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Hedging renewable energy investments with Bitcoin mining

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A R T I C L E I N F O

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A B S T R A C T

Renewable energy sources such as wind power are increasing their share of the world energy matrix. In Brazil, the regulator promotes reverse bid auctions where the winner agrees to begin production a number of years ahead under a long-term contract. If a wind farm project chooses to anticipate construction, it can sell its energy in the short-term market but becomes subject to electricity price volatility. In order to create incentives for early investment, we propose that wind farm investors can hedge electricity price risk by simultaneously investing in a cryptocurrency mining facility that uses electricity as input to produce newly minted Bitcoins. As electricity and Bitcoin prices are uncorrelated, the ability to switch between these outputs allows the wind farm to maximize revenues and minimize losses. We develop a numerical application under the real options approach to determine the financial impact of the investment in a Bitcoin facility for the wind energy producer that will allow it to optimally switch outputs depending on the relative future prices of electricity and Bitcoins. The short-term energy price and Bitcoin price/mining-difficulty ratio are modeled as distinct stochastic diffusion processes. The results indicate that the option to switch outputs significantly increases the generator's revenue while simultaneously decreasing the risk of anticipating the construction. These findings, which can also be applied to other renewable energy sources, may be of interest to both the energy generator as well as the system regulator as it creates an incentive for early investment in sustainable and renewable energy sources.

1. Introduction

The shift towards a cleaner energy matrix is a worldwide trend, as many countries have created incentives to limit carbon emissions from fossil fuel combustion and increase energy production from renewable and sustainable sources of energy [1]. Along with technological advances that have lowered the cost of new power plants, this effort has resulted in significant growth in this area. On the other hand, renewable energy production presents many risks. As it relies on non-controllable perennial natural resources such as wind or sunlight rather than on a finite stock of fuel, its energy generation is intermittent. This fact exposes the producer to volume risk, as it may not be able to fulfill its energy sales contracts in case of a production shortfall. In addition, future electricity prices are uncertain, which also subjects the producer to price risk.

Brazil has one of the cleanest energy matrices in the world, where renewables accounted for 45.3% of the total consumption in 2018, compared to the world average of 13.7%, and 9.7% for the OECD nations. The share of renewables in electricity generation in the country is even higher and accounts for 83.3% of the total, compared to 24.0% and 23.8% respectively for the world and OECD [2]. Over three-quarters of the country's electric power supply comes from hydroelectric dams, making it the third country in the world in this energy source behind only China and Canada. Although new hydropower capacity has come online with the Belo Monte dam inauguration, the construction of large hydroelectric power plants can impact environmental ecosystems [3].

Meanwhile, wind energy generation in Brazil has grown significantly in the past decade, from only 663 GWh in 2007 to 48,475 GWh in 2018. This represents a growth of more than 7000%, making it the country's second electrical energy source after hydropower, and Brazil, the 8th country worldwide in wind energy capacity. The Brazilian Electricity Regulatory Agency (ANEEL) is responsible for fostering the development of this increase by promoting reverse bid auctions in the regulated market where the winner agrees to begin energy production in a set number of years. Several auctions have been held since 2011, which resulted in the celebration of 479 renewable energy projects, of which 203 were wind farms, 121 were photovoltaic power plants, and 155 were hydropower plants [4]. This increase in new renewable sources is due to both the favorable geographical and climate conditions that

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Abbreviations

ADF	Augmented Dickey-Fuller Unit Root test
ANEEL	Agência Nacional de Energia Elétrica - Brazilian Electricity Regulatory Agency
ASIC	Application-Specific Integrated Circuits
BTC	Bitcoin
BTC$	Bitcoin price in USD
BTC$/Diff	Bitcoin price and Mining or Network Difficulty ratio
CAISO	California Independent System Operator
CAPEX	Capital Expenditures in WindFarm
$CAPEX_{BTC}$	Capital Expenditures in Bitcoin mining facility
CCEE	Câmara de Comercialização de Energia Elétrica - Brazilian Electric Energy Clearing Chamber
GMR	Geometric Mean Reversion
GWh	Gigawatt hour
ICO	Initial Coin Offering
k	Risk-Adjusted rate or Cost of Capital
KW	Kilowatt
MCS	Monte Carlo Simulation
MW	Megawatt
MWh	Megawatt hour
NPV	Net Present Value
OECD	Organization for Economic Cooperation and Development
PLD	Price for Liquidation of Differences: Electricity spot price in Brazil
r	Risk-Free rate
TWh	Terawatt hour
USD	United States Dollar

prevail in Brazil and ANEEL's policy of fostering renewables development. The bid auctions for reserve energy dedicated exclusively to renewables have met with significant success, as can be observed in the growth of renewables capacity.

Nonetheless, renewable energy power generation investments still involve significant risks for investors and require specific policies, government incentives, and risk reduction mechanisms. Due to these risks, the amount of units that fail to complete in time has been significant. According to ANEEL [4], as of November 2019, 195 of these units, or 41% of the total, were behind schedule. Considering only wind and solar energy plants, the number of projects behind schedule was 68 out of 324, or 21% of the total. Work had still not begun in 219 of these projects, and 37 had their construction work suspended, representing 712.8 MW of capacity at risk, as shown in the Appendix. These potential delays can create problems for the system regulator if the expected volume of energy generation fails to come online as planned.

This article proposes a hedging mechanism that allows a wind farm venture to reduce risk by simultaneously investing in a Bitcoin (BTC) mining facility, which allows the firm to optimally switch outputs between electricity and Bitcoins depending on the relative values of each of these. This creates an incentive for early investment in the wind farm since anticipating production allows the firm to generate earlier and less risky cash flows. If electricity prices are high, the wind farm can sell its energy in the spot market; otherwise, the firm can switch to Bitcoin mining. This also reduces the risk for the system regulator, as these projects will be more likely to begin providing energy to the regulated long term on the contracted date, as they will come onstream in the free market years earlier.

The logistics of producing and selling digital currencies is simple and limited to the acquisition of computational hardware, also known as cryptocurrency mining hardware, and to the supply of the electric power, network connection, and refrigeration required for the operation. Electricity and Bitcoin prices (BTC$) follow distinct and uncorrelated stochastic processes, which enhances the value of this option to switch outputs. The value of this switch option is a function of the difference in the value of the Bitcoins that are mined and the cost of the energy required to do so, which we denominate the bit-spread. Whenever the bit-spread is positive, it is optimal to switch from energy sales in the spot market to Bitcoin mining. It is assumed that the wind farm will immediately sell the newly minted bitcoins in the market through a cryptocurrency exchange without incurring storage risk or currency volatility. It is also assumed that the exchange is trustworthy and secure communication and crypto-key management technologies are adopted.

The objective of this paper is to determine the impact of this switch option on the risk and return of the project for the wind farm investor. As this option will require a simultaneous investment in a Bitcoin mining facility, the returns must be sufficient to compensate for these additional costs. Furthermore, construction anticipation will reduce the risk for the system regulator of the power plant not coming online as expected.

