Switch Option for Wind Farms: Mining Cryptocurrencies

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Abstract

Rules for long-term energy supply auction in Brazil establish that a power plant, such as wind farms, must supply its contracted energy after a period of years following the winning bid. The constructor can choose to build the energy farm ahead of schedule and sell the produced energy in the open market as an anticipation option. In this work we propose that a wind farm that is bound to supply its energy to the regulated market 5 years after winning the regulator bid, can anticipate the farm construction in up to 4 years and sell its energy produced in the highly volatile free market which might have adverse pricing in regular supply situation since the free market energy should be very low on average. But after anticipating the site construction, the constructor can have a switch option to either sell its energy produced in the free market or, after investing in a cryptocurrency mining facility, mine Bitcoins, yielding another highly volatile income. We modeled these two stochastic variables, energy and Bitcoin prices with two different stochastic processes, and results show that not only the anticipation possibility yields a considerable value to the constructor, but the described switch option from electricity to cryptocurrency significantly increases this value, although simultaneously increasing risk.

Keywords: real options, switch option, renewable energy production, cryptocurrency mining

1 Introduction

The Brazilian Agency for Electricity Supply (ANEEL) regulates the future supply of energy using auction of long-term energy supply for different sources of electricity generation. In these the interested parties will enter a reverse auction for the tariff, or rate, they will receive for the energy produced in the site to be constructed for the duration of the concession. Therefore, the winning party should be able to provide contracted energy in a previously stipulated future date, usually some years ahead as specified in the auction. This volume of energy to be provided at the rate of the winning bid, is called the ensured capacity of the site and corresponds to 50% of the total capacity of the site to be constructed. As an example, if the party wins a A-5 (minus five years) contract, it will have up to 5 years to construct the site after which it will provide the ensured capacity for the duration of the concession which varies accordingly to the type of generation: hydraulic, thermal, or renewable (solar, wind or biomass). But, taking the above example (an A - 5 contract) for a wind farm, the site could be constructed in one year. If the winning party chooses to anticipate the implementation of the site, it could have up to 4 years of energy supply that it could sell in the free (or unregulated) market, to a third party or implement an energy intensive enterprise. The construction of the site ahead of schedule is an option for the winner and if exercised it can sell its energy output in the open market at the Price of Difference Liquidation (PLD) which is determined by Chamber of Commercialization of Electric Energy (CCEE) on a weekly basis regarding energy demand on the national grid (SIN).

In normal market conditions this PLD should be in equilibrium at a low value and direct energy sales to the free market may not provide enough incentive to anticipate the construction. In this paper we suggest that adding an energy intensive venture, in the form of a cryptocurrency mining facility to the site makes for a viable switch option for the producer, which in turn encourages the construction of the facility ahead of time, increasing the winner revenue and possibly increasing social gain from energy auctions.

Cryptocurrency mining is an operation that requires specialized hardware (which may or may not be suitable for other uses) and consumes electric energy as its main input (Tschorsch & Scheuermann, 2016). A cryptocurrency is a token pertaining to a digital ledger that uses cryptography in association with consensus algorithms to create a secure layer for messaging and value transactions. The production and ownership of cryptocurrency is legal in Brazil for individuals and organizations alike, providing proper fiscal declaration.

In the next section we do an analysis of wind energy generation in Brazil, of cryptocurrency mining, as well as a brief review of the Blockchain technology. The third section discusses the stochastic modeling of both price series of Bitcoin since 2014 and of historical PLD in Brazil. The fourth section analyzes the simulation of the switch option of mining cryptocurrencies versus selling electric energy in the open market using Monte Carlo Simulation. The final section brings considerations and review findings from the simulations and discuss shortcomings and improvements to this work.

2 Flexibilities in the Energy sector in Brazil

2.1 Regulated and non-regulated energy markets

Brazil's regulatory space is considered to be favorable to wind farm construction. The country have large wind power production capacity and because of the relatively short time to build a wind plant when compared to an oil or hydro power plant those are being favored by lawmakers.

The first program of incentives for wind power plants – PROINFA created in 2002 – offered 20 years of stable energy sale prices, subsidized government loan among other incentives. This program did not have the desired effect and the expected capacity was not build until several years after the program's target date. Other previous attempts at building wind power infrastructure failed because of the competition with cheap power sources such as biomass and small hydroelectric plants (Dalbem, 2010).

Subsequent wind power infrastructure building auctions showed more interest from the private sector with power producing capacity surpassing the demand. Yet many international players did not take part, maybe because of regulatory uncertainties.

After the energy supply crisis in 2001/2 and the failure of the first wholesale energy market (MAE), the government created a new regulatory environment with wholesale market through auctions between producers and distributors, and a free market between producers and big consumers (with demand greater than 3MW). In 2004 was created the system of auctions in the regulated environment, and in 2008 the mechanism to contract reserve power. The auctions performed to supply the reserve mechanism were for renewable energy, mostly.

Auctions to purchase energy specifically from new (unbuilt) power plants have a period of years previous to the delivery date where the power plant can be built. If the plant is ready ahead of time it is then allowed to sell energy in the free market. Those periods vary, in accordance with the necessity of the regulators, from 3 years (A -3, the most recent being in 2015), 4 years (A -4, the most recent being in 2018), five years (A -5, the most recent being in 2016) and six years (A -6, the most recent being in 2018).[1]

2.2 Real Options in the Energy Sector

The theory of Real Option uses the same mathematical basis developed by Black and Scholes (1973) and Merton (1973) for financial derivatives pricing. A financial option is a derivative that reflects in its price the value of the choice which is given to its buyer. The value of the opportunity to choose whether to take or not an action was for many years an elusive subject in financial markets and it is yet overlook many times in real projects.

Outside of the financial realm projects are priced using discounted cash flow or internal rate of return. Those measures, though undoubtedly useful, fail to capture the option value of real world decisions, such as deciding whether to anticipate the construction of a new plant or waiting for new information.

