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Original Article

A blockchain-based model for token renewable energy certificate offers

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ABSTRACT

This article proposes an investment model for a renewable energy generator that allows it to earn the right to issue Renewable Energy Certificates (RECs) and sell them through quarterly sales auctions promoted by the blockchain. Blockchain technology can further promote the RECs market, as it enables tokenization and distribution of certificates. We did not find articles in the literature that analyze the decision to invest in decentralized autonomous organizations (DAOs) that have rules for issuing and trading RECs specified in smart contracts, which are executed and validated by the blockchain. This article contributes to the literature on blockchain technology applications in the renewable energy market by proposing issuing and selling RECs tokens through a DAO. The relevance of this research is that it shows that simple real option pricing methods can help decision-makers evaluate investment opportunities under uncertainty and flexibility. The tokenization and distribution of RECs via blockchain can promote transaction agility, reduce or eliminate bureaucracy in the means of payment, and increase the security and transparency of transactions. We propose a model for issuing and selling RECs in smart contracts. We assume that the generator has the flexibility to invest now or in one year to enter the platform, considering the energy generated in one year by a single typical 4MW wind turbine. Our model assumes that the price of the REC token follows an inverse demand function subject to stochastic shocks. The results contribute to the understanding of the performance dynamics of digital products under uncertainty and flexibility and show that distributed ledger technology (DLT) may be a viable alternative for renewable energy incentives.

Keywords: *blockchain*, renewable energy certificates, real options approach, market uncertainty, energy sector.

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1. INTRODUCTION

The emission of greenhouse gases has been one of the main factors contributing to global warming and the focus of global concern (Radhi, 2009). To reduce the CO_2 emissions generated by electricity production, one of the primary sources of greenhouse gases, energy producers are investing more and more in clean energy sources. However, such initiatives require significant capital investments in renewable energy sources, often out of reach for many firms. One solution to this problem is the sale of Renewable Energy Certificates (RECs) designed to foster renewable energy production by providing an additional revenue source for these generators.

RECs were first proposed in 1996 as a market-based instrument issued when one megawatt-hour (MWh) of electricity is generated from a renewable energy source and delivered to the grid (Associação Brasileira de Geração de Energia Limpa, 2018). These certificates can be transferred, purchased, sold, withdrawn, or used by the holder to claim that she has used renewable energy. In this sense, RECs help overcome several barriers to purchasing and selling electricity-related renewable energy attributes (Wingate & Holt, 2004).

RECs markets have expanded rapidly and already have significant liquidity worldwide, fostering investment in renewable energy sources. Despite this, the question remains: how can this market be further fostered in a practical way for all stakeholders? Part of the answer can be found in technological innovations, such as distributed ledger technology (DLT), which enables tokenization and cheap distribution of RECs worldwide (Ølnes et al., 2017).

DLT, which also allowed the creation of digital currencies, can promote transaction agility, reduce or eliminate bureaucracy in the means of payment, and increase the security and transparency of transactions (Priem, 2020). In particular, blockchains, a type of DLT, depend on a distributed public accounting system divided into blocks. Each block is cryptographically connected to the previous block, forming a chain of blocks, or a blockchain. The fact that the information in each block is public and immutable allows numerous new applications in the industry based on the blockchain protocol. Programs, also known as smart contracts, can be developed to run on blockchains, with all the benefits this technology offers, such as transparency and security.

This study proposes a model for developing tokens based on RECs, which can be automated and included in a smart contract to run on the blockchain. In our model, the renewable energy generator interested in offering RECs has the option to invest now or in one year to have the right to issue RECs and sell them later through quarterly sales auctions automatically promoted by the protocol itself. We consider that the demand for RECs is deterministic and increases each quarter. However, the unit price of the REC token varies quarterly and is a function of inverse demand subject to continuous stochastic shocks.

This study contributes to the literature on the applications of blockchain technology in the renewables market. It is relevant as it proposes a decentralized autonomous organization (DAO) issuance and sale of RECs tokens. This study uses the real options approach (ROA) to price the deferral option present in the model and analyzes the generator uncertainty's decision-making. Thus, this research shows that simple real options pricing methods can assist decision-makers in the valuation of investment opportunities under uncertainty and flexibility.

This article is structured as follows: after this introduction, we discuss how RECs work. In section 3, we review the related literature, and in section 4, we propose a model for developing token-based RECs. Next, we present a numerical example and discuss the results. Finally, in section 6, we present the conclusions.

2. RECS

In many countries, the structure of generation, transmission, and distribution of energy make it impossible to physically trace the energy source to its point of consumption. In such cases, the electricity from a renewable source is injected into the distribution system, mixed with electrons from other sources (renewable or otherwise), and delivered through the local distributor to companies or homes through the poles and wires. Thus, in this scheme, the local energy distributor is unaware of the origin of these electrons.

