A BLOCKCHAIN BASED MODEL FOR RENEWABLE ENERGY CERTIFICATES TOKEN OFFERS UNDER UNCERTAINTY AND FLEXIBILITY

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Abstract

Renewable Energy Certificates (RECs) are instruments that provide incentives for producers to invest in clean and renewable sources of energy. On the other hand, market exchanges based on Distributed Ledger Technology such as the blockchain network protocol have some advantages over traditional exchanges, such as full transparency, low transaction costs and universal access. In this article we analyze three autonomous models for issuing and selling REC based tokens in the blockchain for the renewable energy generator. In all three models, the generator has the option to invest now or in one year for the right to issue RECs and offer them through quarterly sales auctions, considering the energy generated in one year by a single typical 4MW wind turbine. In Model I, we assume that the token price is fixed following a stable coin concept. In Model II, we consider that the price follows an inverse demand function subject to stochastic shocks. Finally, in Model III, the demand for RECs is uncertain and the purpose is to maximize the generator's profit. Through a numerical application, we verify the validity of the models and conclude, considering the parameters adopted, that the generator should invest in Model II, since it was the one with the highest NPV (US$ 60,992.70). However, if the demand volatility is less than 20%, the optimal model for the generator is Model I. The main contribution of this work is to analyze the performance dynamics of digital products under uncertainty.

Keywords: Renewable Energy Certificates; Real options; Analysis under Uncertainty; Blockchain.

1. Introduction

The emission of greenhouse gases has been one of the main factors contributing to global warming, and the focus of global concern (Lellis, 2007). In order to reduce the CO_2 emissions generated by electricity production, one of the main sources of greenhouse gases, big companies are investing more and more in clean energy sources. However, such initiatives require large capital investments in renewable energy sources, which are often out of the reach or end-use of some companies. One alternative, in this case, is to continue to receive energy from traditional sources and to acquire Renewable Energy Certificates (RECs) in a volume equivalent to the company's consumption, thus achieving its clean energy balance.

Renewable Energy Certificates were proposed in 1996 as market-based instruments issued when one megawatt-hour (MWh) of electricity is generated from a renewable energy source and delivered to the grid (Abragel, 2018). RECs are designed to foster renewable energy production by providing an additional source of revenue for these generators. These certificates may be transferred, purchased, sold, withdrawn or used by the holder to claim that he has used renewable energy. Currently, the certification cycle works as follows: a company that wishes to be an issuer of RECs must adhere to a code and undergo a documentary audit by the local issuer (Instituto Totum, 2018). With all the documents in compliance and the audit completed, the company pays the program fees and, from this, can issue and transfer RECs. In this sense, RECs help overcome several barriers to the purchase and sale of renewable energy attributes associated with electricity, such as access to transmission and pricing policies, intermittence of resources and lack of market liquidity (Wingate and Holt, 2004).

RECs markets have expanded rapidly and already have significant liquidity worldwide and, increasingly, countries are investing in renewable energy sources. Despite this, the question still remains: how can this market be further promoted in a way that is practical for all its stakeholders? Part of the answer can be found in the use of technological innovations, such as Distributed Ledger Technology (DLT), which enables tokenization and cheap distribution of RECs around the world.

The DLT also allows the creation of digital currencies, as well as being a new form of payment, as observed by Extance (2015), Maftei (2014), Negurita (2014), Little (2014), Bryans (2014), Hurlburt and Bojanova (2014), and Brito and Castillo (2013), can promote transaction agility, reduce or eliminate bureaucracy in the means of payment, and increase the security and transparency of transactions. In particular, blockchains, which are a type of DLT, depend on a distributed public accounting system, divided into blocks, where 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 smartcontracts, can be developed to run on blockchains, with all the benefits this technology offers, such as transparency and security.

In this study, we propose three distinct models for the development of tokens based on RECs, which can be automated and included in a smartcontract to run on the blockchain. In the three models proposed, 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 intelligent.

In Model I, we consider that price volatility and the inflation curve are controlled by adjustments in the supply of RECs, since the historical series of daily transactions of RECs is extremely volatile. In this case, we assume that the selling price of the token is fixed in all quarters, following the concept of a stable coin.

On the other hand, in Model II, we consider that the demand for RECs is deterministic and that it has a percentage growth in each quarter. In addition, in this protocol, the unit price of the token varies quarterly and is a function of inverse demand subject to continuous stochastic shocks.

Finally, in Model III, the purpose is to maximize the profit of the renewable energy generator, by choosing the optimal demand. In this case, the demand for RECs is a stochastic variable and the selling price of the token, as in Model II, is a function of inverse demand.