The use of financial options approach to real world projects laid the basis to Real Option field. The same fundamental variables are used, namely: the underlying asset value, the strike price, the expiration date of the option, the volatility of the underlying asset, the risk-free discount rate for the duration of the option and the dividends distribution (or cash flows).

Real options can be useful to evaluate a project under the presence of uncertainty (in the environment) and flexibility for the managers to take action on the changes presented to

[1] More information can be found in the EPE site at http://www.epe.gov.br/pt/leiloes-de-energia/leiloes

them. Another important characteristic is the irreversibility of the investment (Dixit, Dixit, Pindyck, & Pindyck, 1994).

An extensive review of renewable energy projects with real options valuation, as well as a brief review of real option literature, can be found in the work published by Kozlova (2017). Based on that classification, this present work utilizes the price of electricity and price of alternative output as uncertainties, the latter modeled with a geometric Brownian motion (GBM) and the first with a mean reverting process (MRP). A switch option type was chosen, and while this choice is uncommon in wind power research, this can be explained by the novelty use of cryptocurrency mining as an alternative output. So far as we have knowledge, no work has been done with this scope.

2.3 Cryptocurrencies

A long-sought-after problem in computer science was a way to confer intrinsic value to a digital code so that it could behave as a mean of exchange. One relevant thought experiment on this subject was proposed by Nick Szabo in a blog post concerning a BitGold token (Szabo, 2005) and references to this idea can be traced back to the work of David Chaum starting from 1982 (Chaum, 1982). The main concept is the ability to use communication infrastructure to transmit real value from person to person without the need of a trust-lending partner or intermediary.

Advances in cryptography based on the work of Diffie and Hellman (Diffie & Hellman, 1976) enabled the use of digital signatures to hide content of messages being distributed in public channels or to prove ownership and authenticity of signed documents. Those advances fueled the research for secure communication exchange.

The Proof-of-Work technology, specifically the technology denominated Hashcash (Back, 2002), associated with an incentive driven consensus algorithm laid the basis to the development of the first peer-to-peer electronic payment system known as Bitcoin, first deployed in the year of 2009. Bitcoin network provides a layer for direct transactions between participants with no information about each other. The currency being exchanged in the network has volatile value, determined by individuals trading in specialized online exchanges.

To participate directly in the network a gratuitous version of the Bitcoin client must be downloaded from a central repository[1] and executed in personal computers or specialized hardware. Documentation on how to install the client is readily available and constantly updated by developers. Indirect participation on the network is possible through the use of relay software that communicates with a Bitcoin full node.

Participants on the network may wish to contribute to the Proof-of-Work mechanics by applying a hash function on blocks of unsettled transactions. The hash function produces a fixed length and unique string of characters from a given input but it is not possible to predict the outcome without actually using the function, which means that given a desired result the Proof-of-Work is a trial and error, computational intensive process.

The Proof-of-Work algorithm used in Bitcoin demands a predetermined number of leading zeros in the output of the hash function – the difficulty of the hashing operation increases exponentially the more leading zeros are expected. Anyone can participate in the process – which demands only to be connected to the network to receive the appropriate input and have an equipment capable of applying the hash function – but network difficulty has increased continuously because of hardware fabricated with the sole purpose of calculating hashes. Those devices are denominated mining hardware, as the participation in the Proof-of-Work alludes to the the work of a gold miner (Nakamoto, 2008).

Miners, as are denominated the participants that contribute to the Proof-of-Work, receive new units of the currency used in the Bitcoin network, also known as Bitcoins. The difficulty of the network is dynamically adjusted so that each new successful Proof-of-Work solution, which creates a block of aggregated transactions in the global ledger, is found at ten minutes intervals in average. The reward paid to the miners is halved every 210,000 blocks, or about four years, starting from 50 Bitcoins per block in 2009 (currently at 12.5 from 2017 on). The daily rate of Bitcoins received is directly dependent on the hashing capacity of the equipment used by the miners. The main cost of Bitcoin mining, besides the mining hardware, is electric energy consumption (Antonopoulos, 2014).

The transactions arranged in blocks constitute the Blockchain technology, since blocks are linked or chained to their predecessors through a digital signature. One of the proposed benefits of Blockchain technology is that, because there is no central authority to verify every transaction, there is no single point of failure or network clog. Verification is handled in a decentralized consensus obtained through the protocol of building, mining and verifying each block.

Other advantage of using Blockchain consensus is that because Proof-of-Work requires actual computations and since every block is signed and verified by each successor the result is a distributed ledger that is very costly to be tampered with. Blockchain technology is thus seen as a promising new development, and Bitcoin is regarded as one of its flagships.

The current Proof-of-Work infrastructure rely heavily in electric energy, and cheap energy is a determinant to mining profitability (Krause, 2018). Energy consumption by the Bitcoin network is at 3.4 gigawatts on the first half of 2018. Besides raw power, another important factor is heat dispersion, as the mining hardware produces considerable heat. This is mitigated by building mining facilities in naturally cold environments or by the use of cooling infrastructure which further increase power consumption.

3 Model

3.1 Anticipating site construction and switch option

The main objective of this study is to appraise the financial value for a Wind Farm project in North East Brazil, who is bound to enter service in 5 years from the present, that can anticipate the construction of the site and sell its available energy in the free market, up to the moment where it has to provide its contracted capacity to the grid in the regulated market. Alternatively, once the farm is in place, it can also use its energy supply to power a private venture intensive in energy use, for the available time until it is bound to the regulated market. We will model this venture as a Cryptocurrency mining facility, specifically a Bitcoin plant. If the Wind farm chooses to build the mining plant, it can choose, in every time period to either sell energy in the free market at the PLD price or alternatively power the mining facility and farm Bitcoins which are valued in US$.

