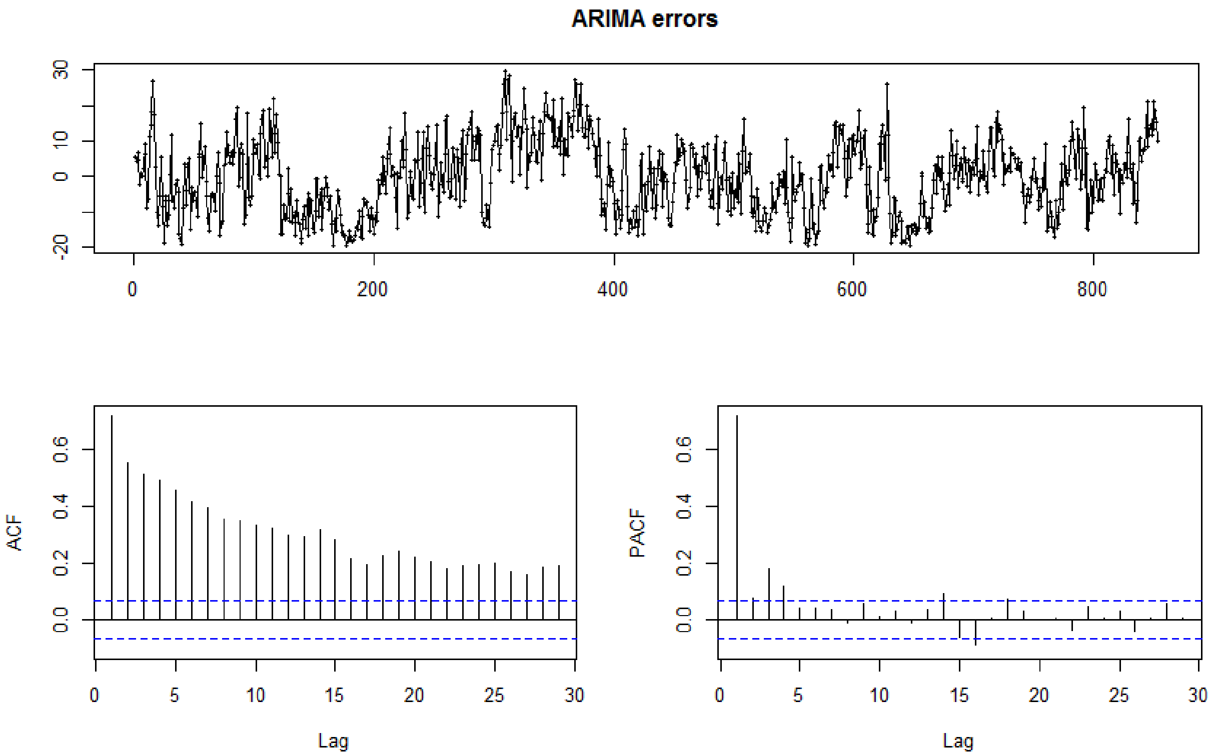


Figure 5: ARIMA Errors

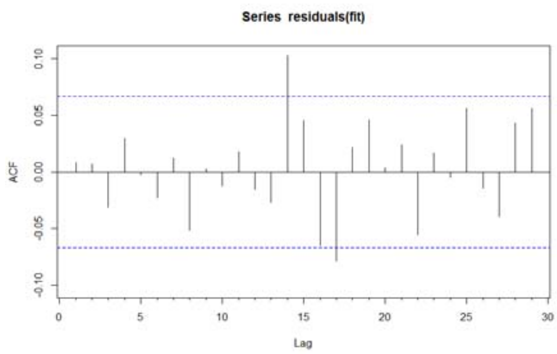


Figure 6: Series Residuals – ACF

For the construction of optimal scheduling model we used the ARIMA(1,0,2) with rainfall as the external variable. The forecast was performed weekly with a horizon of 10 days and the new actual data was incorporated to the model every week to increase accuracy. Figures 7, 8 and 9 show the forecast for the weeks 1, 2 and 18 (the last one). The blue line shows the forecast and the black line represents the actual measures values.