Therefore, the objective of this study is to evaluate, from these proposed models, the optimum model from the point of view of the renewable energy generator. For this, we used the real options approach, which made it possible to evaluate the option of Deferral present in each model and to analyze the decision making under generator uncertainty. This study contributes to the expansion of the literature on the applications of blockchain technology in the renewables market and is relevant, as it proposes three Decentralized Autonomous Organizations (DAOs) issuance and sale of RECs tokens. In addition, this research shows that simple pricing real options methods can assist decision makers in evaluation investment opportunities under uncertainty and flexibility.

This article is structured as follows: after this introduction, in section 2, we review the related literature. In section 3, we discuss how RECs work and, in section 4, we propose the three models for the development of token-based RECs. In section 5, we analyze the results and compare the proposed models. Finally, in section 6, we present the conclusions of this study and the suggestions for future research.

2. Literature Review

The theory of real options arose from the need to take into account managerial flexibility in project evaluation, which is not contemplated by traditional techniques, such as the Discounted Cash Flow (DCF) method (Copeland and Tufano, 2004). This new approach adapts the pricing models of financial options developed by Black and Scholes (1973) and Merton (1973), allowing the treatment of investment under uncertainty and flexibility.

Myers (1977) is credited as one of the first authors to use real options to determine the value of having flexibility and investment capacity in the future. It showed that companies that have a high debt risk will miss valuable investment opportunities, while companies that have low debt risk will be able to take advantage of future investment opportunities. Mcdonald and Siegel (1985), Titman (1985), Majd and Pindyck (1987) and Triantis and Hodder (1990) further developed the field, providing solutions for particular applications. Some years later, Dixit and Pindyck (1994) and Trigeorgis (1996) synthesized the main concepts and possible applications of this methodology.

Once the electric sector has initiated a process of deregulation, with a high level of competitiveness and increased market uncertainty, traditional project evaluation techniques have become insufficient to adequately deal with these additional risk and uncertainty factors (Fernandes, Cunha and Ferreira, 2011). In this sense, the use of more sophisticated valuation techniques, such as the real options approach, is now 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 perspective of the real options analysis, Lee (2011) evaluates the investment opportunities in renewable energy, showing that this method is effective in quantifying how the uncertainty of investment planning influences the development of renewable energy. The results reaffirm that the value of renewable energy development increases as the underlying price increases, time to maturity, risk free rate and volatility. But, it decreases as the exercise price increases.

Fontoura, Brandão and Gomes (2015) evaluate the feasibility of converting a biomass plant project based on elephant grass in a biorefinery, investing in a charcoal production unit and/or a second generation ethanol represent the options of this model. Through the adoption of a hybrid model of energy commercialization, the authors conclude that the values of the options are positive and that the proposed scheme represents a viable and interesting opportunity for the sustainable diversification of the energy matrix. Detert and Kotani (2013) investigate the optimal decision time for investments in alternative energy sources in uncertainty situations using the real options approach. To do this, 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.

Dias et al. (2011) study the case of an existing sugarcane mill that produces both sugar and ethanol, which has both the option of expanding production and the option of renovating its old cogeneration plant. This work was developed because of concerns about the possible exhaustion of fossil fuel reserves worldwide. The results show that the refurbishment of the cogeneration plant adds almost the same value as the flexibility to choose the ideal time to invest in the expansion of the plant, which is significant considering that cogeneration is not the main business of the sugarcane plant. Kim, Park and Kim (2017) propose a real options model that allows evaluating the investment in renewable energy in the developing countries. The main concern of the authors is to deal with uncertainties such as: the rapid change of technologies and the conditions of the host government. To test the validity of the model, the authors analyze the case involving a hydroelectric project in Indonesia and conclude that the proposed tool can help host countries and investors in the evaluation of renewable energy projects with high volatility and risk. 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. From the results found, 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.

According to Martínez-Ceseña and Mutale (2011), the initial costs and uncertainties caused by the variability of the renewable energy source, changes in support schemes and other factors can make renewable energy projects unattractive when they are subject to traditional financial assessments, as the discounted cash flow method. In this way, the authors propose a methodology, based on the real options approach, for the planning of renewable energy generation projects. Using a case study of hydropower, the authors conclude that projects planned under the proposed methodology can generate greater profits.

Boomsma, Meade and Fleten (2012) analyze, through the real options methodology, the moment of investment and the choice of capacity for renewable energy projects from different support schemes, such as feed-in tariffs and certificate negotiation of renewable energy. To test the proposed model, the authors apply it in a Nordic case study based on wind energy and conclude that feed-in tariffs encourage prior investments, but once the investment is made, trade in renewable energy certificates creates incentives for projects. According to Fleten et al. (2016) investors of 214 hydroelectric projects in Norway are not based on the real options model. In light of this information extracted through interviews, the authors investigate how the decisions to invest in renewable energy behave. For this, the authors evaluate the implicit subsidies in the decisions of the investors, through two models: the one of options kings and the one of liquid present value. Based on the sample analyzed, the results show that the real options model describes significantly better the behavior of investments in renewable energy.