We assume that the Wind Farm plant can be fired up in 12 months after start of construction. Therefore, with a: A minus 5 years contract, it could operate freely during up to 4 years. We also assume that a corresponding blockchain mining plant can be put together in 4 month time, and operate for 24 months (2 years) after which time its hardware will be outdated and also depreciated, with no resale value. For the wind farm, the cost related to the anticipation project is equivalent to the Capital Expenditure in year 4 (start the farm in 5 years minus 1 year of construction), minus this same value in present value at the effective start of construction considering the anticipation. In case of the mining facility being implemented, the depreciation to be considered will be the sum of the wind farm depreciation (which depreciates for the whole time of anticipation plus the regulated concession span) plus that of the mining facility (which depreciates in two years' time).

We will assume two scenarios. In the first, the wind farm will anticipate construction to operate the mining facility for two years. Therefore, construction of the wind farm will start in year 3, and operate for two years either selling energy to the grid at the PLD value, or mining Cryptocurrencies (Bitcoins). In the second scenario we assume the concessionaire will start construction of the wind farm immediately, and put together a mining facility to operate in years 2 and 3, after which time it must reinvest in a new set of hardware to operate the mining facility for another 2 years (4 and 5).

As the wind regimes of the North East of the country (which is the most favored region for wind farming) are seasonal and more intense in the winter months, making them complementary to the raining period, we will assume a deterministic seasonal regime for the power output of the wind farm based on Lira *et al.* (2017). In the regulated market the generator is limited to its assured capacity in the contract, but during the anticipation period the power generator is free to use all of its output. Also the mining facility capacity will not be able to use the full output of the farm since it is situated in a high temperature region and part of the output must be used for refrigeration of the operating facility, different from other mining regions such as Iceland where the natural temperature is enough to refrigerate the unit which is highly endothermal.

3.2 Modelling Bitcoin Price

Bitcoin price series are available from as early as 2010 at online exchanges around the world. Cryptocurrencies, such as Bitcoin, are traded continuously around the globe, 24 x 7, without weekend or holyday stoppage. Aggregate price series exist and as of the date of this writing are easily found without charge. Although highly volatile, as last year's performance shows, Bitcoin market capitalization has been continuously growing attaining 125 billion USD as of Dec 2018. The series used to build a model for price forecast were obtained from cryptocompare.org website, downloading data with R language script, which allows for the download of up to 2,000 daily observations.

To minimize the impact of exponential gains of the last several years a shorter series of 1,600 daily observations was used, starting in August 2014 up until the end of October 2018. The one-step difference of the series was obtained and the resulting series was log transformed. These are displayed in Figure 1 in historical value and in Figure 2 in $\log_{10}$ scale. Although the exponential valuation is evident over the time span, it also becomes apparent that the drop in value in 2018 had already happened in 2014-2015 in almost the same magnitude.

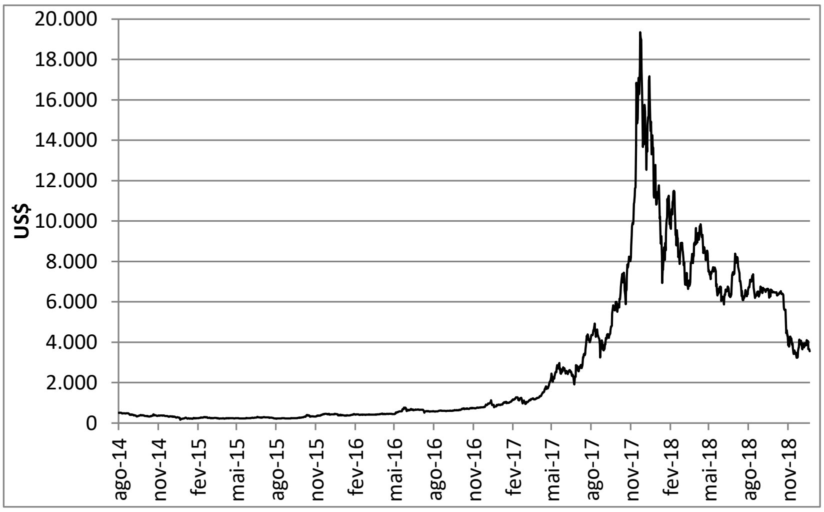

Figure 1 – Bitcoin price from August 2014 to present

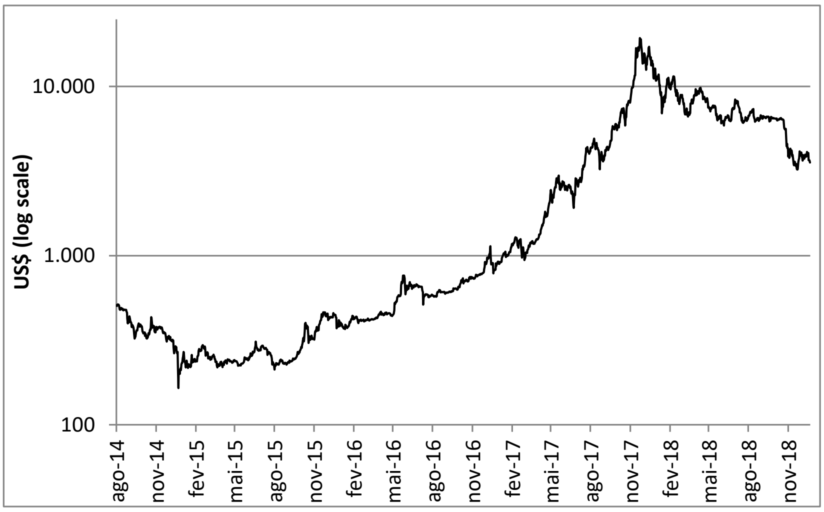

Figure 2 - Bitcoin price in $\log_{10}$ scale

As we need to model Bitcoin prices for the model to be used, it is essential to determine also which stochastic model should be used for this time series modeling. We first run an Advanced Dickey-Fuller test with intercept and trend on the log of the series displayed. The t-Statistic obtained is: -2.64515, which does not reject the presence of a unit root even at 10% level (-3.1284) for this number of samples. It returns a probability of 0.26, which would be the level at which the unit root would be eventually rejected. Therefore, we have a strong indication of a Geometric Brownian Motion (GBM) diffusion type of behavior.