In order to achieve this objective, a formal and original model of the price and technology dynamics of Bitcoin mining is developed, which involves an energy-intensive computational process. The option to switch the outputs of a portfolio comprised of a wind farm and a Bitcoin mining facility is modeled under the real options approach by taking into account the stochastic dynamics of both energy prices and the ratio between Bitcoin prices and network difficulty. In order to illustrate the use of the model, a numerical application is made to the case of a typical wind farm in the Brazilian Northeast region. Our results suggest that this strategy may allow a wind farm to increase value and reduce risk significantly while creating incentives for early investment in the project.

This article is organized as follows. The next section provides a review of the literature on real options and renewable energy and an overview of wind energy generation in Brazil and cryptocurrency mining. In section 3, the stochastic modeling of short-term electricity prices in Brazil and a composite variable of the price of Bitcoin divided by the network mining difficulty is discussed. In section 4, the value of the option to switch outputs between short-term electricity sales and Bitcoin mining is determined, and in section 5, the results are present. Finally, we conclude.

2. Literature review and background

2.1. Real option analysis

Real Option theory derives from the work of initially developed by Black and Scholes [5] and Merton [6] for financial derivatives pricing as applied to real, rather than financial assets. While real assets are usually priced using discounted cash flow methods, this approach fails to capture the value of flexible real-world decisions, such as the option to anticipate, defer or abandon the construction of a new plant, to expand production, or to switch inputs or outputs. Tourinho [7], Myers and Majd [8], Brennan and Schwartz [9], McDonald and Siegel [10], and others further developed the basic concepts of this approach and applied it to different types of managerial flexibility. Pindyck [11], Dixit [12], Trigeorgis [13], and Dixit and Pindyck [14] also showed that real options could be useful to evaluate a project under the presence of uncertainty and flexibility for the managers to take action on the changes presented to them.

Concerning the valuation of renewable energy projects, there is an extensive literature on the use of the real options approach to this field. Dias et al. [15] analyze a sugar and ethanol-producing plant in Brazil which has both the option to expand and to add a cogeneration unit to allow the sale of surplus energy generated by burning sugarcane bagasse, where the existence of the second option is conditional to the exercise of the first option. Brandão, Penedo, and Bastian-Pinto [16] discuss the value of the input switching options embedded in the production of biodiesel fuel and show that the choice of model and parameters has a significant impact on the results of the valuation. In a paper more closely related to ours, Dalbem, Brandão, and Gomes [17] analyze the option to anticipate the construction of a wind farm plant in order to sell energy in the spot market. They conclude that due to the low price that prevailed at the time, no value was created, which made it unlikely that this option would be exercised. Oliveira et al. [18] model energy prices with mean reversion and jumps using Monte Carlo Simulation for a biomass cogeneration project. For a more detailed discussion of the application of real options to renewable energy projects, we refer the reader to Kozlova [19] for a comprehensive review of the field, as well as a brief review of real options literature.

2.2. Wind energy in Brazil

Brazil's geography and regulatory space are considered favorable for wind farm construction and development. The country has a large wind power production capacity, and due to the relatively short time to build a wind farm when compared to hydropower plants, those are being favored by the electrical energy regulatory agencies as well as for environmental and sustainability issues. The regulatory environment of the Brazilian Electricity System involves a wholesale market with auctions between producers and distributors and a free market between producers and consumers with demand greater than 3 MW. In 2004, the auction system in the regulated environment was created, followed by a mechanism to contract reserve power in 2008. Since then, auctions for the reserve mechanism have been mostly for renewable energy.

ANEEL regulates the future supply of energy using long-term energy supply auctions for different sources of electricity generation. The parties interested in developing the power plant enter into a reverse auction for the tariff or rate they wish to receive for the energy produced for the duration of the concession. The winning party must then provide the contracted amount of energy at a stipulated future date, usually a few years ahead. The volume of energy to be provided at the winning rate is called the assured capacity of the site and typically corresponds to 50% of the total capacity of the site to be constructed.

Since the winner of the auction has a set number of years to begin delivery of the energy, if the power plant is built ahead of time, it can sell its energy in the free market until then. The delivery start time varies between three (A-3) and six (A-6) years, depending on the needs of the regulator. If the party wins an A-6 contract, it will have six years to build the site, after which it must provide the assured capacity for the duration of the concession. Assuming a two-year construction period for a wind farm, the firm must commence building at the end of year four at the most, as shown in Fig. 1.

On the other hand, if the firm chooses to commence building immediately, it will have four years of energy generation that can be sold in the short-term market. The electricity spot price in Brazil is known as the PLD (Price for Liquidation of Differences), which is a weekly energy settlement price determined by the Brazilian Electric Energy Clearing Chamber (CCEE). In normal market conditions, the PLD should be in equilibrium at a low value, and direct energy sales to the short-term market may not provide enough incentive to anticipate the construction. Nonetheless, in the past decades, the electricity spot prices in Brazil have shown significant volatility, with its average value increasing markedly. For the regulator, anticipation of construction guarantees that the required energy will be available in the future as expected and eliminates the risk of eventual delays or project cancelation. In this article, we suggest that adding an energy-intensive venture to the site, such as a cryptocurrency mining facility, provides the wind farm protection against low PLD prices, increases the value of the project, and encourages early investment.

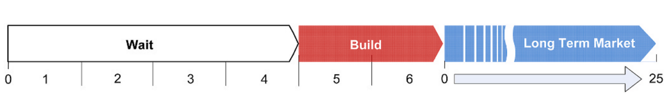


Fig. 1. Traditional A −6 Wind farm project with a wait time of four years to begin construction and start of operations for energy sales in the Long Term regulated market at the end of year 6.

2.3. Cryptocurrencies

Since the advent of modern digital communications, there has been a search for a currency that could incorporate the best characteristics of this technology. However, the ease by which documents could be repeatedly copied in this medium was a difficult barrier to overcome. The solution to this problem began with a method of validation named Hashcash developed by Back [20], which adopted an algorithm that associated the emission of digital coins with a computational-intensive mechanism known as proof-of-work. This mechanism prevented coins produced in this way from being copied without applying the same computational effort again. In 2004 a method to reutilize those coins in subsequent transactions was developed by Finney [21], which allowed digital coins to hold value after being transacted. Though both technologies were revolutionary, they were not enough to create general-purpose digital cash as intended.

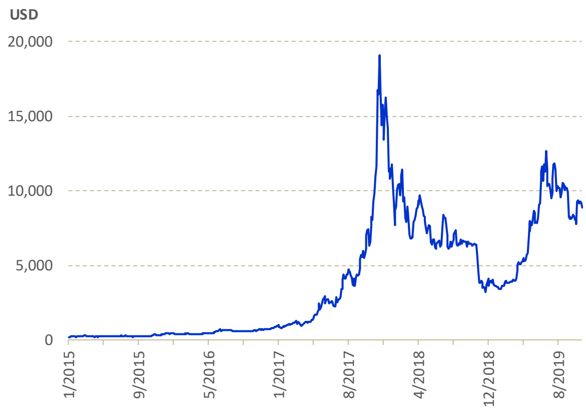
The breakthrough in electronic cash came with the publication of the Bitcoin whitepaper in 2008 by an anonymous group under the pseudonym of Satoshi Nakamoto [22]. The paper associated Back's and Finney's technology with a distributed database storage developed in 1991 that would later become known as blockchain [23].