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

Kitzing et al. (2017) develop a model of real options for evaluating wind energy investments, considering optimal timing and capacity constraints as part of optimization. The authors believe that this approach is well suited for the comparison of different support schemes, such as: FIT, feed premiums and Tradable Green Certificates (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 the renewable support, as well as the development of bespoke incentive schemes.

Although there are some applications of real options in renewable energy, studies have not been found in the literature that analyze the decision making under uncertainty of the renewable energy generator before three distinct and autonomous organizations (DAOs) whose rules of emission and sale of RECs are specified in smartcontracts, which are executed and validated by blockchain.

3. Renewable Energy Certificates

In many countries, the structure of generation, transmission and distribution of energy makes it impossible to physically trace the source of energy to its point of consumption. In such cases, the electricity from a renewable source is simply injected into the distribution system, mixing with other electrons from other sources (renewable or otherwise), and delivered through the local distributor to companies or homes through the poles and wires. Therefore, in this scheme, neither the local distributor of energy can inform about the origin of these electrons.

Renewable Energy Certificates, known worldwide as RECs, have emerged as a solution to the traceability problem of environmental energy attributes. The RECs originated through a global certification system, the I-REC (International REC Standard), 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 that has been injected into the system and the platform goes on to ensure that that REC will not be used for more nobody.

In addition, the I-REC platform allows plants to gain the right to transact the certificates and become issuers of RECs. To do so, these plants must undergo a certification cycle before joining the I-REC code. Initially, the plant must present detailed information about its enterprise and undergo a documentary audit by the local issuer, in which it is verified if the energy source is renewable, if the energy is legally installed, if the energy is interconnected in the system grid and whether there is a dual beneficiary of the ECN. With all the documents evaluated and accepted by the audit, the plant may begin to issue, sell and transfer RECs to buyers through the I-REC platform, where they will be registered as a participant.

The benefits of RECs are diverse. For certification organizations, the main benefit 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, there are markets that 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 be used to 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 supports the preservation of natural resources, sustainability and the development of renewable energy. In addition, the certificates 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 Down Jones Sustainability Index (DJSI).

4. Model

All three models assume an initial investment, which will allow the entry of the renewable energy generator in the platform and the creation of new tokens, and quarterly sales auctions, in which a number of tokens will be made available to the market, as shown in Figure 1:

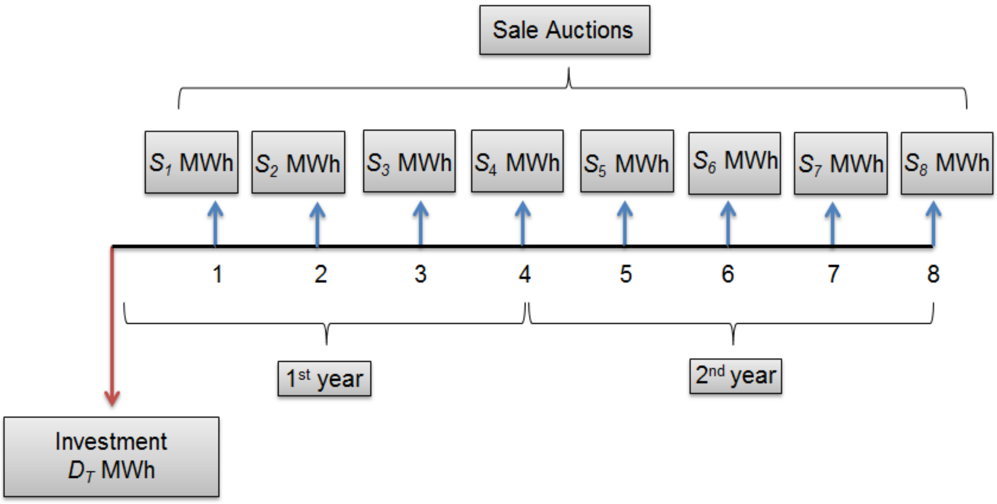

Figure 1 – General Scheme of Sale Auctions

Note that the renewable energy generator investment takes place at date zero and that the supply of RECs to the market (S_t) will occur for eight quarters (or two years). In addition, all three models consider that the generator has the flexibility to invest now or in a year to enter the platform, considering the energy generated in one year by a single typical 4MW wind turbine. So, the generator has a European option to defer for one year its investment to have the right to issue and sell RECs, being responsible for evaluating the best decision-making in each model.