RECs, or "guarantees of origin" (GoOs), have emerged as a solution to the traceability problem of environmental energy attributes (Aldrich & Koerner, 2018a). The RECs originated through a global certification system, the International REC Standard (I-REC), which enables, in a practical and reliable way, to verify the origin of the energy consumed as well as the trade of certificates. The I-REC platform allows consumers to choose the type of renewable energy they want through RECs generated by wind, biomass, and solar power plants. By acquiring a REC, which proves that 1 MWh has been injected into the system from a renewable energy source, the consumer appropriates that energy and the platform ensures that particular REC will not be used again.

According to Wingate and Holt (2004), RECs, also known as green labels, green certificates, renewable energy credits, and tradable green certificates (TGCs), represent the separable set of non-energy attributes (environmental, economic, and social) associated with the generation of renewable electricity. The authors believe that the REC is the currency of the renewable energy markets (compliance and voluntary markets) that allows access, allocation, and claiming the use of renewable generation on a shared network. In this perspective, this mechanism serves as a tool to achieve corporate greenhouse gas reporting goals and state policy mandates under the standards of the renewable energy portfolio.

The benefits of RECs are diverse. For certification organizations, the main advantage is that registration in the I-REC becomes a way to obtain additional revenue, which is a direct incentive for the producer to continue investing in renewable energy generation. On the other hand, for those who acquire the RECs, the main benefit is the proof of the origin of the electricity consumed and the corresponding reduction of emission of greenhouse gases. Currently, some markets only accept this type of credit, such as the projects that seek Leadership in Energy and Environmental Design (LEED) certification, whose purpose is the construction of green buildings. Another advantage of obtaining RECs is that they can report indirect emissions through energy consumption in the Brazilian GHG Protocol Program, which aims to record and publish greenhouse gas emissions inventories.

Therefore, RECs bring recognition to clean energy users and support the preservation of natural resources, sustainability, and renewable energy development. The certificates also make it possible to achieve the sustainability goals of many organizations and improve indicators for reporting programs such as the Carbon Disclosure Program (CDP), the Corporate Sustainability Index (ISE), and the Dow Jones Sustainability Index (DJSI).

3. LITERATURE REVIEW

3.1 Blockchain Technology

Recent advances in information and communication technology, such as the internet and smart metering, have brought about new opportunities to improve energy efficiency and increase the use of renewable energy sources. This has allowed the increase in emissions and REC transactions (Bertoldi & Huld, 2006). As such, new technologies, such as blockchain, also have the potential to bring benefits to this field.

Transparency is crucial in renewable energy markets, since the purchase of green energy, both the kilowatt-hour (kWh) itself and its clean attributes, happen differently from other products. Buyers are unable to control or observe how their facilities are powered. In this way, those who want to feed their facilities with renewable energy depend on an accounting tool (RECs), where they can prove ecological purchases, allowing for reliable verification. Currently, system operators and regulators use a record on their electrical system to track the details, ownership, and status of each REC.

While RECs have helped improve transparency in the renewable energy markets, these improvements are still insufficient to meet the growing needs of renewable energy generators and buyers (Aldrich & Koerner, 2018b). For example, developers and buyers need to go through an expensive process that differs from market to market and depends on obsolete technological platforms to obtain proof of generation and green energy purchases. As a result, market share is generally limited to companies with sophisticated teams and energy companies with renewable energy portfolio goals required by regulation. Buying and selling renewable energy needs to be less bureaucratic to unlock access and increase market share. In this perspective, it is believed that a way to eliminate the current barriers of this market is to bet on a new disruptive and rapid global technology, such as blockchain, which can promote agility in transactions and reduce or eliminate bureaucracy in the means of payment and increase security and transparency of operations (Boff & Ferreira, 2016).

The blockchain protocol was first proposed by Nakamoto (2008) and is the foundation on which bitcoin was created. This protocol is a type of DLT, where transactions are grouped in blocks. In this protocol, users cryptographically sign their transactions and send them to the network, where miners validate all transactions, confirming that the user who spent the money has money to spend and the user's authenticity (Jamison & Tariq, 2018). Miners then choose which transactions to include in their block and the order in which they are included. As only one block can be added at a time, a computationally and energy-intensive mechanism known as proof of work must be completed before a miner can add her block to the blockchain. The first miner to successfully do so and have her block validated by the users, known as nodes, receives a number of newly minted bitcoins in reward. This procedure allows the blockchain to function without any trust between the parties involved (Pelucio-Grecco et al., 2020).