The effort to write data to Bitcoin's blockchain is rewarded by transaction fees paid by users and by the emission of newly minted digital coins. Anyone can attempt to write a block of valid transactions on the distributed ledger, but the network only accepts it if it is the first to generate a digital signature known as *hash*. The effort of generating a *hash* is an energy-intensive process called cryptocurrency mining, which in the case of the Bitcoin network, requires the use of custom-built computational hardware known as ASICs (Application Specific Integrated Circuits). The greater the mining capacity, or *hashrate,* held by a participant, the greater the chances of being the first to find the correct digital signature for the next block of transactions.

The current proof-of-work infrastructure relies heavily on electric energy [24]. Energy consumption by the Bitcoin network is significant, and as of January 2020 was 75 TWh, which is equivalent to the annual energy consumption of Chile [25]. Similar to the heat-rate of a gas turbine, we define the bit-rate as a measure of the efficiency of the Bitcoin mining facility regarding its electric energy consumption. The bit-rate is a function of the network difficulty and the mining hardware used, the specification of which is publicly available, and is expressed in the amount of electrical energy required to produce one Bitcoin or MWh/BTC. The technological evolution of mining hardware is quick, and mining equipment is usually assumed obsolete within two years as the bit-rate increases to infinity.

Similar to the spark-spread [26], the bit-spread represents the dollar value of the Bitcoin mining operation, which is a function of the bit-rate and the relative values of Bitcoin and Electricity prices. Haliplii et al. [27] explore the profitability of Bitcoin mining using a real options framework. The authors, however, assume that electricity prices remain constant, which may skew some of the results.

Works that discuss the use of cryptocurrency mining as a hedging mechanism for renewable energy generation are scarce in the literature. In a paper closest to ours, Shan & Sun [28] analyze the benefits the California Independent System Operator (CAISO) would accrue if the renewable energy production of California curtailed in 2018 was used to mine Bitcoins. Using historical data, they conclude that this value could be as high as $48.1 million, depending on the type of equipment. Our paper differs from Shan & Sun [28] as we model Bitcoin prices, hash



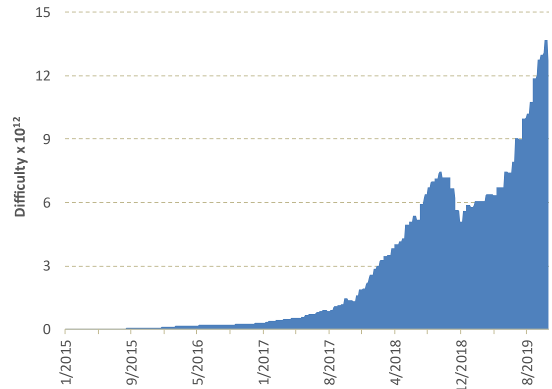


Fig. 2. Historical Bitcoin prices in USD (BTC$) (left) and Bitcoin mining difficulty (Hashrate) (right) from January 2015 to November 2019. Source: www.blockchain.info.

rates, and electricity prices as dynamic stochastic diffusion processes rather than use static historical values, and consider that the wind farm has the flexibility to optimally decide whether to sell energy or mine Bitcoins.

2.4. Blockchain and renewable energy

One of the first comprehensive reviews of blockchain applications in the energy sector was done by Andoni et al. [29], who reviewed and classified 140 commercial listed blockchain and research initiatives and provided a detailed analysis of energy applications and P2P energy trading. They showed that 19% of the 140 projects were related to cryptocurrencies, tokens, and investment and that some of the first blockchain applications in the energy sector were the use of Bitcoin for energy payments. Andoni et al. [29] also describe a waste-to-power energy plant with a cryptocurrency mining facility, where investors can purchase an energy token named KWATT through an ICO (Initial Coin Offering) process. Investors can then decide to either sell energy to the grid or use it to mine cryptocurrency. This provides a switch option that is similar to our model, but contrary to our paper does not provide an electricity price hedge for the power producer. Orcutt [30] reports that Bitcoin mining facilities totaling 1400 MW are currently under development in west Texas where they will be powered by the large wind power generation capacity available in that area, and in Morocco, the first phase of a 900 MW wind farm Bitcoin mining facility is underway [31]. Blockchain is recognized as one of the 10 top strategy technologies [32]. Castellanos, Coll-Mayor & Notholt [33] and Zhao, Guo & Chan [34] list and analyze blockchain applications in the renewable energy sector, such as green energy certificates guarantee of origin.

3. Model

The model considers a wind farm in Brazil that is bound to enter service in 6 years under an A-6 contract, that the construction of the site will begin immediately and that the available energy will be sold in the short-term market until the moment where the wind farm must begin to deliver its contracted capacity. A Bitcoin mining plant that will be built on the same site as the wind farm is also modeled. This allows the wind farm to optimally switch from selling energy in the short-term market each month to producing Bitcoins at the mining facility and selling those instantly on an online exchange.

The wind farm is assumed to become operational 24 months after the start of construction and the only cost involved is the cost of anticipating the capital investment by four years. The Bitcoin mining facility will be built in 3 months and operate for two years, after which it will be fully depreciated due to technological obsolescence. A scenario where new mining hardware is purchased near the end of the fourth year and operated for an additional two years is also considered.

In the base case, the firm sells all power produced at PLD for four straight years. The first switching scenario considers that at each monthly period, the producer can choose whether to sell power at PLD or use it to produce Bitcoins during years 3 and 4. The second switching scenario assumes that the producer will purchase a new set of mining hardware at the end of year 4 in order to operate the mining facility during years 5 and 6 also.

The model assumes a deterministic seasonal regime for the power output of the wind farm based on Lira et al. [35]. In the regulated market, the generator is limited to its assured capacity in the contract. However, during the anticipation period, the power generator is free to use all of its output. In addition, the mining facility was designed to operate non-stop and will have a maximum capacity of consumption equal to the lowest month of power generation. The mining facility will be unable to use the full energy output of the wind farm as part of this power must be used for refrigeration purposes.

3.1. Modeling Bitcoin price and mining difficulty

Cryptocurrencies, such as Bitcoin, are traded continuously around the globe, 24 h a day, and 7 days a week. Although highly volatile in price, Bitcoin market capitalization has grown, attaining 130 billion USD as of December 2019 Figure 2.