4.1. Model I

In Model I, the offer of RECs is organized in a way that its price mimics the workings of a stable coin, which is a crypto-currency whose main purpose is to minimize price volatility. The motivation for the development of this model originated from the fact that the historical series of daily transactions of RECs is extremely volatile. Considering this, we assume that the unit price of the token is fixed in all quarters and that the quantity of RECs to be offered (S_t) in the sale auctions is strictly equal to the expected demand for RECs for the same period (D_t).

The quarterly demand for RECs follows the function presented in equation (1). This function is based on the seminal paper of Grenadier (1996), which proposes that the price of an asset follows an inverse (convex) function of the demand subject to continuous stochastic shocks. Since the token price is fixed in our model, we modify the original model of Grenadier (1996) by placing the demand for RECs in evidence in this function. It is important to note that by making this modification, this becomes a concave function.

$$D_t = \max\left[\left(3 - \frac{P}{C_t}\right) \times D_0, 0\right] \tag{1}$$

where: D_t is the demand in quarter t; P is the fixed unit price of the REC (US$/REC); D_0 is the initial demand; and, C_t represents a multiplicative demand shock, which follows a Geometric Brownian Motion (GBM), as shown in equation (2).

$$dC_t = \mu C_t dt + \sigma C_t dz_t \tag{2}$$

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 increment of Wiener, where $\varepsilon \approx N(0,1)$.

After estimating the total demand for RECs, we can calculate the investment that the generator must make to enter the platform, defined in equation (3).

$$I = \lambda \times \sum_{t=1}^{8} E\left[D_t\right] \tag{3}$$

where: I is the investment; $E[D_t]$ represents the expected value of demand in quarter t; and, λ is the marginal unit fixed cost of entry into the platform in US$/REC.

On the other hand, the generator's revenue in each quarter (R_t) will depend both on the supply of RECs in the same period (S_t) and on the unit price of the REC (P), as shown in equation (4).

$$R_t = P \times S_t \tag{4}$$

But we have previously defined that the supply of RECs is strictly equal to the demand for RECs. Therefore, equation (4) can also be written as equation (5):

$$R_t = P \times D_t \tag{5}$$

Therefore, the generator's Net Present Value (NPV) of participating in this protocol is defined by equation (6):

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

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

Since the traditional DCF method does not capture the uncertainty and managerial flexibility present in this case, we adopt the real options approach using the discrete binomial tree model proposed by Cox, Ross and Rubinstein (1979) (CRR). The model parameters are presented in equation (7):

$$u = e^{\sigma\sqrt{dt}}, \quad d = \frac{1}{u} \quad \text{e} \quad p = \frac{1 + r_f - d}{u - d} \tag{7}$$

where: σ is the volatility adopted in the stochastic process of uncertainty, which in this case is the shock (C_t); and, r_f is the risk-free rate.

It should be noted that this option pricing model requires the use of the risk-neutral measure that can be determined by deducting the risk premium from the asset's rate of return and then discounting cash flows at the free rate of risk. Thus, the shock-neutral process is defined by equation (8).

$$dC_t^R = (\mu - \zeta_C) C_t^R dt + \sigma C_t^R dz_t \tag{8}$$

where: ζ_C represents the shock risk premium; μ is the return rate of the shock; and, dC_t^R is the incremental variation of the neutral shock to the risk in the time interval *dt*.

As discussed by Freitas and Brandão (2009), the market risk premium can be observed directly or can be determined through CAPM (Capital Asset Pricing Model), where $\mu = r_f + \zeta$ and $\zeta = \beta\left(E\left[R_M\right] - r_f\right)$. On the other hand, the risk premium of incomplete market assets, as is the case of the uncertainty of this first model (C_t), can only be calculated through indirect methods.

In order 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 shows the equation (9):

$$\int_{t=1}^{n} f\left(C_t\right) e^{-\mu t} dt = \int_{t=1}^{n} f\left(C_t^R\right) e^{-(\mu - \zeta_C)t} dt \tag{9}$$

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

From this, assuming that the other variables of equation (9) are known, the risk premium value can be determined by equivalence.

Note that we have defined only how uncertainty should be addressed in this model. To incorporate the flexibility, we assume some premises: if the generator chooses not to delay, it will follow the general auction scheme shown in Figure 1; but, if he chooses to postpone, his investment happens in the fourth quarter (I_A) and starts to assume the value presented in equation (10).

$$I_A = \left(\lambda \times \sum_{t=5}^{12} E\left[D_t\right]\right) \times (1+k)^4 \tag{10}$$

In addition, both the uncertainty value and the amount of RECs to be offered will correspond to the estimated values for the fifth quarter onwards, as shown in Figure 2.