Some studies already propose applying this technology to the renewable energy markets. Mihaylov et al. (2014), for example, develop a new decentralized digital currency called NRGcoin. The authors believe that the main contribution of this new mechanism is to convert locally produced renewable energy directly into NRGcoins, regardless of their market value. In addition, the authors propose a new commercial paradigm for buying and selling green energy on the blockchain network, creating a microeconomic ecosystem that allows for the negotiation of locally produced renewable energy at competitive prices. On the other hand, Mengelkamp et al. (2018) rely on a private blockchain to develop a decentralized market platform, aiming to negotiate the generation of local renewable energy without an intermediary. As local renewable energy markets allow consumers to trade locally produced generation directly in their community, the authors believe blockchain is the primary information and communication technology for this market.

Li et al. (2019) use blockchain technologies to optimize the financial and physical operations of energy distribution systems. The authors propose a set of blockchains embedded in smart contracts to manage energy and financial flows between operating micronetworks, decentralizing the management of transactional energy. Their results show that this technology promotes a significant evolution from traditional energy distribution systems to active distribution networks.

An interesting approach is proposed by Castellanos et al. (2017). Ethereum's blockchain and smart contracts enable proactive consumers with distributed energy resources, known as prosumers, to sell GoOs to subsidize renewable energy producers. The authors propose two strategies for this: the first is based on the average price of GoOs in 2014, and the second is based on the price difference between grey and green energy. This study shows that it is more advantageous for prosumers to follow the second strategy.

3.2 ROA

ROA arose from the need to consider managerial flexibility in real asset valuation, which is not captured by traditional techniques, such as the discounted cash flow (DCF) method (Copeland & Tufano, 2004). This approach adapts the pricing models of financial options developed by Black and Scholes (1973) and Merton (1973), allowing the treatment of investment in real assets under uncertainty and flexibility.

Myers (1977) is credited as one of the first authors to use ROA to determine the value of having flexibility and investment capacity in the future and showed that companies with high debt risk will miss valuable investment opportunities. In contrast, companies with low debt risk will take advantage of future investment opportunities. Dixit and Pindyck (1994) and Trigeorgis (1996) synthesized this methodology's main concepts and possible applications a few years later.

Once the electric sector began deregulating, which resulted in higher competitiveness and increased market uncertainty, traditional project evaluation techniques have become insufficient to adequately deal with these additional risk and uncertainty factors (Fernandes et al., 2011). In this sense, more sophisticated valuation techniques such as the ROA are necessary to evaluate investment projects in the energy sector.

Although the literature presents several applications of real options in the evaluation of technologies and policies of electric power generation, the use of this methodology in problems related to renewable energy is recent. From the real options analysis perspective, Lee (2011) evaluates the investment opportunities in renewable energy, showing that this method effectively quantifies how investment-planning uncertainty influences renewable energy development. The results reaffirm that the value of renewable energy development increases with increases in the underlying asset's price, time to maturity, risk-free rate, and volatility, but decreases as the exercise price increases.

Delapedra-Silva (2021) analyzes wind power commercialization contracts celebrated in the period of 2009 to 2018 and determines the uncertainties and real options embedded in these projects. Gonçalves and Ferreira (2008) develop a real options model to determine the value created for an agent in the electricity market when the flexibility to switch inputs between diesel and biodiesel is introduced in the analysis. The authors use Monte Carlo simulation to model the fuel choice as a sequence of European options. The results show that the inclusion of biodiesel on a large scale in the market generates significant value for agents who hold diesel-powered equipment as real assets.

Fontoura et al. (2015) evaluate the feasibility of converting a biomass power plant project based on elephant grass in a biorefinery by investing in charcoal and second-generation ethanol production units. This allows the plant to optimally switch production between these three outputs, depending on their relative prices. They conclude that this flexibility adds value to the project and contributes to the sustainable diversification of the energy matrix. Detert and Kotani (2013) investigate the optimal decision time for investments in alternative energy sources in uncertain situations using the ROA. They analyze a case study in Mongolia in which the uncertainty is the price of coal and compare the attractiveness of continuing to use coal-based infrastructures or switching to renewable energy sources.

Kim et al. (2017) propose a real options model to evaluate the investment in renewable energy in the developing countries. The authors' main concern is dealing with uncertainties, such as the rapid change of technologies and the conditions of the host government. The authors conclude that the proposed tool can help host countries and investors evaluate high-risk renewable energy projects. Oliveira et al. (2014) analyze the feasibility of investing in a biomass and natural gas cogeneration unit in an industrial plant in Brazil that has the flexibility to choose between an increase in production or the generation of excess energy for sale in the short-term market term. The authors conclude that the investment is feasible and that the option adds significant value to the project, which suggests that biomass residues can be a sustainable energy alternative.