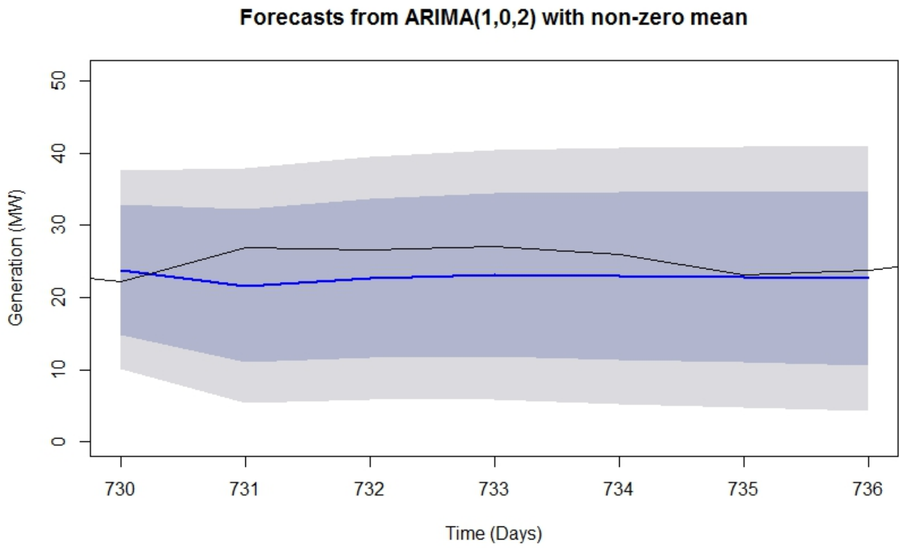


Figure 7 : Forecast week 0

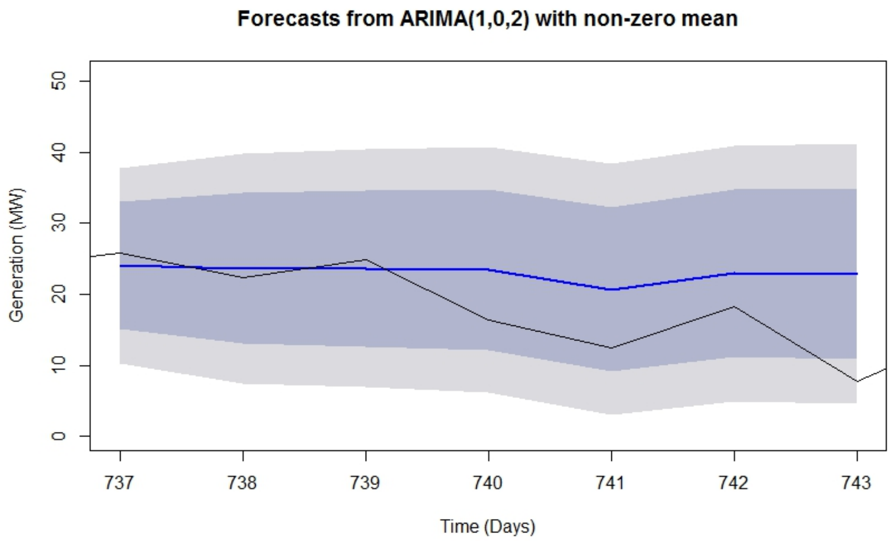


Figure 8: Forecast Week 1

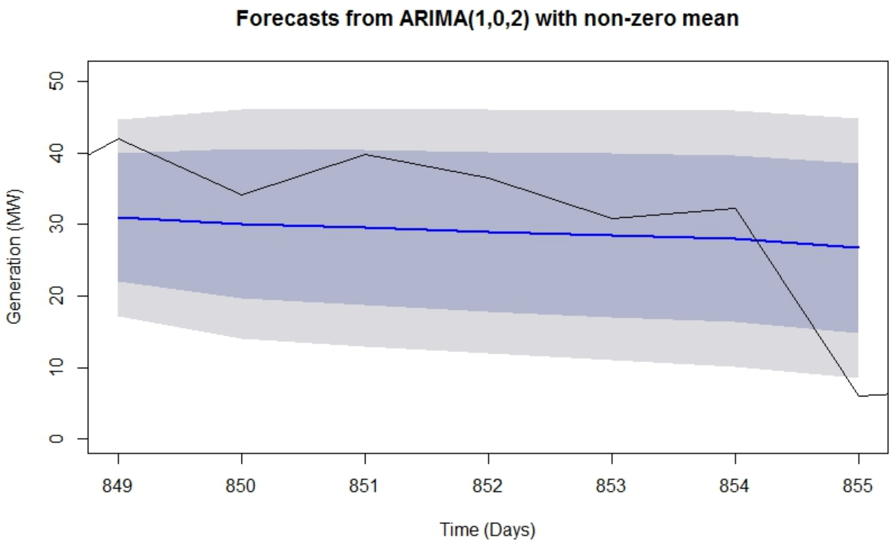


Figure 9: Forecast week 17

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

The objective of the model is to minimize downtime costs due to scheduled maintenance interruptions. Given that the months of March, April, May and June are historically the periods with the lowest wind speeds of the year in the Brazilian Northeast, we focus on an 18 week maintenance scheduling window beginning on March 1st, as shown in Figure 3.

We assume the wind farm has some discretion, within bounds, to decide when this interruption will occur, and that 4 maintenance teams will be working simultaneously. Each of these teams works on a single wind turbine at a time and is able to perform the required maintenance in 2 days. Since the wind farm has a total of 28 wind turbines, 14 days are required to carry out the maintenance of all the turbines. During the maintenance period, four of the 28 wind turbines are taken offline at a time for two days, reducing production by 4/28, or 1/7 