Given that Bitcoin mining is a trial and error process, the time a particular miner spends to find a proper signature for a block of transactions is a random variable and can be approximated by Eq (1) [36].

$$T = D * 2^{32} \,/\, H \tag{1}$$

where D is the network difficulty; H is the mining hardware hash rate; T is the average time in seconds to find a proper hash for a Bitcoin block of transactions and 2^{32} is the expected number of hashes to find a valid block. Assuming a constant flow of production, which can be achieved by participating in mining pools and sharing the profits according to the hash rate of each participant, the revenue of Bitcoin mining can be estimated using a modified version of Eq (1). By including additional variables such as the network reward, which is the number of Bitcoins earned for each valid block found, and the USD/Bitcoin exchange rate, the mining revenue can be determined as shown in Eq (2).

$$\pi = P * R * H * t \,/\, (D * 2^{32} \qquad)(2)$$

where P is the BTC$; R is the amount of Bitcoin earned as a reward per block; t is the length of time the equipment is used for mining in seconds, and π is the revenue of the Bitcoin miner. As the block reward R is set by the network within a specific time-frame and the hash rate H and time t are decided by the miner, the only exogenous variables are in the price P

and the network difficulty D.

The network difficulty is a determining factor in the earnings from mining operations. At every 2016 blocks or approximately every two weeks, the mining difficulty is automatically adjusted to take into account increases in the global hash rate so that the 10 min time interval between each generated block remains constant. Due to this adjustment, Bitcoin mining should have very narrow margins, and the profitability is mostly dependent on the price of electrical power used for the proof-of-work calculations. This work models the revenue stream of a mining farm as a function of the ratio of BTC$ and the network difficulty.

To model the BTC$/Diff ratio, the stochastic process of this uncertainty must be determined. The ADF test [37] with intercept and trend on the log of these monthly series provides a *t*-statistic value of −2.029, which does not reject the existence of a unit root even at a 10% confidence level. Likewise, the variance ratio test does not stabilize below 1, which is a strong indication that the series follows a Geometric Brownian Motion (GBM) diffusion process. Thus, the price/difficulty ratio is modeled as shown in Eq (3).

$$dB = \mu B dt + \sigma B dz \tag{3}$$

where B is the BTC$/Diff ratio to be modeled, μ is the drift parameter, σ the volatility parameter, dt the time increment, and dz the standard Weiner process where $dz = \varepsilon\ dt^{0.5}$ $\varepsilon \approx N(0,1)$. The simulation equation for the price B rate is given by Eq (4).

$$B_t = B_{t-1} e^{\left(\mu - \sigma^2/2\right)\Delta t + \sigma\sqrt{\Delta t}\ N(0,1)} \tag{4}$$

The calculated parameters in monthly values are shown in Table 1.

The decreasing trend of this variable implies that cryptocurrency production suffers diminishing gains, which is observed in practice by real-life miners. This is due to the fact that as mining hardware technology improves and more miners join the network, the output from older mining equipment decreases.

It is assumed the investor will always choose the latest technology available at the time of purchase. Thus, the negative drift is applied at the start of the first two-year mining period at the end of year 2. If the firm chooses to purchase new equipment at the end of year 4 in order to benefit from a second two-year mining period, the value of the BTC $/Diff variable is brought back to its starting level, and the negative drift will come into effect again (see Fig. 3).

3.2. Modeling electricity (PLD) price

Weekly series of spot energy prices (PLD) are available for the North-Eastern region of Brazil, where most wind farms are located between January 2000 and November 2019, as informed by the Brazilian Electrical Energy Clearing Chamber (CCCE) [38] and converted to USD/MWh. These are shown in Fig. 4.

As was done for the previous variable, in order to determine the most appropriate stochastic process to model PLD series, first an Augmented Dickey-Fuller (ADF) test was run with intercept and trend on the log of the series. The *t*-Statistic obtained is −4.154976, which rejects the presence of a unit root even at a 1% level (−3.967667) for this number of samples. Therefore, there is a strong indication that the series is mean reverting. In order to confirm this, a Variance Ratio test was ran on the log of the series. As the value of the Variance Ratio for PLD rapidly drops below 1 and converges to values below 0.1 after 300 days, it confirms the presence of a mean reversion for this time series. Therefore, the PLD energy price was modeled as a Geometric Mean Reversion (GMR)

Table 1
GBM parameters for BTC$/Diff modeling in monthly and yearly periods.

	Month	Year equivalent
μ	−3.66%	−43.9%
σ	22.28%	77.2%

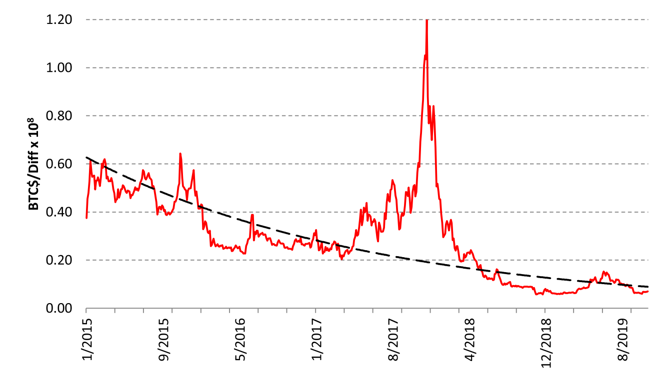


Fig. 3. Average monthly Bitcoin price/difficulty ratio (BTC$/Diff) between January 2015 to November 2019. Source: Authors.

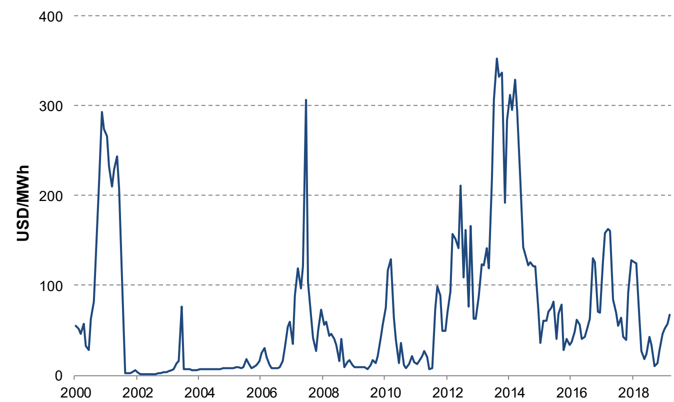


Fig. 4. PLD electricity spot prices for the Northeastern region of Brazil from Jan/2000 to Nov/2019. Source: CCEE [43].

diffusion process, as proposed by Schwartz [39], and shown in Eq (5).

$$dP = \eta\left(\ln \overline{P} - \ln P\right) P\, dt + \sigma_P P\, dz \tag{5}$$

where P is the price modeled, η is the mean reversion speed parameter of the process; σ_P is the volatility of the PLD price; $\overline{P}$ the mean or equilibrium level of the PLD price; dt the time increment and dz is the standard Weiner increment. In order to calibrate these parameters, we used the approach described by Dias et al. [15]. The question remains on the time span to choose for this purpose, as it seems from the series in Fig. 4 that the mean level of prices has changed during this period.

Hydropower capacity is still by far the primary source of electrical energy in Brazil, accounting for more than 80% of the installed energy generation capacity. Since 2007 though, a lack of regular rainfall has drained the reservoirs of the Southeast region, which accounts for the majority of the storage capacity of the country, and also in the North-east, where most of the wind farm capacity is located. This has led to a systematic increase in energy prices, as can be observed in Fig. 4. Nevertheless, the proposed model was calibrated using the full time span from July 2000 to November 2019 in order to better model the expectation of future energy prices.