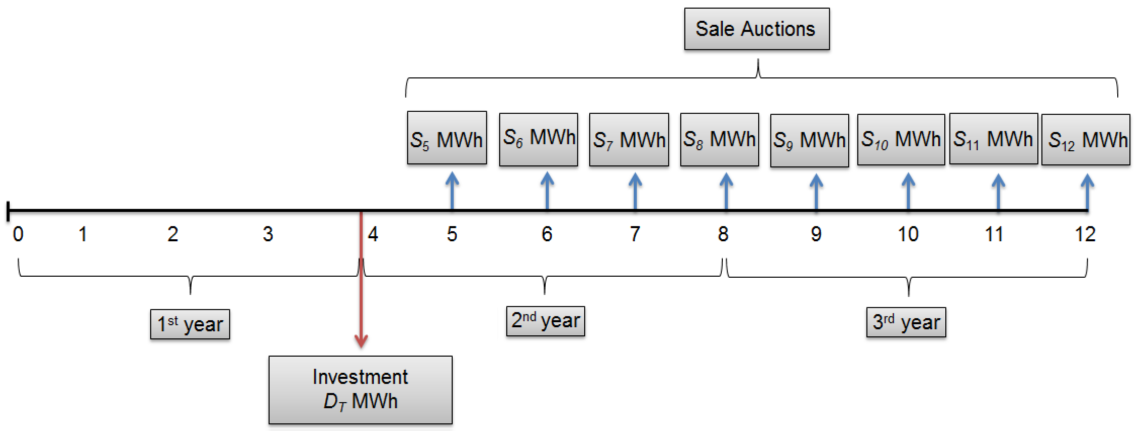

Figure 2 – Deferring the Investment in Model I

4.2. Model II

In Model II, we also consider that the quantity of RECs to be offered (S_t) in sales auctions is strictly equal to the expected demand for RECs for the same period (D_t). However, in this case, the demand for RECs is deterministic and has a percentage growth every quarter, as shown in equation (11).

$$D_t = D_0 \left(1+\alpha\right)^t \tag{11}$$

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

Although the demand is deterministic, the unit price of the REC changes every quarter and is defined as a function of inverse demand subject to continuous stochastic shocks, as shown in equation (12). Note that, in this case, we are using exactly the model proposed by Grenadier (1996).

$$P_t = \left[3 - \frac{D_t}{D_0}\right] \times C_t \tag{12}$$

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 GBM, as well as in Model I.

From this, we verify that the investment that the renewable energy generator must make to enter this platform is defined by equation (13):

$$I = \lambda \times \sum_{t=1}^{8} D_t \tag{13}$$

where: I is the investment and λ is the marginal unit fixed cost of entry into the platform in US$/REC.

And, the generator's revenue (R_t) is determined by equation (14):

$$R_t = P_t \times S_t \tag{14}$$

where: S_t is the supply of RECs in each quarter t.

Since the supply of RECs is equal to the demand for RECs, the expression of revenue can also be defined by equation (15):

$$R_t = P_t \times D_t \tag{15}$$

Thus, as in Model I, we can determine the generator's NPV, through equation (6) ; and model the uncertainty (C_t) through the binomial tree CRR model, using the same concept of risk neutrality presented previously.

To capture flexibility, we assume other premises: if the generator chooses not to defer, it will follow the standard auctions scheme shown in Figure 1; On the other hand, if the generator chooses to delay, his investment happens in the fourth quarter (I_A) and starts to assume the value defined in equation (16).

$$I_A = \left(\lambda \times \sum_{t=1}^{8} D_t\right) \times (1+k)^4 \tag{16}$$

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, which is defined by the multiplicative shock of demand (C_t), will continue to follow a GBM since the first quarter.