We also ran a Variance Ratio test, on the log of the series to confirm the GBM stochastic process adequacy. Figure 3 shows the graphical result of the test. As the value of the Variance Ratio shows convergence to 1, after 365 days of lag (one year), we can assume that this confirms the presence of a GBM for this type of time series.

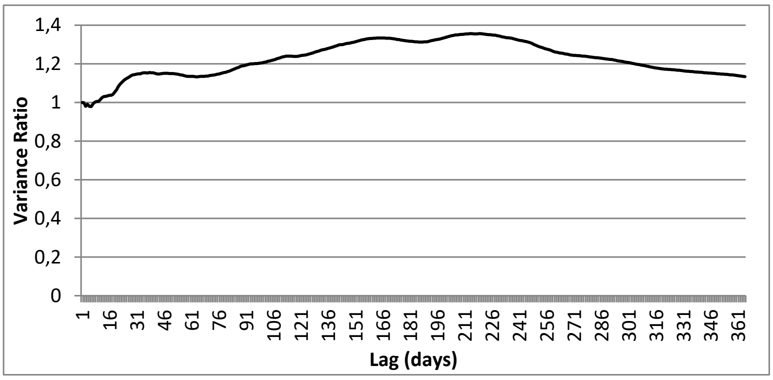

Figure 3 – Variance Ratio of Bitcoin Price series

The Geometric Brownian Motion (GBM) diffusion process has the differential equation displayed in equation (1).

$$dB = \mu B dt + \sigma B dz \qquad (1)$$

Where *B* is the bitcoin price to be modeled, μ is the drift parameter, σ the volatility parameter, *dt* the time increment, and *dz* the standard Weiner process. The simulation equation for the price *B* is given in (2).

$$B_t = B_{t-1} e^{\left(\mu - \sigma^2/2\right)\Delta t + \sigma\sqrt{\Delta t} \times N(0;1)} \qquad (2)$$

In order to determine the parameters μ and σ of the Bitcoin series, we calculated the series of differentiated log of the original series. The average and standard deviation was then calculated to obtain parameters μ and σ parameters for the GBM model. Table 1 displays the results thus obtained. Values are calculated from daily observations, but are also given in monthly (which will be used for the model) and yearly values for reference as of its magnitudes.

Table 1– Parameters for the GBM model for Bitcoin.

	Day	**Month**	**Year**
μ	0.17%	5.32%	63.8%
σ	4.0%	21.98%	76.2%

The starting value for the Bitcoin price simulation will be taken as: BTC = 5,000.00 US$, since this is the price it had when this study began. It is also the middle level of the previous level of price during most of the 2018 year – around 6,400.00 US$ - and the present value of 3,800.00 US$. As it is a price with a significant level of volatility as can observed in Table 1, we assume it is expected to recover to its previous level of 2018 in 18-month time. With this assumption we also assumed a more parsimonious monthly drift value of μ: 2% instead of the 5.32% value of Table 1. We will perform a sensitivity analysis on these values further on.

3.3 Modelling Electricity (PLD) Price

Weekly series of spot energy prices (PLD) are available for the North Eastern region of Brazil, since most Wind farms are located in this sub-region, between January 2000 and December

2018, as informed by the Brazilian Electrical Energy Clearing Chamber (CCEE) in US$ / MW. These are displayed in Figure 4.

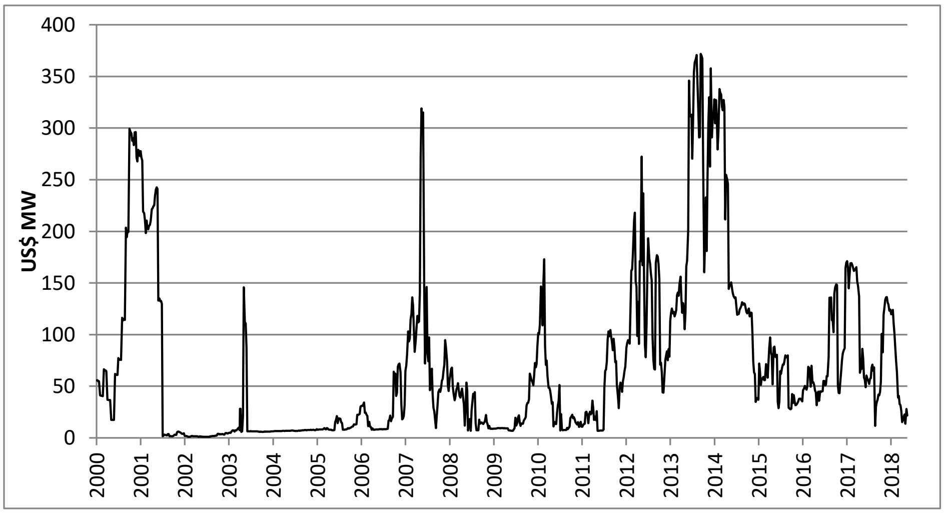

Figure 4 – PLD energy prices for NE region of Brazil

As we need to model PLD prices for the model to be used, it is essential to first determine which stochastic model should be used. We first run an Advanced Dickey-Fuller test with intercept and trend on the log of the series displayed. The t-Statistic obtained is: -4.154976, which rejects the presence of a unit root even at 1% level (-3.967667) for this number of samples. Therefore, we have a strong indication of a Mean Reversion Model diffusion type of behavior.