Boomsma et al. (2012) also use the ROA to determine the timing of the investment and the choice of capacity for renewable energy projects from different support schemes, such as feed-in tariffs (FITs) and certificate negotiation of renewable energy. To test their model, the authors apply it in a Nordic case study based on wind energy and conclude that FITs encourage prior investments. Still, trade in RECs creates incentives for projects once the investment is made. According to Fleten et al. (2016), a study of 214 investors in hydroelectric projects in Norway showed that they do not rely on real option models. Nonetheless, by comparing the expected subsidies with subsidies observed in a closely related market, they show that the ROA is a meaningful descriptor of management investment behavior, even if they did not formally use a real options model in their analysis.

Ritzenhofen and Spinler (2016) assess the impact of adjustments to FIT schemes, which are widely used as policy instruments to promote investments in renewable energy sources and verify the relationship between the guaranteed value paid for electricity produced and the propensity to invest renewable energy sources. The authors propose a regime change model to quantify the impact of regulatory uncertainty induced by regulators considering changes from a FIT scheme to a more market-oriented regulatory regime.

Kitzing et al. (2017) develop a real options model to evaluate wind energy investments, considering optimal timing and capacity constraints as part of optimization. The authors believe that this approach is well suited for comparing different support schemes, such as FIT, feed premiums, and TGCs. The results indicate that TGC schemes may require profit margins up to 3% higher than FIT schemes due to the greater variation in profits. On the other hand, FIT schemes can consider 15% smaller design sizes. The analysis of this trade-off should be considered so that there are better strategic projections of renewable support. Bastian-Pinto et al. (2021) propose a hedging mechanism that allows a wind farm venture to reduce risk by simultaneously investing in a bitcoin mining facility. They use ROA to evaluate the option to switch outputs between electricity and bitcoins depending on the relative values of each of these. Their results show that intermittent power producers can benefit from this hedging mechanism because this switch option may increase profitability while reducing risk, fostering the growth of the construction of new renewable energy sites.

Eryilmaz and Homans (2016) use the ROA to model wind power investment decisions under policy uncertainty. The authors develop a dynamic optimization model to examine investment thresholds of private power generating companies, given the federal government's uncertain decision about the continuation of the production tax credit (PTC) policy and the stochasticity of prices in the market for RECs. Their findings show that the relationship between the investment profitability threshold and policy depends on REC prices and REC price volatility, since these parameters affect the profitability limit required by investors.

Although there are some applications of real options in renewable energy, we did not find in the literature studies that analyze the decision of the renewable energy generator to invest in DAOs that have RECs emission and trading rules specified in smart contracts, which are executed and validated by blockchain.

4. MODEL

We propose a DAO that requires an initial investment to allow the entry of the renewable energy generator into the platform, which creates new tokens and promotes quarterly sales auctions that will make available a number of tokens to the market, as shown in Figure 1.

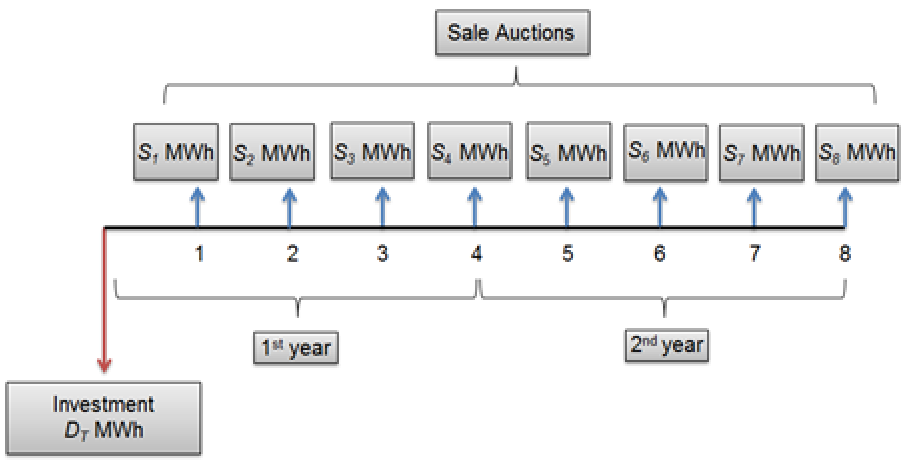

Figure 1 *General scheme of sale auctions*
Source: *Elaborated by the authors.*

We assume that the renewable energy generator investment takes place at time 0 and that the supply of RECs to the market (S_t) will occur for 8 quarters (or 2 years). Our model also assumes that the generator has the flexibility to invest now or in one year to enter the platform, considering the energy generated in one year by a single typical 4MW wind turbine. This is equivalent to the generator having a European option to defer their investment for one year.