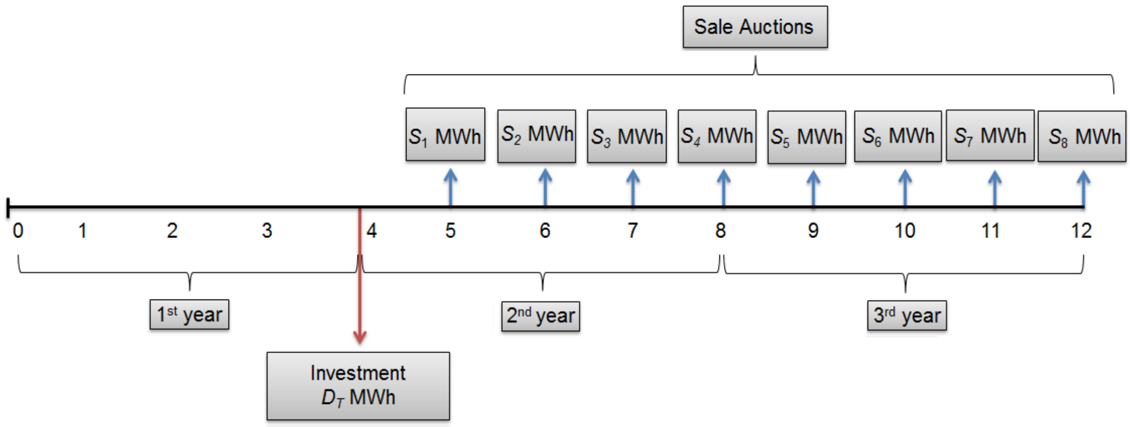

Figure 3 – Deferring Investment in Model II

4.3. Model III

In Model III, we follow the same logic that the amount of RECs to be offered (S_t) in the sale auctions is strictly equal to the expected demand for RECs for the same period (D_t). However, in this case, the demand for RECs is not deterministic, it is a stochastic variable that follows a GBM, as shown in equation (17).

$$dD_t = \mu D_t dt + \sigma D_t dz_t \tag{17}$$

where: dD_t is the incremental variation of demand in the time interval dt; μ represents 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 increment of Wiener, where $\varepsilon \approx N(0,1)$.

One of the differences of this model to the previous one is that the uncertainty is no longer in the shock (C_t) but in the demand itself (D_t). In this case, we change the original idea proposed by Grenadier (1996) so that the unit price of the REC varies every quarter, following a function of inverse demand subject to deterministic shocks, as shown in equation (18). It should be emphasized that this function, different from that developed by Grenadier (1996), is concave, since the uncertainty is no longer in the shock.

$$P_t = \max\left[\left(3 - \frac{D_t}{D_0}\right) \times C_t, 0\right] \tag{18}$$

where: P_t is the unit price of REC in quarter t; D_0 é the initial demand; e, C_t is the shock in quarter t, which is defined by equation (19).

$$C_t = C_0(1+\alpha)^t \tag{19}$$

where: C_0 represents the initial shock; α is the growth rate of the shock in each quarter.

From this, we can evaluate the investment that the renewable energy generator must make to enter this platform, through equation (3), as in Model I. On the other hand, to calculate the generator's revenue we use equation (15), defined in Model II.

The other difference, the main one, between the second and third models is that the objective of this is to maximize the profit of the generator by choosing the optimal demand. In this sense, since the generator's revenue is a concave function, we can apply the First Order Condition, as shown in equation (20).

$$\frac{\partial R_t}{\partial D_t} = 0 \tag{20}$$

After defining the optimal demand and including it as an absorbing barrier in the stochastic process of demand, we calculated the generator's NPV, through equation (6), as well as in the other two models. To model the uncertainty, which in this case is the demand for RECs, we also use the binomial tree CRR model. However, as uncertainty derives from the demand in this model, we must use the risk-neutral process defined in equation (21):

$$dD_t^R = (\mu - \zeta_D) D_t^R dt + \sigma D_t^R dz_t \tag{21}$$

where: ζ_D represents the demand risk premium; μ is the rate of return of the demand; and, dD_t^R is the incremental variation of the risk-neutral demand in the time interval dt.

As in the other models, we consider the equality between the expected values of the traditional and risk-neutral valuation gains to calculate the risk premium. However, in this case, the cash flows are demand functions, as shown in equation (22):

$$\int_{t=1}^{n} f\left(D_t\right) e^{-\mu t} dt = \int_{t=1}^{n} f\left(D_t^R\right) e^{-(\mu-\zeta_D)t} dt \tag{22}$$

where: $f\,(.)$ represents the cash flows of the generator.

Finally, to insert the flexibility into the model, we assume the same premises defined in Model I.

5. Numerical Example

In order to verify the validity of the three models, we first define the common parameters to the three models, as shown in Table 1. It is important to note that the initial demand for RECs, growth rate, volatility and drift were determined based on the history of daily transactions of RECs between 2014 and 2018, provided by Instituto Totum (2018).

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%	21.55%
Discount Rate (k)	6.00%	26.25%
Risk Free Rate (r)	1.30%	5.30%
Volatility (σ)	30.00%	185.61%
Drift (μ)	5.00%	21.55%
Marginal Unit Cost (λ)	US$ 1.50/REC	US$ 1.50/REC

Table 1 – Common Parameters to the Three Models

5.1. Model I Results and Analysis

With the values of initial shock and initial demand determined in Table 1 and assuming that the unit sale price of the token is fixed and equal to US$ 2.00 in all quarters, we can determine the demand for RECs in each quarter and, consequently, the investment that the generator must make at the initial moment, as well as the generator's revenue in the eight quarters.