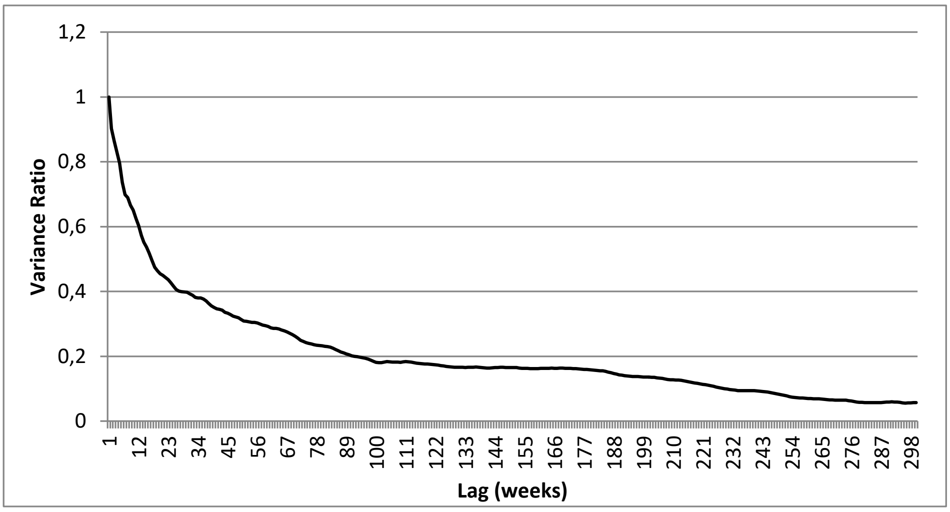

Figure 5 - Variance Ratio of PLD Price series

In order to confirm the presence of mean reversion, we ran a Variance Ratio test, on the log of the series. Figure 5 displays the graphical result of the test. As the value of the Variance Ratio for PLD rapidly drops below 1, we have confirmation of the presence of a mean reversion for this time series.

Therefore, the energy price of PLD was modeled as a Geometric Mean Reversion (GMR) diffusion process, as proposed by Schwartz (1997), and shown in Equation (3):

$$dP = \eta\left(\ln\bar{P} - \ln P\right)Pdt + \sigma_P P dz \tag{3}$$

where η is the mean reversion coefficient parameter of the process; σ_P is the volatility of the PLD price, $\bar{P}$ the mean or equilibrium level of the PLD price, and *dz* is the standard Weiner increment.

In order to calibrate these parameters, we used the approach described by Bastian-Pinto *et al* (2011). But it is apparent in the series displayed in Figure 4 that the mean level of prices has changed in the time span displayed. Since 2007 a lack of regular rainfall has drained the reservoirs of south east region of Brazil as well as those of the north eastern region, where most of the wind farms are located. The hydro capacity of the country is still by far, the main energy supplier of the country, counting around 80% of the whole energy generation installed capacity. This has led to an increase in non-regulated energy prices, as can be observed. Therefore we chose to calibrate the proposed model using a time span from July 2007 to present, in order to better model the expectation of future energy prices.

As defined in Bastian-Pinto *et al* (2011)the expected value equation for the model defined in (3) is shown in (4).

$$E\left[P_t\right] = \exp\left\{\ln\left(P_{t_0}\right)e^{-\eta(t-t_0)} + \left[\ln\left(\bar{P}\right) - \frac{\sigma^2}{2\eta}\right]\left(1-e^{-\eta(t-t_0)}\right) + \frac{\sigma^2}{4\eta}\left(1-e^{-2\eta(t-t_0)}\right)\right\} \tag{4}$$

While the risk neutral simulation equation is (5).

$$P_t = \exp\left\{\ln\left[P_{t-1}\right]e^{-\eta\Delta t} + \left[\ln\left(\bar{P}\right) - \frac{\sigma^2}{2\eta} - \Pi\right]\left(1-e^{-\eta\Delta t}\right) + \sigma\sqrt{\frac{1-e^{-2\eta\Delta t}}{2\eta}}N\left(0,1\right)\right\} \tag{5}$$

Where Π is the risk neutral adjustment that will be determined by a numerical approach, to be described latter on, and Δt the time increment to be used in the regression. If we consider a year to be Δt=1, then, for a monthly increment: Δt=1/12, a weekly increment: Δt=1/52 and a daily increment: Δt=1/365. Simulations in this paper will be performed for monthly periods of Cash Flows.

According to Bastian-Pinto *et al* (2011)all other parameters were calibrated from the log of the PLD time series, by running the regression (6).

$$\ln\left(P_t/P_{t-1}\right) = \underbrace{\left(1-e^{-\eta\Delta t}\right)\left(\ln\bar{P} - \sigma^2/2\eta\right)}_{a} + \underbrace{\left(e^{-\eta\Delta t} - 1\right)}_{b-1}\ln P_{t-1} \tag{6}$$

Parameters are defined by (7), (8) and (9).

$$\eta = -\ln(b)/\Delta t \tag{7}$$

$$\sigma = \sigma_\varepsilon\sqrt{\frac{2\ln b}{(b^2-1)\Delta t}} \tag{8}$$

Where σ_ε is the standard error of the regression, and

$$\bar{P} = \exp\left[\frac{a}{(1-b)} + \frac{\sigma_\varepsilon^{\,2}}{(1-b^2)}\right] \tag{9}$$

But as pointed by Schwartz (1997) the model defined by (3) does no converge to (9) but to (10) .

$$\bar{P}^* = \bar{P}\exp\left(-\frac{\sigma^2}{4\eta}\right) \tag{10}$$

Therefore we use this value as the equilibrium mean of the process. Table 2 displays the values thus obtained. Values are calculated from weekly observations, but are also given in monthly (which will be used for the model) and yearly values for reference as of its magnitudes.

Table 2 - Parameters for the MRM model for PLD

	Week	**Month**	**Year**
η	0.0503	0.2178	2.6135
σ	32.1%	66.8%	231.3%
PLD $\bar{P}^*$		94.06 USD/MW	

The initial value, at t_0, for the simulation of the PLD time series is the last value of the PLD displayed in Figure 4: P_o = 20.00 US$/MW.