As defined in Dias et al. [15], the risk-neutral simulation for this stochastic process is defined by Eq (6).

$$P_t = exp\left\{\ln(P_{t-1})e^{-\eta\Delta t} + \left[\ln\left(\overline{P}\right) - \frac{\sigma_P^2}{2\eta}\right]\left(1 - e^{-\eta\Delta t}\right) + \sigma_P\sqrt{\frac{1 - e^{-2\eta\Delta t}}{2\eta}}\right\} \tag{6}$$

where Δt is the time increment to be used in the regression. Simulations in this paper will be performed for monthly periods of cash flows.

Table 2
Parameters for the GRM model for PLD.

	Month	Year
η	0.0804	0.96456
σ	55.70%	192.95%
$\overline{P}$	32.88 USD/MWh	
P_{max}	150 USD/MWh	

Table 3
WindFarm parameters and specifications.

Capacity (monthly output)	7154 MW (Nominal)	
$CAPEX_4$ (in year 4)	9,540,000 USD	
$CAPEX_0$ (Cost of a 4-year anticipation)	2,527,815 USD	
Risk Adjusted rate or Cost of Capital (k)	8% (year)	0.64% (month)
Risk Free rate (r)	5% (year)	0.54% (month)

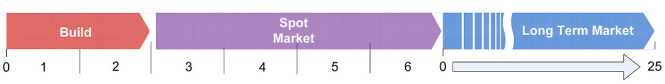


Fig. 5. Base Case scenario: Immediate construction of the power plant with a duration of two years followed by four years of short term spot market sales at PLD prices.

According to Dias et al. [15] all other parameters (η, σ_P and $\overline{P}$) are calibrated by running a regression of the increment of the log of the P_t time series against the log of P_{t-1}. The values obtained are displayed in Table 2.

The initial value, at t_0, for the simulation of the PLD time series is the last value of the PLD displayed in Fig. 4: $P_o = 75.00$ USD/MWh. It also considers the regulatory cap for PLD price at $P_{max} = 150$ USD/MWh, as an upper limit for simulation of PLD prices.

The value of $\overline{P}$ listed in Table 2 is already adjusted for the risk-neutral approach, necessary to value real options. For this conversion, we use the numerical estimation approach developed by Freitas & Brandão [40].

Bitcoin prices and mining hash rates are global uncertainties driven by worldwide demand and supply. In contrast, PLD electricity prices in NE Brazil are mostly correlated to hydroelectric reservoir levels and expected climate conditions. Thus, we assume that the Bitcoin price/difficulty ratio and PLD electricity prices are uncorrelated. This is also confirmed by a Pearson Correlation factor of only 0.0287, and thus both variables are stochastically modeled as independent and uncorrelated uncertainties. Our model also assumes that managers are rational and will always optimally exercise the option to switch outputs at the appropriate times, and does not take into account any human failings to maximize value.

4. Numerical application

4.1. Cash flow and investment structure of the base case scenario

The base case is an A-6 wind energy project that will begin construction immediately, which allows it to sell its energy in the spot market for four years. We use the data developed in Fontanet [41], who models a typical wind farm in Brazil with conditions similar to the one in this study, which are shown in Table 3.

The capital expense ($CAPEX_4$) in year 4 is the investment cost of the wind farm required in year 4 in order for it to start operations in year 6. If construction is to begin immediately, this investment must be anticipated to year 0. The only costs involved in this case are the capital costs of anticipating this investment, which is the difference between the year 4 $CAPEX_4$ and the same value discounted to time zero, or $CAPEX_0 = CAPEX_4 - CAPEX_4/(1+k)^4$, which is USD 2,527,815. This scenario is illustrated in Fig. 5.

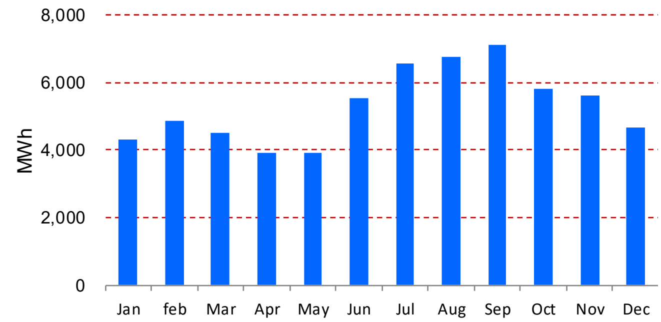


Fig. 6. Windfarm average monthly energy generation as impacted by the seasonality of the wind regime. Original data in average wind speed (m/s), converted to energy generation using maximum farm capacity. Source: Lira et al. [40]. In this scenario, the firm will earn the monthly cash flows shown in Eq (7).

Table 4
Bitcoin mining plant specifications.

Cost of mining processor	1900 USD
Number of mining processors	1750
$CAPEX_{BTC}$ (USD)	3,325,000 USD
Equipment life	2 years

It also considers that when selling energy in the free market, the volume of electricity sales is limited by the plant capacity and wind speed regime in the region, as described by Lira et al. [35]. Fig. 6 shows the monthly power generation averages for the wind farm.

$$\mathrm{EECF_t} = \mathrm{P_t} \times \mathrm{Output_t} \times (1 - \mathrm{T}) \times (1 - \mathrm{VariableCosts}) - \mathrm{FixedCosts} \tag{7}$$

where:

$EECF_t$: Cash Flow from energy sales in month *t*.
P_t: Stochastic energy price in month *t*.
VariableCosts: 14% of total revenue.
FixedCosts: USD 13,200 per month.
Output $_t$: Monthly energy production as in Fig. 6.
T: Revenue Tax rate (8 % × 34 % + 9 % × 12 % = 3.08%) in Brazil.

$EECF_t$ will be earned by the constructor for 48 consecutive months after the construction period of 24 months. The time zero value of the base case scenario is determined by Eq (8).

$$V = \sum_{25}^{72} EECF_t \Big/ (1+r)^t \tag{8}$$

r is used as the discount rate since $EECF_t$ is already estimated under the risk-neutral approach.

4.2. Switching between Electricity and Bitcoin sales

Once the wind farm is in place and producing energy, the firm can invest the value of $CAPEX_{BTC}$ in a Bitcoin mining plant that operates on the wind farm electricity output. Data for this mining plant is shown in Table 4.

The Bitcoin mining operations will generate the cash flows described in Eq (9).

$$\mathrm{BCCF_t} = \mathrm{B_t} \times \mathrm{Output_t} \times (1 - \mathrm{T}) \times (1 - \mathrm{VariableCosts}) \times (1 - \mathrm{RefrigCost}) - \mathrm{FixedCosts} \tag{9}$$

where:

$BCCF_t$: Cash flow from Bitcoin sale in month t
B_t: BTC$/Diff in *t* (stochastic and modeled with (4)
RefrigCost: Estimated in 15% of total energy consumed by mining.