of the total. Maintenance can begin at any time during this period, and once started, maintenance is carried out uninterruptedly during 14 days until all work is completed. We also assume that there are no additional costs to postpone the allocation of maintenance teams, that once the decision is made the work will begin immediately, and that the loss of generation must be returned to the customer through energy purchases in the free market at PLD plus a premium. Thus, ideally, this interruption should occur in periods of both low generation and low PLD.

The generation forecast is divided into a short term and a long term horizon. The short-term forecast is considered in the model as deterministic while the long-term forecast is assumed stochastic. Each week new forecasts for the remainder of the 18 week period are made, and if the optimal maintenance start moment occurs at any time in the next 7 days, maintenance is scheduled. Otherwise, maintenance is deferred for another week and the process is repeated.

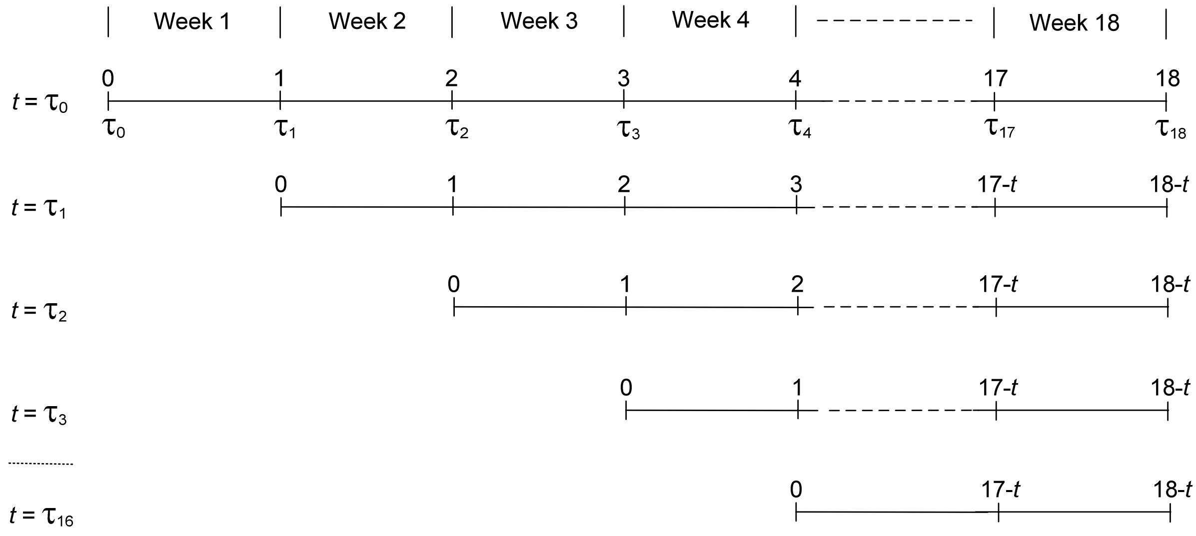


Figure 10 – Maintenance Model

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 Π = q x ω.