To understand the logic of a European call option, which in this research is represented by the option to defer the investment, we present in Figure 2 a simple example of how such an option can be calculated with a binomial tree. In this example, we assume that the investment (US$ 3,000) in a project can be deferred. With this, we can wait for the uncertainty about its future value (high = US$ 5,500 and low = US$ 2,200) to be resolved before deciding to invest or not. In this sense, the decision would be to invest in the project in the upside scenario. However, in the downside scenario, the section is not to invest in the project.

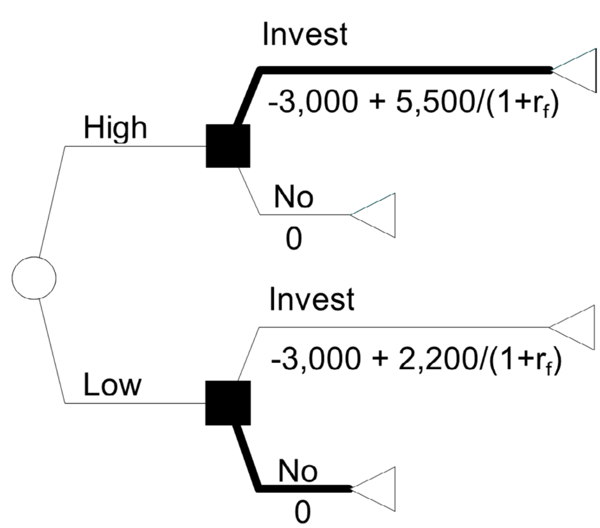

Figure 2 *Simple example of a European call option*
Source: *Elaborated by the authors.*

Note that the option to defer affects the risk of the project, preventing it from having a negative outcome. Thus, the risk of the project with this flexibility is lower. Therefore, the calculation of the option value requires specific methods and cannot be determined through the DCF method. This example is close to the model we propose in the following section.

4.1 Proposed Model

First, we consider that the quantity of RECs offered (S_t) in sales auctions is strictly equal to the expected demand for RECs for the same period (D_t). In addition, we assume that the demand for RECs is deterministic and has a percentage growth every quarter, as shown in equation 1,

$$D_T = D_0 e^{\alpha t} \quad (1)$$

where D_t is the demand in each quarter t, D_0 is the initial demand, and α is the demand growth rate each quarter.

Although the demand is deterministic, the unit price of the REC changes every quarter. It is defined as a function of inverse demand subject to continuous stochastic shocks, as shown in equation 2. Note that we are using exactly the model proposed by Grenadier (1996),

$$P_t = \left[3 - \frac{D_t}{D_0}\right] C_t \quad (2)$$

where P_t is the unit price of the REC in each quarter t, and C_t represents a multiplicative demand shock, which follows a geometric brownian motion (GBM), as shown in equation 3,

$$dC_t = \mu C_t dt + \sigma C_t dz_t \quad (3)$$

where dC_t is the incremental variation of the shock in the time interval dt, μ represents the drift, that is, the expected growth rate of demand for RECs, σ is the volatility of demand for RECs, and $dz_t = \varepsilon\sqrt{dt}$ represents the standard Wiener increment where $\varepsilon \approx N(0,1)$.

From this, we verify that the investment that the renewable energy generator must make to enter this platform is defined by equation 4,

$$I = \lambda \times \sum_{t=1}^{8} D_t \quad (4)$$

where I is the investment and λ is the marginal unit fixed cost of entry into the platform in US$/REC. The generator's revenue (R_t) is determined by equation 5,

$$R_t = R_t \times S_t \quad (5)$$

where D_t is the demand for RECs in each quarter t, which is equal to the supply of RECs (S_t) for the same period. Thus, we can determine the generator's net present value (NPV) through equation 6,

$$NPV = -I + \int_{t=1}^{n} E\left[R_t\right] e^{-kt} dt \quad (6)$$

where $E[R_t]$ is the expected value of future revenues, n represents the total number of quarters, and k is the weighted average cost of capital (WACC).

Since the traditional DCF method does not capture the uncertainty and managerial flexibility present in the model, we adopt the ROA using the discrete binomial tree model proposed by Cox et al. (1979) [Cox-Ross-Rubinstein market model (CRR model)]. This option-pricing model requires the use of the risk-neutral measure. To determine this measure, we deduct the risk premium from the asset's rate of return and then discount cash flows at the risk-free rate. Thus, the risk-neutral process is defined by equation 7,

$$dC_t^R = \left(\mu - \zeta_C\right) C_t^R dt + \sigma C_t^R dz_t \quad (7)$$

where dC^R_t is the incremental variation of the neutral shock C^R to the risk in the time interval dt, ζ_C represents the shock risk premium, and μ is the return rate of the shock.