Considering that the Bitcoin mining facilities must be ready to begin operation together with the wind farm, the capital investment in mining equipment must take place in month 22, as there is a three-month build up time. Once operations begin, the firm can choose each month whether to sell all its produced energy at PLD or to use this energy to create Bitcoins in the mining facilities. The choice made by maximizing the corresponding value of the expected cash flow of Eq. (7) or Eq. (10). This can be modeled as a bundle of sequential European switch options with monthly exercise periods and no switching costs. These options can be priced with Monte Carlo Simulation (MCS), which is very flexible and easily allows the use of different types of stochastic processes, such as those used for the variables in this article. Therefore, in each monthly period where there is the possibility of switching between both types of operation, the cash flow of the project *PCF* will be estimated by Eq (10).

$$PCF_t = \text{Maximum}\ [\lambda_t \times BCCF_t + (1\text{-}\lambda_t)\times\ EECF_t;\ EECF_t] \qquad (10)$$

where λ_t is a proportion of the produced energy given by the total consumption of the Bitcoin mining facility (including refrigeration).

Also, when the investment is made in the mining facility, this value of $CAPEX_{BTC}$, as listed in Table 4, is included in the estimation of PCF_t, whether selling energy or Bitcoins. Now the time zero value of the project with Bitcoin mining scenarios is determined by Eq (11).

$$V = \sum_{25}^{72} PCF_t/(1+r)^t \ (11).$$

Two Bitcoin mining scenarios are analyzed. In the first scenario, a single investment in Bitcoin mining equipment is made at the end of year 2, and the firm will have the option to switch outputs during two years, from year 3–4. After year 4, given that the mining equipment will be obsolete and no Bitcoins can be mined efficiently anymore, the firm can now only sell its electricity output in the short-term market, as illustrated in Fig. 7.

The second scenario assumes that the firm will make an additional investment in new mining equipment at the end of year 4 so that mining operations can continue for another two years, as shown in Fig. 8.

Both the PLD prices, which is a local uncertainty, and the Bitcoin price/difficulty ratio, which is a global uncertainty, are modeled as uncorrelated stochastic variables with distinct diffusion processes, as shown in Section 3. Fig. 9 presents a flowchart of the numerical application.

5. Results

5.1. Base case: immediate wind farm construction for energy sales in the free market

The base case scenario considers the immediate construction of the plant, which will take two years, followed by four years of energy sales in the spot market at PLD prices. Under an A-6 contract, the cost of anticipating the original capital investment scheduled for year 4 is the difference between the original year 4 CAPEX and the present value of this CAPEX at $t = 0$. After the two-year investment period, the firm will begin receiving the cash flows from energy sales described in Eq. (12). We estimate the present value of this scenario using Monte Carlo Simulation in order to determine the probability distribution of the Net Present Value (NPV). These are displayed in Fig. 10 .

This scenario yields a positive expected NPV of USD 1.51 million but also has a 38% probability of having a negative NPV. This suggests that

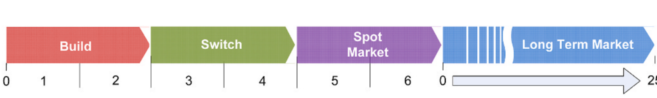


Fig. 7. First switching scenario: A single investment in Bitcoin mining equipment and two years of switching capability between electricity and Bitcoin sales. After the fourth year, the mining equipment becomes obsolete, and the firm can only sell electricity in the spot market at PLD prices.

Fig. 8. Second switching scenario: An additional investment in Bitcoin mining equipment in order to continue operations and allow for output switching for two more years.

anticipating the construction of the wind farm by four years solely to sell electricity in the spot market is a risky decision, as it exposes the firm to the volatility of the PLD price dynamics.

5.2. First switching scenario

We now consider the case where along with the construction of the wind farm, a Bitcoin mining facility with the characteristics listed in Table 4 is built during the three months prior to the farm becoming operational. The mining facility will operate for two years, after which further mining efforts become inefficient as the bit-rate increases to infinity, and the equipment becomes obsolete. Thus, for the final two years, the wind farm directs the totality of its energy production for sale in the spot market.

For the Bitcoin diffusion process, we adopt a drift value of μ: 3.66%, only after the acquisition of the mining equipment, as explained in section 3.3. Again, we estimate the present value of these cases running 50,000 iterations of a Monte Carlo Simulation in order to determine the probability distribution of the NPV results and compare these to the ones obtained from the scenarios without the switch options (Fig. 11).

The average NPV of this first scenario (two years of Bitcoin mining) is USD 3.6 million, which represents an increase of 139.4% over the base case, while the probability of a negative NPV occurring drops to 24%. This indicates that the ability to mine Bitcoins for two years adds significant value and reduces the risk of the project. Fig. 12 shows the percentage of times where it will be more advantageous for the wind farm output to sell electricity directly in the short-term market at PLD prices or to mine Bitcoins for the two-year switching period. It can be seen that as the bit-rate of the mining equipment increases in the hash rate of the blockchain network, the efficiency of Bitcoin mining decreases, and direct electricity sales become more advantageous.

5.3. Second switching scenario

The first switching scenario assumes that Bitcoin mining capacity runs out in two years due to the ever-increasing mining difficulty. In the second switching scenario, we consider the case where the firm makes additional investment in new state-of-the-art mining equipment, which brings back down its bit-rate and allows it to operate the mining facility for an additional two years. This is scenario two: 2 + 2 years of Bitcoin mining.

The NPV of this second scenario is USD 5.74 million, an increase of 281.3% over the base case, while the probability of a negative NPV is further reduced to 15%, down from 38% of the base case. This represents an even greater improvement over the base case both in expected NPV and in risk reduction (Figure 13).

Under this scenario, the mining efficiency decreases during the first two years, followed by an instant increase in the third year as new modern equipment enters operation in the third year. Fig. 14 shows the probability that each output will be the optimal choice during the four-year switching period. The increase in efficiency at the start of year 3 can also be clearly seen.

6. Discussion

The Brazilian system regulator promotes reverse bid auctions where the winner will receive a fixed income during the life of the project, thus guaranteeing a return on its investment. Therefore, while anticipating

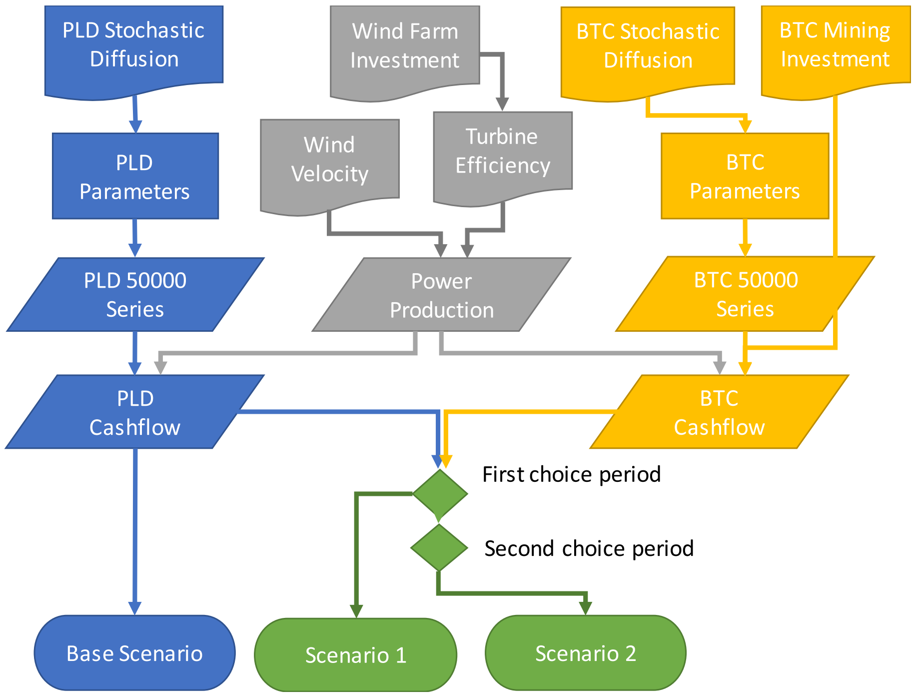


Fig. 9. Flowchart of the numerical application.