For this, we need to model the uncertainty of this first model, which is given by the demand shock (C_t). In this sense, we first calculate the risk premium ($\zeta_C = 3.56\%$ a.t. or 15.02% a.a.) using numerical methods, considering the mathematical equivalence between the PVs (Present Values) of the traditional static valuation and the risk-neutral valuation.

After that, we calculate the upside and downside factors of the binomial tree (u = 1.35 and d = 0.74). And, from these values, we determine the risk-neutral probabilities of the model (p = 44.92% and $1-p$ = 55.08%). Using DPL software, 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.

From the modeling of uncertainty, we verify that the expected demand value for the next two years is equal to 121,767 MWh and that the generator's investment in this platform is equal to US$ 182,650.34. In addition, through this binomial tree, we find that the generator's NPV is equal to US$ 5,224.23.

However, note that we still do not consider the flexibility in this calculation, which is given by the generator's option to postpone its investment. To include it in the model, we developed the binomial tree shown in Figure A.2. In this case, the expected demand for RECs is equal to 129,539 MWh and, consequently, the generator's investment is I_A = US$ 245,310.64. In addition, considering the option to postpone the investment for one year, we find that the generator's NPV is equal to US$ 40,044.68. In this sense, the Deferral option promoted a growth of approximately 666.52% in the generator's NPV. Note that this option is extremely valuable to the generator due to the high volatility of demand for RECs.

5.1.1. Sensitivity Analysis

According to the Model I results, the volatility of demand for RECs (σ) is extremely high and is one of the parameters that makes the generator's option to defer its investment valuable. In this sense, although the volatility was calculated based on real data on the transactions of RECs in the market, it is interesting to perform a sensitivity analysis to verify, from the variation of this parameter, the impact on the generator's NPV, as shown in Figure 4.

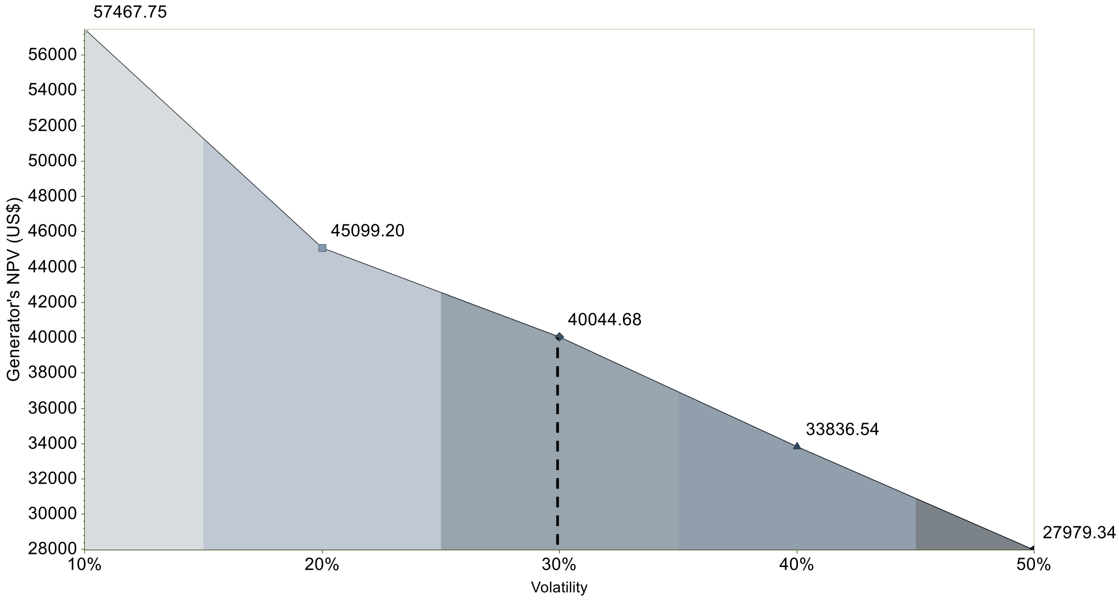

Figure 4 – Sensitivity Analysis of Volatility for Model I

For this, we consider that the volatility can assume values between 10.00% and 50.00% and, as we can see, the generator's NPV decreases as the volatility increases. This result is not expected, since in most cases of real options we analyze convex functions, which follow the rule that the greater the uncertainty, the greater the value of the option. However, the result of the sensitivity of the volatility is valid, since the NPV function in the Model I is concave and behaves contrary to that described above. That is, in this case, it is pertinent to state that the greater the uncertainty, the lower the value of the option.