3.4 Cash Flow and Investment Structure of the Cases Modeled

The basic case in this paper is the anticipation of the wind farm site construction. We use the data developed in Fontanet (2012) who models a typical wind farm in Brazil with conditions similar to the one in this study. These are listed in Table 3.

Table 3 – Wind Farm Specifications

	Assured	Nominal
Capacity (monthly output)	3,577 MW	7,154 MW
CAPEX (US$)	9,540,000.00 US$	
Monthly depreciation	40,000 US$	
Weighted Average Cost of Capital WACC	8% (year)	0.64% (month)
Risk Free rate	5% (year)	0.54% (month)

In the case of anticipation of the wind farm construction, the Capital Expenditure to be considered is the value in Table 3, minus this same value discounted at the corresponding WACC, for the time frame of the anticipation: either 2 years or 4 years, depending on the scenario. This amounts to US$ 1,361,241 in the 2 year anticipation scenario and 2,528,300 in the 4 year anticipation scenario.

The normal operation of the Wind Farm, under the regulated market in a A -5 years grant, is described in Figure 6.

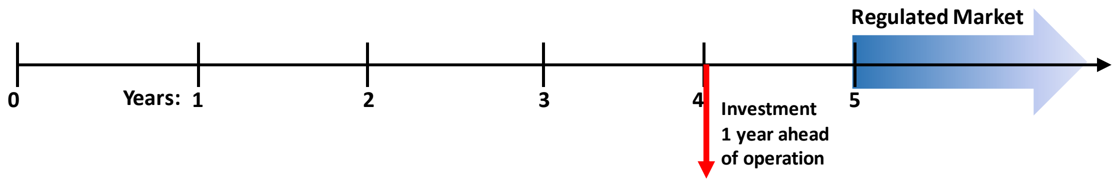

Figure 6 – Wind Farm A minus 5 years operation in the regulated market

Both scenarios of construction anticipation are shown in Figure 7.

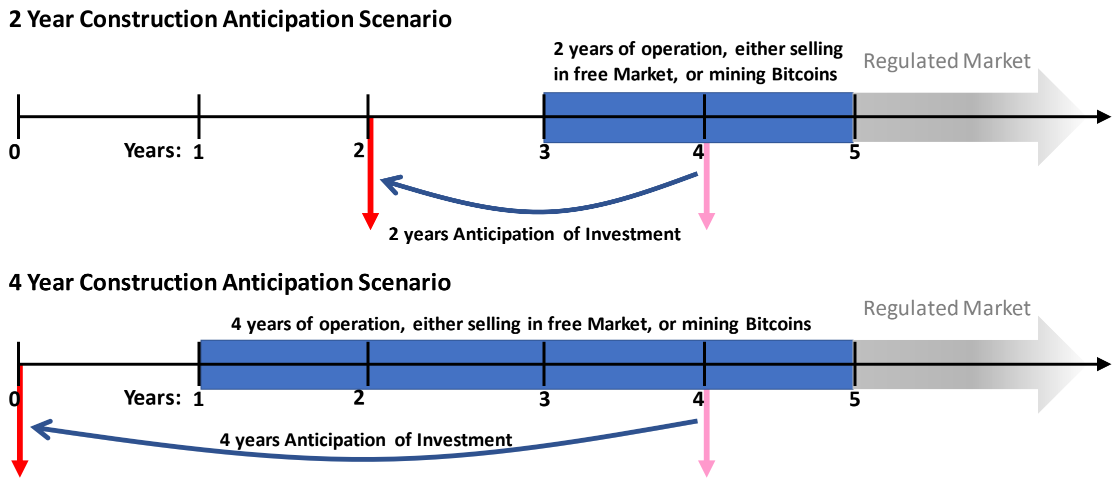

Figure 7 - Scenarios of construction anticipation

We also consider that when selling energy to the free market, the plant can commercialize up to its full capacity, but this will be limited to the wind regime in the region, which is describe by Lira *et al* (2017) and is shown in Figure 8, when we consider the average of generation subject to the wind speed regime.

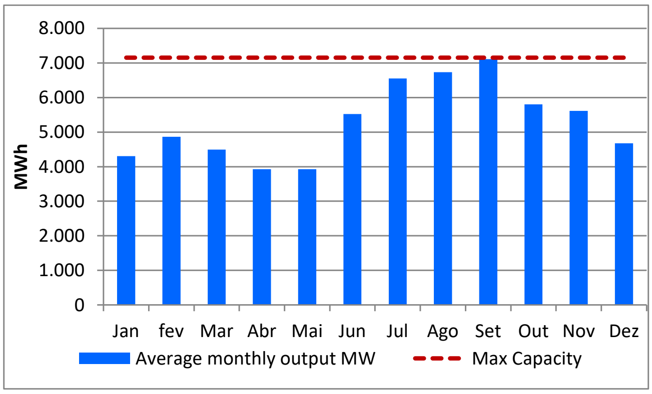

Figure 8 – Wind Farm monthly output

In the case of only energy sale to the free market (PLD), the constructor will earn the following monthly Cash Flow as in (11).

$$EECF_t = (PLD_t \times Output_t \times 0.86 - \text{Depreciation}) \times (1\text{-}T) + \text{Depreciation} \qquad (11)$$

Where:

$EECF_t$: Cash Flow from Energy Sale in month t

PLD_t: Energy price in t (stochastic and modeled with (5))
Output $_t$: Energy seasonal monthly production as in Figure 8
T: applicable income tax rate (34% In Brazil)
A value of 14% is considered as variable costs on income (taxes, fares and others).

$EECF_t$ will be earned by the constructor for either 24 consecutive months after the construction period of 12 months in the 2 years anticipation scenario, or 48 months in the 4 years anticipation scenario as in Figure 7.

3.5 Switch option when mining Cryptocurrencies

Once the wind farm is in place and producing energy, the constructor has the possibility on investing in a Bitcoin mining plant that used the wind farm energy output. Data for this mining plant are listed in Table 4.