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 17 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. (0).

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

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 16.

$$\Pi_{\tau_0,16} = \tilde{q}_{17}\tilde{\omega}_{17} + \tilde{q}_{18}\tilde{\omega}_{18}$$

Once the cost of stopping in all the possible 16 two week periods is calculated, the period with the lowest opportunity cost can be determined as

$$\min \Pi_{\tau_0,\mathrm{j}} \quad \tau_0 = 0; \quad j = 0,1,2,....16$$

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 $\Pi_{\min} \in \Pi_{\tau_0,\mathrm{j}} \quad j = 1,2,3,...16$ the firm waits another week to decide and moves to $t=\tau_1$. There are now 17 weeks left in the season to perform the maintenance. The cost of stoppage for the first week is:

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

And for subsequent weeks until week 15:

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

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

……………………..

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

or

$$\Pi_{\tau_1,\mathrm{j}} = \tilde{q}_{j+1}\tilde{\omega}_{j+1} + \tilde{q}_{j+2}\tilde{\omega}_{j+2} \quad j = 1,2,3,...16-\tau_1$$

Once the cost of stopping in all the possible 16 two week periods is calculated, the period with the lowest opportunity cost can be determined as:

$$\min \Pi_{\tau_1,\mathrm{j}} \quad j = 0,1,2,....16-\tau_1,$$

where:

$$\text{If} \begin{cases} \Pi_{\min} = \Pi_{\tau_1,0} & \text{stop immediately} \\ \Pi_{\min} \in \Pi_{\tau_1,\mathrm{j}} \quad j = 1,2,3,...16-\tau_1 & \text{wait} \end{cases}$$

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_{16}, 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.

$$\Pi_{\tau_{16},0} = \bar{q}_1\bar{\omega}_1 + \tilde{q}_2\tilde{\omega}_2 \quad \text{and} \quad \Pi\min = \Pi_{\tau_{16},0}$$

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 Brazilian northeast region was selected for the study because of the significant importance of this region for the Brazilian energy matrix due to high wind speeds. The year of 2016 was used to apply the model and generate the results. We compared these results to perfect information model and also to the current practice. 10.000 generation and price simulations were performed for each week.

We assume that maintenance will occur if there is at least a 50% probability that it is optimal to stop immediately. The optimization model suggests that the best time to stop is on 10th week. The estimated stoppage costs related to start maintenance on 10th week is R$ 100,564.27 and the probability that this week is the optimal one is 64.3%. Figure 11 shows the calculated probabilities for each one of 18 weeks. The model indicates the optimal stop on week 10 which is the first week that the probability is above 50% from week 0.

Week	Stop Probability
0	0,00%
1	0,00%
2	0,00%
3	0,00%
4	0,00%
5	9,89%
6	0,01%
7	0,00%
8	0,00%
9	9,54%
10	**64,30%**
11	39,65%
12	22,36%
13	54,70%
14	80,30%
15	74,76%
16	61,39%
17	100,00%