Freitas and Brandão (2010) discussed that the market risk premium can be observed directly or can be determined through the capital asset pricing model (CAPM), where $\mu = r_f + \zeta$ and $\zeta = \beta(E[R_M] - r_f)$. On the other hand, the risk premium of incomplete market assets, such as the uncertainty present in this model (C_t) can only be calculated through indirect methods.

Therefore, to evaluate the shock risk premium, we consider that the expected value of the gains in the risk-neutral valuation, regardless of possible options, should be strictly equal to the expected value of the gains in the traditional static valuation, as shown in equation 8. Then, if the other variables of equation 8 are known, the risk premium value can be determined by equivalence,

$$\int_{t=1}^{n} f\left(C_t\right) e^{-\mu t} dt = \int_{t=1}^{n} f\left(C_t^R\right) e^{-(\mu - \zeta_C)t} dt \quad (8)$$

where $f(.)$ represents the generator's cash flows.

After determining the shock risk premium, we use equation 9 to calculate the parameters of the CRR binomial tree,

$$u = e^{\sigma\sqrt{dt}},\ d = \frac{1}{u}\ and\ p = \frac{e^{(\mu - \zeta_C)} - d}{u - d} \quad (9)$$

where σ is the volatility adopted in the stochastic process of uncertainty, which in this case is the shock (C_t).

Up to this point, we have defined only how uncertainty should be addressed in this model. To incorporate the flexibility, we adopt some assumptions: if the generator chooses not to defer, she will follow the standard auctions scheme shown in Figure 1; on the other hand, if the generator chooses to delay, her investment happens in the fourth quarter (I_A) and starts to assume the value defined in equation 10:

$$I_A = \left(\lambda \times \sum_{t=1}^{8} D_t \right) e^{4r} \quad \boxed{10}$$

Since the demand for RECs in the first four quarters is not realized, we believe that it will be repeated over the next four quarters, promoting a one-year displacement in the model, as shown in Figure 3. However, the uncertainty, defined by the multiplicative shock of demand (C_t), will continue to follow a GBM since the first quarter. Thus, the generator will maximize its choice based on equation 11,

$$V_{option} = max\left[NPV; \sum_{t=5}^{12} \left(E\left[R_t \right] / e^{r_f t} \right) - I_A; 0 \right] \quad \boxed{11}$$

where V_{Option} is the generator's NPV considering the option to postpone the investment.

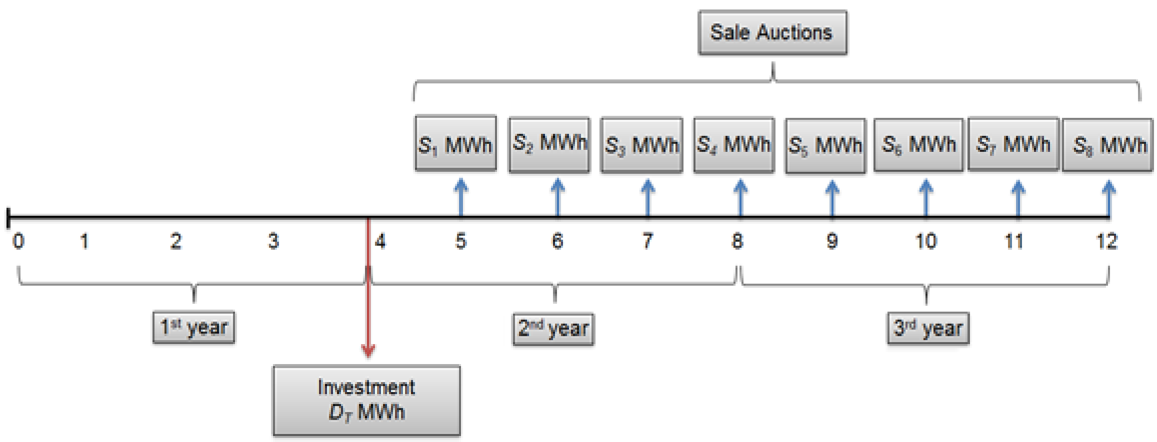

Figure 3 *Deferring investment scheme*
Source: *Elaborated by the authors.*

4.2 Numerical Example

Our numerical example considers the energy generated in one year by a single typical 4MW wind turbine and the parameters shown in Table 1. Note that the initial demand for RECs, growth rate, volatility, and drift were determined based on the history of daily transactions of RECs in the period of 2014 to 2018, provided by Instituto Totum (2018).