Table 4 – Mining plant specifications

Cost of mining unit	700 US$
N. of mining units	3,400
CAPEX (US$)	2,325,000.00 US$
Total Monthly depreciation (wind farm + mining plant)	140,000.00 US$

The constructor can at this point choose to mine Bitcoins, which will earn him the cash flow as in (12).

$BCCF_t = (B_t \times Output_t \times En\_use \times 0.86 - \text{Tot Deprec.}) \times (1\text{-T}) + \text{Tot Deprec.}$ (12)

With:

$EECF_t$: Cash Flow from Energy Sale in month t
B_t: price in t (stochastic and modeled with (3))
En_use: 79,863 (*KWh/Bitcoin*)

It takes 3 months for the constructor to put together the mining plant, and as it has to be in place at the start of the wing farm operation, this investment must be done in month 35 in the 2 year anticipation scenario, and in months 9 35 again for the 4 year anticipation scenario. In this last case we consider that the constructor will reinvest in the mining plant after 2 years of operation, since the hardware used has only 2 years of operational life.

Now the constructor has a switch option to choose between cash flows generated by (11) or by (12), where in both cases the depreciation it that of Table 4. Also in both possibilities of cash flow the CAPEX of the mining plant is considered.

4 Results

4.1 Wind Farm construction anticipation and sale to free market

In this topic we only consider selling of the energy generated at the PLD price for the anticipation of the wind farm in both scenarios. These values will be used as reference for comparison with the results from the Switch Option scenarios. As mentioned earlier the values of CAPEX in both scenarios are the present value of the original investment to be spent in year

4 of the original project under the [A -5] contract, minus the same amount discounted at the WACC rate to the start of the anticipation scenarios. After 12 months of the investment, the constructor will receive the cash flows described in (11). As there is no option in this case, the cash flows are discounted at the WACC rate, and PLD is modeled by (5). Therefore, there is no need to consider the risk premium Π in this equation. We estimate the present value of this cases using Monte Carlo Simulation, in order to have a distribution of Net Present Values (NPV) results and compare these to the ones to be obtained from the scenarios with the switch options. These are displayed in Figure 9 and Figure 10.

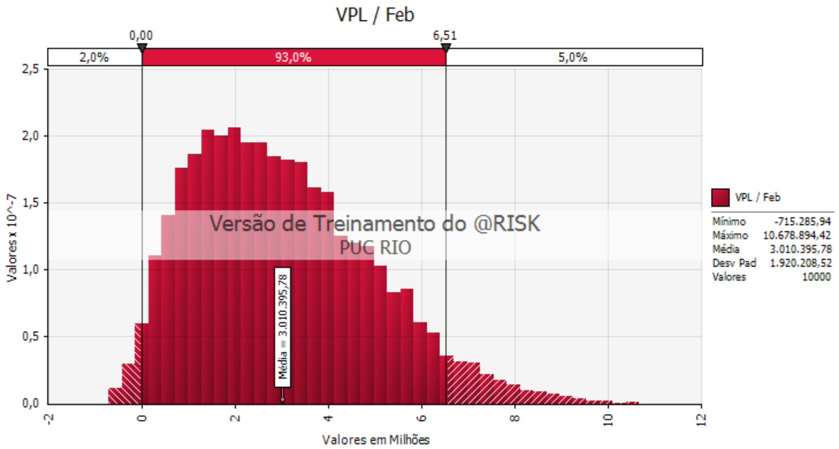

Figure 9 – NPV distribution for 2 years anticipation of energy sale scenario

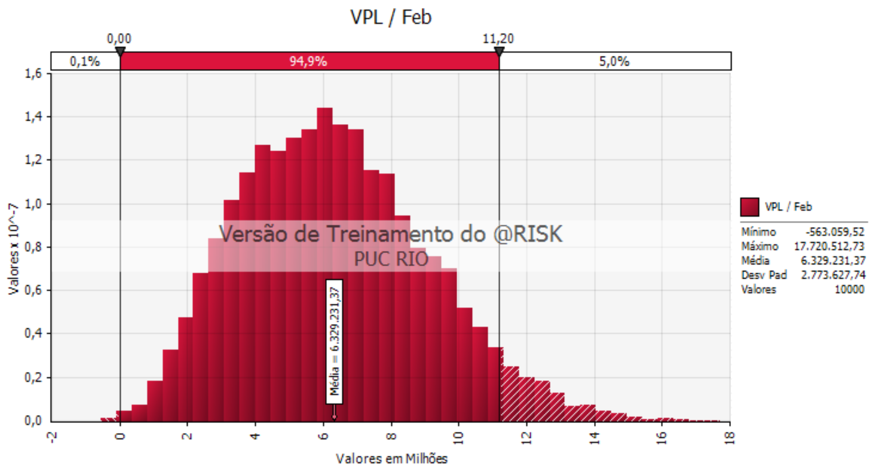

Figure 10 - NPV distribution for 4 years anticipation of energy sale scenario

From these simulations two aspects can be clearly pointed out: both scenarios of construction anticipation show positive and strong NPVs. While anticipating construction in 2 years yields a NPV of US$ 3,010,396, with a 2.0% probability of having a negative value, a 4 year anticipation will yield a NPV of US$ 6,329,231, and now with only 0.1% probability of a negative value. This result is 250% of the net investment required to earn it, which not only indicate a significant return but also a low risk associated to it. And this last aspect is contrary to our previous expectations, which assumed that the risk in being exposed to the volatile PLD price dynamic would drive off constructors from such an anticipation project. After all, it's because of this price volatility that the regulated market was put together.