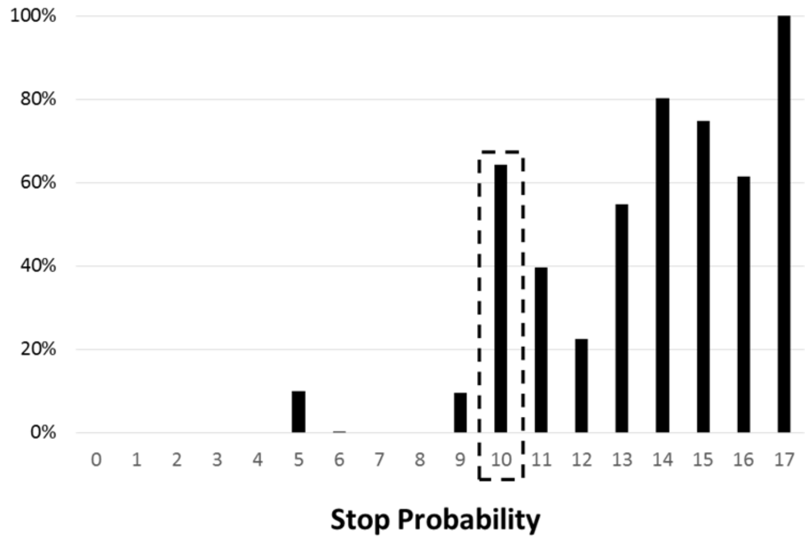
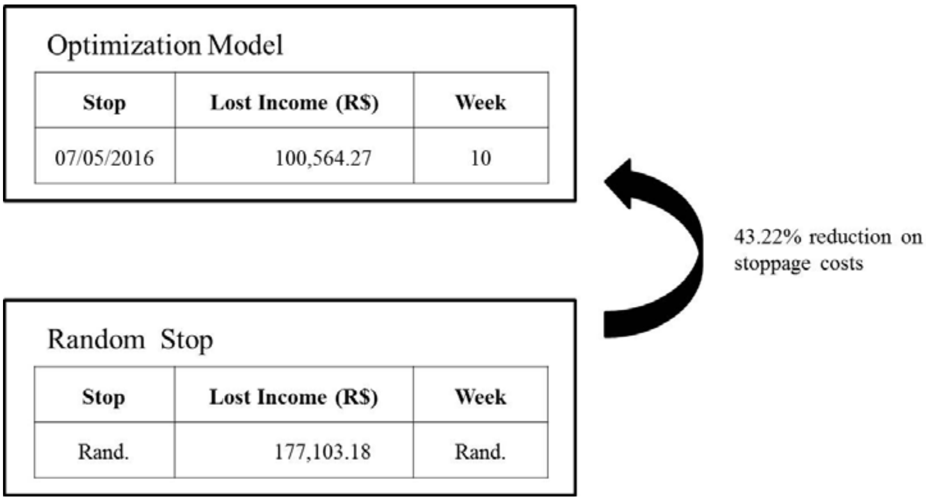


Figure 11: Stop Probabilities

5.1 – Comparison between proposed optimization model and random stop model

In order to ensure that the model has a good power of prediction we compared the model results to a model where the start of maintenance is randomically selected, what is similar to the current maintenance practice for the wind farm. The estimated stoppage costs (lost income) of a random stop model is R$ 177,103.18. The optimization model represents a reduction of 43.22% (figure 12) in stoppage costs, indicating that the proposed optimization model is better than a random model.


Optimization Model

Stop	Lost Income (R$)	Week
07/05/2016	100,564.27	10

Random Stop

Stop	Lost Income (R$)	Week
Rand.	177,103.18	Rand.

Figure 12: Optimization model vs. random stop

5.2 – Comparison between proposed optimization model and random stop model

In order to verify how far the proposed optimization model is from a perfect information model, the results were compared to a situation where all the wind speed and electricity price information for the full period is available before any decision. With perfect information, the optimal week to stop is week 9 and the costs associated with the maintenance (lost income) are R$ 76,949.76. The proposed optimization model would provide 30.67% greater cost when compared to the perfect information model.

Optimization Model

Stop	Lost Income (R$)	Week
07/05/2016	100,564.27	10

30,69% increase on stoppage costs

Perfect Information Model

Stop	Lost Income (R$)	Week
30/04/2016	76,949.76	9

Figure 13: Optimization model vs. Perfect Information

6 – Conclusions

In this article, we develop a model to determine the optimal maintenance schedule for a wind farm. Actual data from a wind farm in Brazilian northeast region was used to develop and test the model, which was built using ARMAX forecast model and simulation techniques to determine the optimal schedule for maintenance.

The results were compared with a random model and also with maintenance scheduling with perfect information, in order to determine the predictive power of the model. The results suggest that this model may provide significant advantages over a stopping decision that randomly chooses a week to begin maintenance within the opportunity window of March to June, and is close to the optimal stopping date considering perfect information on future wind speeds and electricity prices.

7– References

ABEEólica. (2017). Dados Mensais - Abril 2017. São Paulo, SP: ABEEólica - - Associação Brasileira de Energia Eólica.