Table 1
Parameters

Parameters	Quarterly values	Annual values
Initial shock (C_0)	1.00	1.00
Initial demand (D_0)	15,000 MWh	15,000 MWh
Growth rate (α)	5.00%	22.14%
Discount rate (k)	6.00%	27.12%
Risk free rate (r)	1.30%	5.34%
Volatility (σ)	30.00%	60.00%
Drift (μ)	5.00%	22.14%
Marginal unit cost (λ)	US$ 1.50/REC	US$ 1.50/REC

REC = Renewable Energy Certificates.
Source: *Elaborated by the authors.*

5. RESULTS AND ANALYSIS

From the definition of the initial demand and its growth rate in Table 1, we determine the total demand for RECs for the next two years (D_T = 151,267 MWh) using equation 1. After this, we calculate the generator's investment (I = US$ 226,900.25) using equation 4. Then, in order to define the generator's revenue, we model the multiplicative demand shock (C_t). For this, we calculate by numerical methods the risk premium value (ζ_C = 4.70% per quarter or 20.68% per year) considering the mathematical equivalence between the PVs shown in equation 8. We then determine the upside and downside values of the binomial tree (u = 1.35 and d = 0.74) and the risk-neutral probabilities (p = 43.05% and $1 - p$ = 56.95%) using equation 9.

Using the software DPL, we model the uncertainty for the next eight quarters, incorporating the generator's revenue as the cash flow of the model, as shown in Figure A.1 (Appendix). Through this binomial tree, we find that the generator's NPV is equal to US$ 22,144.70. In this calculation, we do not consider the generator's option to defer for one year its investment, so this is the deterministic NPV, which can also be determined using the DCF method and equation 6.

To include this managerial flexibility in the model, we must redesign the binomial tree, as shown in Figure A.2 (Appendix), and consider that the generator's investment becomes equal to I_A = US$ 239,011.22 (equation 10). Considering the option to postpone the investment and equation 11, we find that the generator's NPV is equal to US$ 59,657.50. Note that the defer option is extremely valuable, as it promoted a growth of approximately 169.40% in the generator's NPV.

5.1 Sensitivity Analysis

We perform a sensitivity analyses on the volatility. We assume volatility values between 5 and 50%, and we determine the impact of this in the generator's NPV, as shown in Figure 4.

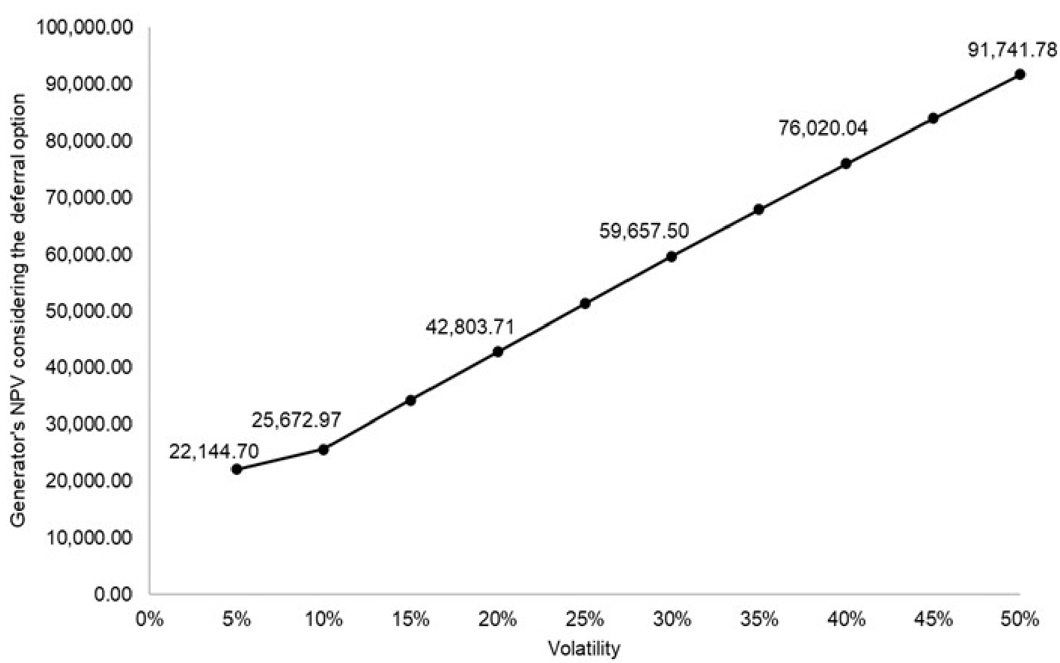

Figure 4 *Sensitivity analysis of volatility*
NPV = net present value.
Source: *Elaborated by the authors.*

We can observe that the generator's NPV can takes on values between US$ 22,144.70 and US$ 91,741.78. Therefore, the generator's NPV increases with volatility, consistent with the fact that NPV is a convex function.