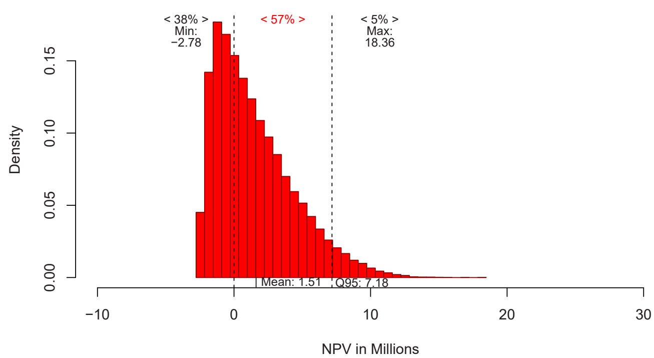


Fig. 10. Base case scenario: NPV distribution of the base case considering immediate construction and four years of energy sales in the spot market in millions of USD.

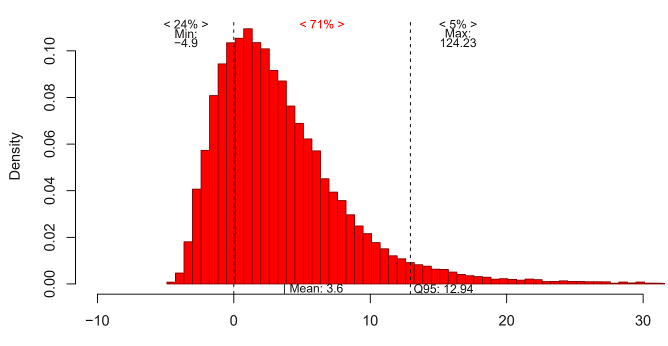


Fig. 11. NPV distribution of the first switching scenario, which considers two years switch option of Electricity x Bitcoin in millions of USD.

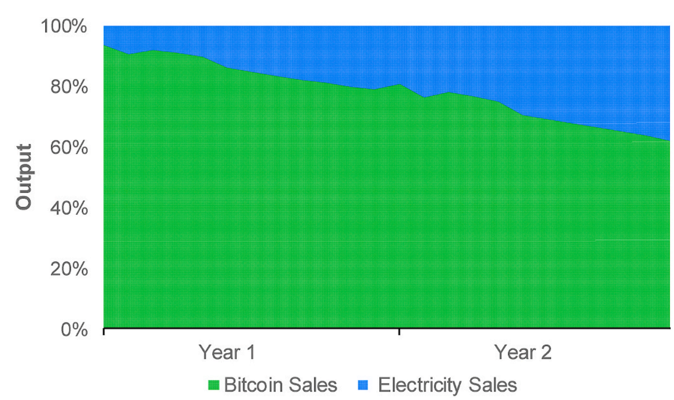


Fig. 12. Switching option probabilities of sales of Bitcoins produced and Electricity sales in the short-term spot market for the first switching scenario. The uneven pattern of the probabilities is due to the seasonal nature of the wind regime and the consequent variation in the energy output of the windfarm.

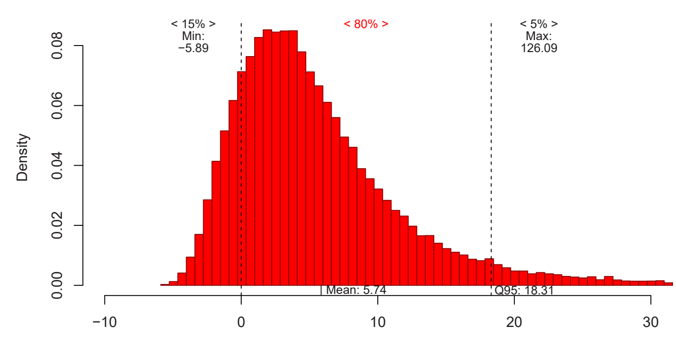


Fig. 13. NPV distribution of the second switching scenario of 2 + 2 years of Switch option Electricity x Bitcoin in millions of USD.

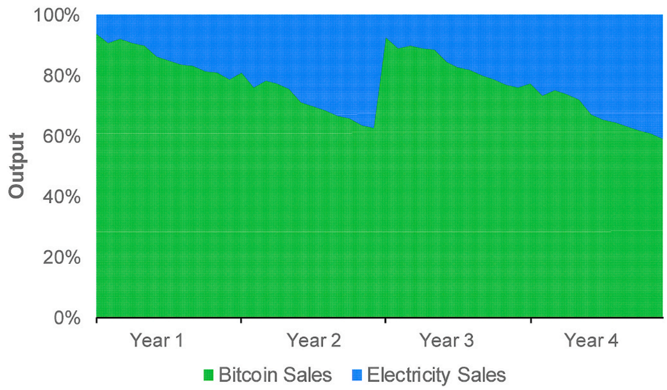


Fig. 14. Switching option probabilities between sales of Bitcoins produced and Electricity sales in the short-term spot market for the second switching scenario. Again, the uneven pattern of the probabilities is due to the seasonal nature of the wind regime and the consequent variation in the energy output of the windfarm.

Table 5
Summary of results for all investment scenarios.

	Mean of NPV (USD)	Prob of Negative NPV (%)	NPV Increase over Base Case (%)
Base Case	1,505,392	38%	–
2 Years	3,603,851	24%	139.4%
2 + 2 Years	5,739,867	15%	281.3%

the construction of a wind farm wind may increase the project NPV, it also increases the risk. By incurring in the additional cost of investing in a Bitcoin mining facility, the wind farm can create a natural hedge against low electricity prices for itself as we show. The main results of all the scenarios are summarized in Table 5.

The results indicate that anticipating the construction of the wind farm by four years increases the value of the project by $1.5 million. Nonetheless, given the high volatility of electricity spot prices, the Monte Carlo Simulation (MCS) shows that this alternative adds significant risk to the project and a high probability of a negative NPV. The investment in a two-year Bitcoin mining plant increases the returns to $3.6 million while reducing the risk to 24% while extending this investment for a total of four years reduces the risk even further to 15% while the NPV increases an additional 60% to $5.74 million. Anticipation of the construction of renewable capacity generation is also in the interest of the regulator, as it guarantees that this capacity will be available on the scheduled date as planned and help meet the carbon reduction goals.