Ahlstrom, Jones, L., Zavadil, R., & Grant, W. (2005). The future of wind forecasting and utility operations. *IEEE Power and Energy Magazine, 3*(6), 57-64. doi: 10.1109/mpae.2005.1524621

ANEEL. (2016). Wind energy generation data. Retrieved 18 October, 2016, from http://www.aneel.gov.br/aneel-essencial/-/asset_publisher/c4M6OIoMkLad/content/evolucao-da-energia-eolica-no-Brasil?inheritRedirect=false

Archer, C. L., Simão, H. P., Kempton, W., Powell, W. B., & Dvorak, M. J. (2017). The challenge of integrating offshore wind power in the U.S. electric grid. Part I: Wind forecast error. *Renewable Energy, 103*, 346-360. doi: http://dx.doi.org/10.1016/j.renene.2016.11.047

Black, F., & Scholes, M. (1973). The Pricing of Options and Corporate Liabilities. *The Journal of Political Economy, 81*(3), 637-654.

Dixit, A. K., & Pindyck, R. S. (1994). *Investment under Uncertainty*. Princeton: Princeton University Press.

Endrenyi, J., Aboresheid, S., Allan, R. N., Anders, G. J., Asgarpoor, S., Billinton, R., . . . Singh, C. (2001). The present status of maintenance strategies and the impact of maintenance on reliability. *IEEE Transactions on Power Systems, 16*(4), 638-646. doi: 10.1109/59.962408

Endrenyi, J., Anders, G. J., Bertling, L., & Kalinowski, B. (2004, 16-16 Sept. 2004). *Comparison of two methods for evaluating the effects of maintenance on component and system reliability.* Paper presented at the 2004 International Conference on Probabilistic Methods Applied to Power Systems.

Majd, S., & Pindyck, R. S. (1987). Time to Build, Option Value, and Investment Decisions. *Journal of Financial Economics, 18*(1), 7-27.

McCall, J. J. (1965). Maintenance Policies for Stochastically Failing Equipment: A Survey. *Management Science, 11*(5), 493-524. doi: 10.1287/mnsc.11.5.493

McDonald, R., & Siegel, D. (1986). The Value of Waiting to Invest. *Quarterly Journal of Economics, 101*(4), 707-728.

McDonald, R. L., & Siegel, D. R. (1985). Investment and the Valuation of Firms When There is an Option to Shut Down. *International Economic Review, 26*(2), 331-349. doi: 10.2307/2526587

Merton, R. C. (1973). Theory of Rational Option Pricing. *The Bell Journal of Economics and Management Science, 4*(1), 141-183.

Myers, S. C., & Majd, S. (1983). Calculating abandonment value using option pricing theory. *Sloan School of Management*, 1462-1483.

Patra, S. B., Mitra, J., & Earla, R. (2006, 21-24 May 2006). *A New Intelligent Search Method for Composite System Reliability Analysis.* Paper presented at the 2005/2006 IEEE/PES Transmission and Distribution Conference and Exhibition.

Pinto, L. I. C., Martins, F. R., Pereira, E. B., Fisch, G. F., & Lyra, R. F. d. F. (2014). Confiabilidade nas estimativas do regime do vento fornecidas pelo brams no estado de Alagoas: influência do aninhamento e da resolução horizontal de grades. *Revista Brasileira de Meteorologia, 29*, 242-258.

Sherif, Y., & Smith, M. (1981). Optimal maintenance models for systems subject to failure–a review. *Naval Research Logistics (NRL), 28*(1), 47-74.

Tourinho, O. A. F. (1979). *The valuation of reserves of natural resources: an option pricing approach.* Doctoral PhD Dissertation, University of California, Berkeley.

Trigeorgis, L. (1993). The Nature of Option Interactions and the Valuation of Investments with Multiple Real Options. *Journal of Financial and Quantitative Analysis, 28*(1), 1-20.

Trigeorgis, L. (1995). *Real options in capital investment : models, strategies, and applications*. Westport, Conn.: Praeger.

WWEA, W. W. E. A. (2016). WWEA HALF-YEAR REPORT: WORLDWIND WIND CAPACITY REACHED 456 GW (pp. 3). http://www.wwindea.org: Word Wind Energy Association.