6. CONCLUSION

This work analyzes the investment under uncertainty of the renewable energy generator interested in offering RECs in an autonomous model of issuance and sale of tokens based on RECs. In this proposed model, the generator has the option to invest now or in one year to have the right to issue RECs and offer them through quarterly sales auctions, which are automatically promoted through the intelligent protocol developed in the blockchain. To evaluate this investment, we use the ROA that allows calculating the generator's NPV, considering both the uncertainty and managerial flexibility related to the option of deferral.

Considering the parameters adopted and that the REC token price is a function of inverse demand subject to stochastic shocks, we find that the generator's NPV is equal to US$ 22,144.70 in the case that there is no flexibility to postpone the investment. By including the flexibility to defer the investment, we find that the generator's NPV equals US$ 59,657.50. Therefore, the option promoted a growth of approximately 169.40% in its NPV.

This work contributes to the understanding of the dynamics of the performance of digital products under uncertainty and the expansion of the literature regarding applications of blockchain technology in the renewable energy market. In addition, this study is relevant and original, as it analyses investments under uncertainty and flexibility of the renewable energy generator in two different DAOs. This research also highlights that simple option-pricing methods can aid decision-making when there is uncertainty and flexibility and allow for a better valuation of these investment opportunities.

Market exchanges based on DLT present many advantages over traditional exchanges, such as full transparency, low transaction costs, and universal access. The model proposed in this article shows that DLT technology may be a viable alternative to base incentives for the growth in renewable energy sources.

Limitations of this research include the fact that there is still not enough data available on RECs transactions in the market, as the time series of the Instituto Totum (2018) has information only for the period of 2014 to 2018. In addition, in this study, we consider a single uncertainty and only one managerial flexibility to defer the investment. Suggestions for future work include adding more sources of uncertainty and analyzing different types of options, such as abandoning the platform.

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APPENDIX

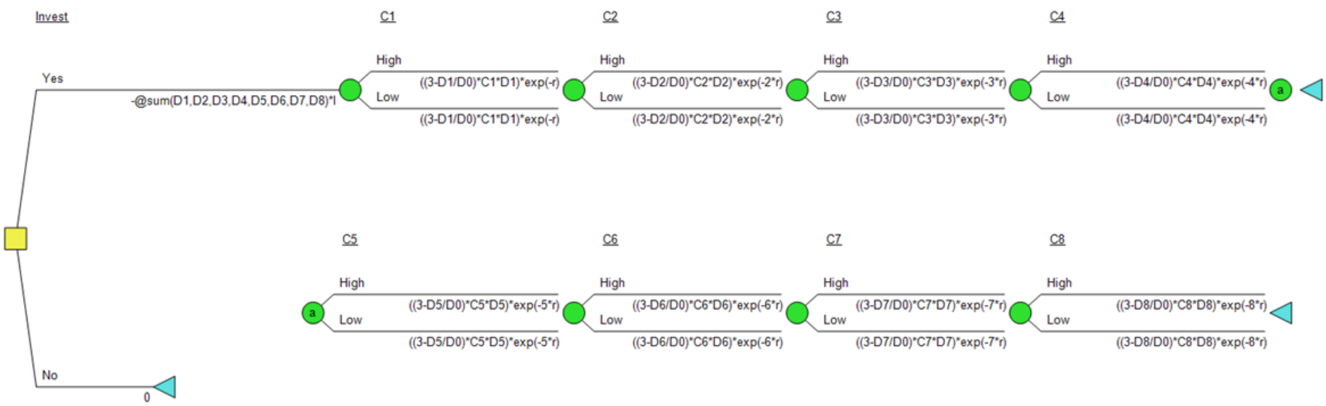

Figure A.1 *Binomial tree*
@sum(D1, D2, D3, D4, D5, D6, D7, D8) is the sum of expected demand from t =1 to t = 8 (151,267 MWh); C (C1, C2, …, C8) is the multiplicative demand shock; D0 is the initial demand (15,000 MWh); I is the marginal unit fixed cost of entry into the platform [US$ 1.50/Renewable Energy Certificate (REC)]; r is the risk-free rate (1.30%).

Source: *Elaborated by the authors.*

Figure A.2 *Binomial tree with deferral option*
@sum(D1, D2, D3, D4, D5, D6, D7, D8) is the sum of expected demand from t =1 to t = 8 (151,267 MWh); C (C1, C2, …, C12) is the multiplicative demand shock; D0 is the initial demand (15,000 MWh); I is the marginal unit fixed cost of entry into the platform [US$ 1.50/Renewable Energy Certificate (REC)]; r is the risk-free rate (1.30%).

Source: *Elaborated by the authors.*