The advent of the COVID-19 pandemic shows that the model is robust as the increase in Bitcoin prices and the significant fall in electricity spot prices in Brazil would provide an opportunity for the wind farm to profit by switching to bitcoin mining with cheap energy. Both stochastic variables were calibrated based on data series that did not include the market turbulence resulting from the pandemic crisis. Nevertheless, the observed volatility was within the parameters adopted in this study. This shows that the model developed here has practical application and is of value to renewable energy managers even in difficult times.

Although this article applies the model to a particular case in Brazil, the model can be easily adapted to other regions, countries, and regulatory environments as long as the investor has some degree of flexibility. The real options model and approach proposed is subject to the wind farm having enough anticipation time to profit from the flexibility of switching its outputs. However, ANEEL only promoted A-6 auctions for wind energy in 2017, 2018, and 2019. All previous auctions had been at most A-5, which does not allow a second "round" of bitcoin mining investment before entering the regulated market. The time to the beginning of energy delivery depends on the regulator's strategy, but can also be used as an incentive strategy for investors, who can then implement hedge mechanisms such as the one modeled in this article.

Limitations of this study include the assumption that wind farm investors have access to capital required to anticipate construction, since these costs are typically not covered by the long-term energy contract won at the auction. The same applies to the investment in the Bitcoin mining facility. It is also assumed that the decision to sell electricity or mine Bitcoins is made at the beginning of each month and that prices of both variables will be remain constant until the time of the next decision. This simplification has also been used by other authors such as Bastian-Pinto, Brandão & Alves [42], Brandão et al. [16] and Oliveira et al. [18], which is minimized by the use of a monthly, rather than yearly, time discretization and allows for the use of European Options modeling with MCS. Another potential limitation are the risks of transacting with Bitcoins. Muftic [43] identifies four major Bitcoin trading vulnerabilities: problems caused by users, by miners, by hackers, and man-in-the-middle attacks. Nonetheless, in its 11 years of existence, the Bitcoin blockchain has shown itself to be very robust, which suggests that this risk can be minimized by not storing the digital asset and the use of state-of-the-art Information and Communications Technology (ICT).

7. Conclusions

In this article, we show that the construction of renewable energy sources such as wind farms in Brazil has suffered from significant delays that create problems for the system regulator (ANEEL) and affect the energy security of the country. Ideally, in an A-6 auction, the firm would invest immediately and sell the energy generated to earn revenues in the short-term spot market during the four years prior to the beginning of its commitment to the long-term market in year 6. We show that due to the high volatility of the PLD spot prices, this is unlikely to occur due to the high risk involved, and most projects will be designed to come on-stream on the latest date possible, if at all.

In order to create incentives for early investment, we propose a wind farm investment model that involves simultaneously building a Bitcoin mining facility. This allows the firm to switch outputs between electricity and Bitcoin sales, depending on their relative prices and the efficiency of the mining operations, or bit-rate. While both electricity and Bitcoin prices are highly volatile, these uncertainties are uncorrelated and follow distinct stochastic processes. Because Bitcoin mining is more profitable when energy prices are low, the option to switch between these two outputs offers significant gain by hedging between uncorrelated assets.

Our results suggest that the option to switch outputs by investing in Bitcoin mining equipment significantly increases the value of anticipating wind farm construction, be it a two-year mining or a four-year mining window. In addition, this particular switch option reduces the risk of the project, providing further incentives for the early construction of the renewable energy power plant.

The main conclusion we can derive from these results is that the power industry, especially intermittent power producers that rely on natural sources of power, can benefit from this hedging mechanism. In our case, Bitcoin was the option of choice due to the simplicity of the mining infrastructure construction, maintenance, and costless switching, but other energy-intensive assets can be used. This type of switch option may increase profitability while reducing risk and its widespread use could foster the growth of the construction of new renewable energy sites globally.

The findings of this article may be of use to the Brazilian Electricity System regulator (ANEEL) in developing policies that foster more timely completion of planned renewable power units by creating incentives towards the production and sale of cryptocurrency mined by energy generators. Investors in renewable energy plants also benefit from this switching strategy as it may provide higher returns at lower risk on their capital.

Credit author statement

Carlos L. Bastian-Pinto: Conceptualization, Methodology, Formal analysis, Supervision.Felipe V. de S Araujo: Conceptualization, Software, Formal analysis, Writing - original draft.Luiz E. Brandão: Methodology, Validation, Investigation, Writing - review & editing.Leonardo Lima Gomes: Validation.

Data

R language programming code and data used in this article is publicly available at:

https://notebooks.azure.com/felvds/projects/switch-option-for-wind-farms.

A step-by-step run of the numerical application is available online at: https://felipevdsaraujo.github.io/Hedging-Renewable-Energy-Investments-with-Bitcoin-Mining/

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.rser.2020.110520.

Appendix

Wind farm projects in Brazil that have had their execution suspended or have low probability of timely completion as of Nov 2019, according to ANEEL [3].

Project Id	Auction	Project	Location	Power Capacity (KW)
31120	None	São Salvador	BA	18,900
31271	None	Ventos de Santo Adriano	PI	18,900
31402	May/13	Abil	BA	23,700
31403	May/13	Tabua	BA	15,000
31404	May/13	Angico	BA	8100
31405	May/13	Jabuticaba	BA	9000
31406	May/13	Taboquinha	BA	21,600
31407	May/13	Folha de Serra	BA	21,000
31408	May/13	Jacarandá do Cerrado	BA	21,000
31418	May/13	Acácia	BA	16,200
31424	May/13	Vaqueta	BA	23,400
31535	Sep/13	Curupira	RS	23,100
31536	Sep/13	Fazenda Vera Cruz	RS	21,000
31562	Sep/13	Povo Novo	RS	8400
31685	None	Santa Veridiana	PI	29,700
31686	None	Santa Verônica	PI	29,700
31687	None	São Moises	PI	29,700
31688	None	São Felix	PI	29,700
31689	None	São Basílio	PI	29,700
31690	None	Santo Anastácio	PI	29,700
31691	None	Santo Amaro do Piauí	PI	29,700
32090	None	Amescla	BA	13,500
32091	None	Angelim	BA	21,600
32093	None	Barbatimão	BA	16,200
32098	None	Cedro	BA	12,000
32101	None	Facheio	BA	16,500
32102	None	Imburana Macho	BA	16,200
32104	None	Jataí	BA	16,200
32106	None	Juazeiro	BA	18,900
32108	None	Sabiu	BA	13,500
32111	None	Umbuzeiro	BA	18,900
32113	None	Vellozia	BA	16,500
32245	None	Manineiro	BA	14,400
32246	None	Pau D″Água	BA	18,000
32362	Aug/14	Mulungu	BA	13,500
32363	Aug/14	Pau Santo	BA	18,900
32364	Aug/14	Quina	BA	10,800

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