4.2 Construction anticipation and Switch Option between energy and Bitcoin sale

Now we consider that in each of the scenarios developed, once the construction has been anticipated, the constructor can implement a mining facility with the characteristics listed in Table 4. In this case the investment in the facility will be undertaken 4 months before the wind farm can be fired up: month 34 in the 2 year anticipation scenario, and month 10 in the 4 year anticipation scenario. In this case we consider the risk premium Π for both stochastic variables: PLD price and Bitcoin price. Again we estimate the present value of this cases using Monte Carlo Simulation, in order to have a distribution of Net Present Values (NPV) results and compare these to the ones to be obtained from the scenarios without the switch options. These are displayed in and.

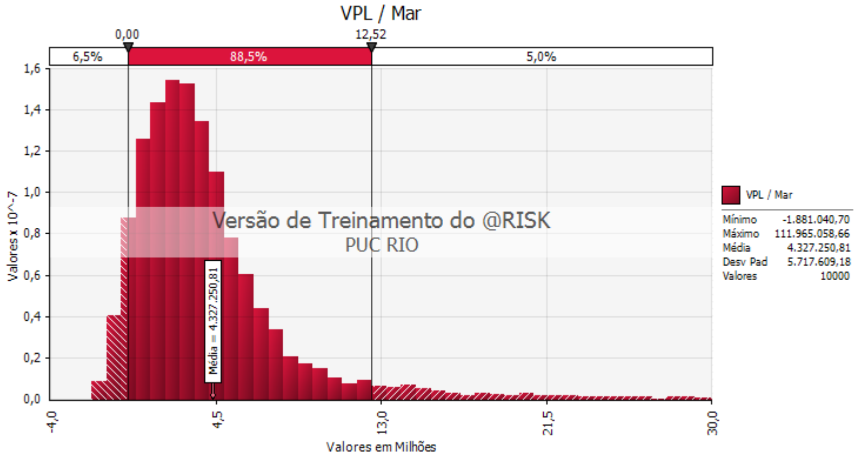

Figure 11 - NPV distribution for 2 years anticipation scenario Switch option PLD x Bitcoin

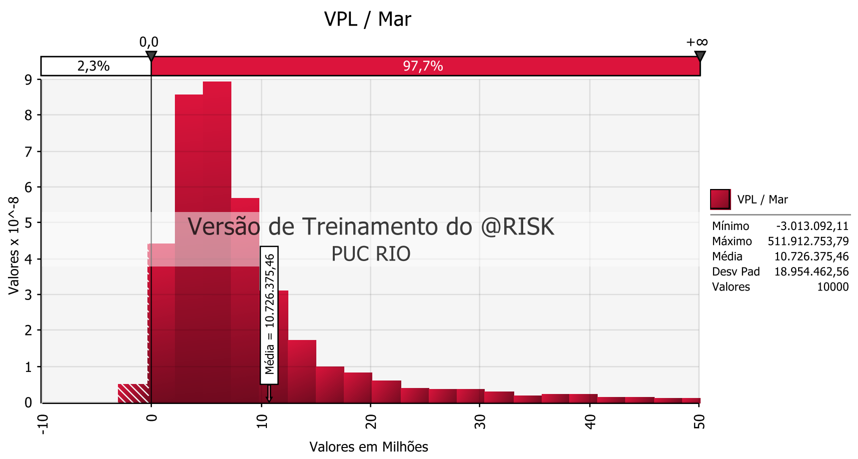

Figure 12 - NPV distribution for 4 years anticipation scenario Switch option PLD x Bitcoin

Again, from these simulations two aspects can be clearly pointed out: both scenarios of switch option show positive and strong NPVs. While the 2 years switch option yields a NPV of US$ 4,282,128, with a 42.4% increase over the PLD only sale scenario, and a 6,7% probability of having a negative value, the 4 year switch option will yield a NPV of US$ 10,726,375, with a 69.5% increase over the PLD only sale scenario, and a 2,3% probability of having a negative value. These results yield a significant result increase over the base case in both scenarios of construction anticipation.

As these appear to be strongly influenced by the initial value and drift for the Bitcoin price simulation, and considering that this variable is highly volatile, we perform a sensitivity analysis of the Switch option of 4 years, to these two inputs. As can be observed in Figure 13 and considering that the base case of construction anticipation has an NPV of US$ 6,329,231, only very few possibilities with drift bellow 0.005 (0.5%) and initial value under US$ 4,000 will yield negative values and even so not very expressive.

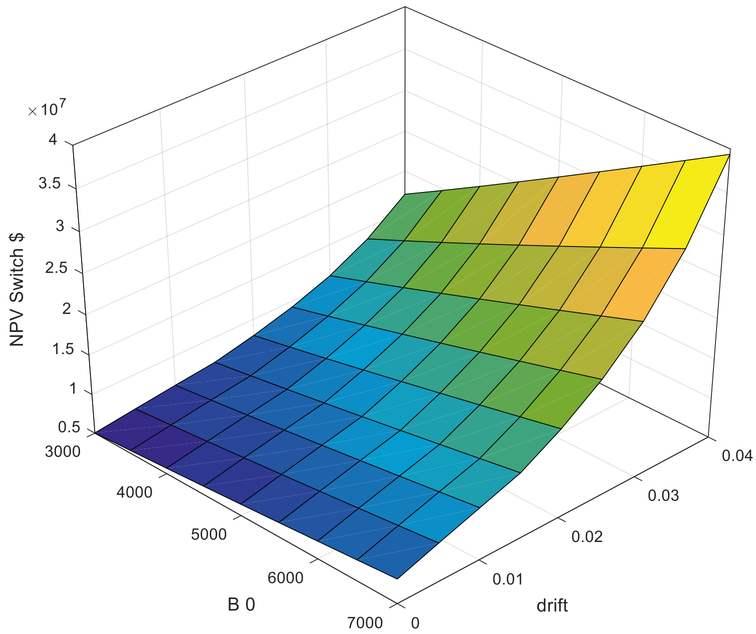

Figure 13 – Sensitivity analysis of NPV Switch Option for 4 year, and Bitcoin drift and initial value

5 Conclusions

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