Another important parameter to perform the sensitivity analysis is the marginal unit cost of entry into the platform (λ). Although it has been estimated based on the current market value of the REC, we believe that it is interesting to see how the variation of this parameter can impact the generator's NPV, as shown in Figure 5.

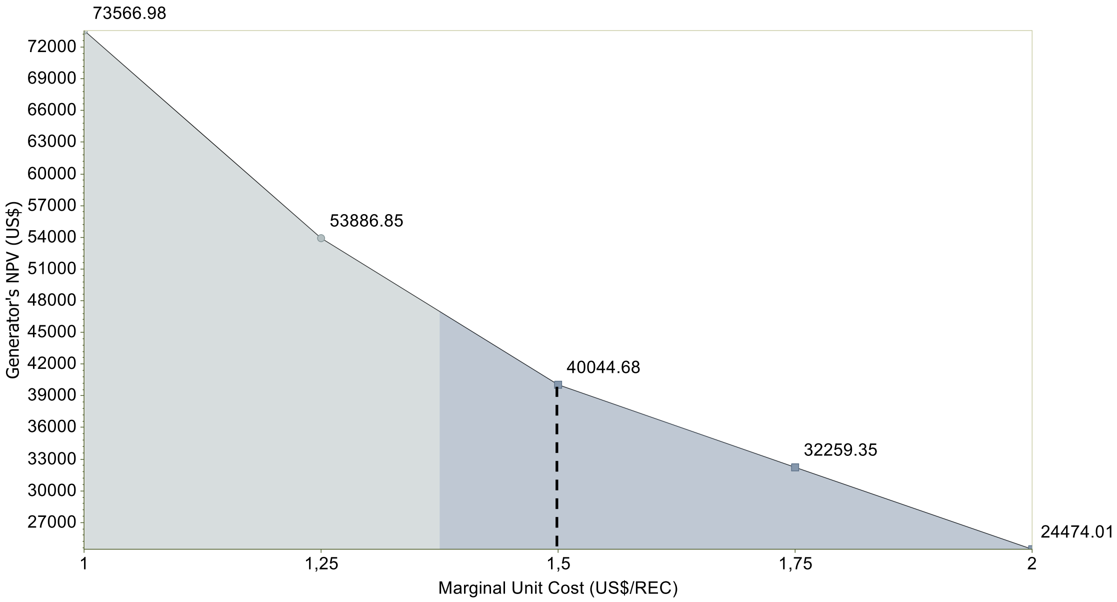

Figure 5 – Sensitivity Analysis of the Marginal Unit Cost of Entry for Model I

In this analysis, we consider that the marginal unit cost can assume values between US$ 1.00 and US$ 2.00. As this cost directly impacts the value of the generator's investment, the higher this parameter, the lower the generator's NPV. Note that the generator's NPV increases by 83.71% when the parameter value decreases by 50.00% and that the generator's NPV decreases by 61.12% when the parameter value increases by 50.00%.

5.2. Second Model Results Analysis

From the definition of the initial demand and its growth rate in Table 1, we can determine the expected demand values in each quarter for the next two years, as shown in Table 2.

t	Demand (D_t)
1	15,750
2	16,538
3	17,364
4	18,233
5	19,144
6	20,101
7	21,107
8	22,162
Total (D_T)	**150,398 MWh**

Table 2 – Projection of Quarterly Demand

As the total demand for RECs for the next two years is equal to 150,398 MWh, the generator's investment will be equal to US$ 225,597.70. From this, we can model the multiplicative demand shock (C_t), which represents the uncertainty in this second model and that defines the generator's revenue. In this sense, we use the upside and downside values of the binomial tree (u = 1.35 and d = 0.74); calculate by numerical methods the value of the risk premium ($\zeta_C = 4,66\%$ a.t. or 19,98% a.a.), considering the mathematical equivalence between the PVs; and, consequently, the risk-neutral probabilities (p = 43.12% and $1\text{-}p$ = 56.88%).

Based on this, using the DPL software, 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.3. Through this binomial tree, we find that the generator's NPV is equal to US$ 23,769.94. In this calculation, we do not consider the generator's option to defer for one year its investment.

To include this managerial flexibility in the model, we need to redesign the binomial tree, as shown in Figure A.4; and, consider that the generator's investment becomes equal to I_A = US$ 284,811.89. So, considering the option to postpone the investment, we find that the generator's NPV is equal to US$ 60.992.70. Therefore, the option promoted a growth of approximately 156.60% in its NPV.

5.2.1. Sensitivity Analysis

As in Model I, we perform sensitivity analyzes on two parameters: the volatility and the marginal unit cost of entry into the protocol. First, we consider that the volatility can assume values between 10.00% and 50.00% and we evaluate the impact of this in the generator's NPV, as shown in Figure 6.

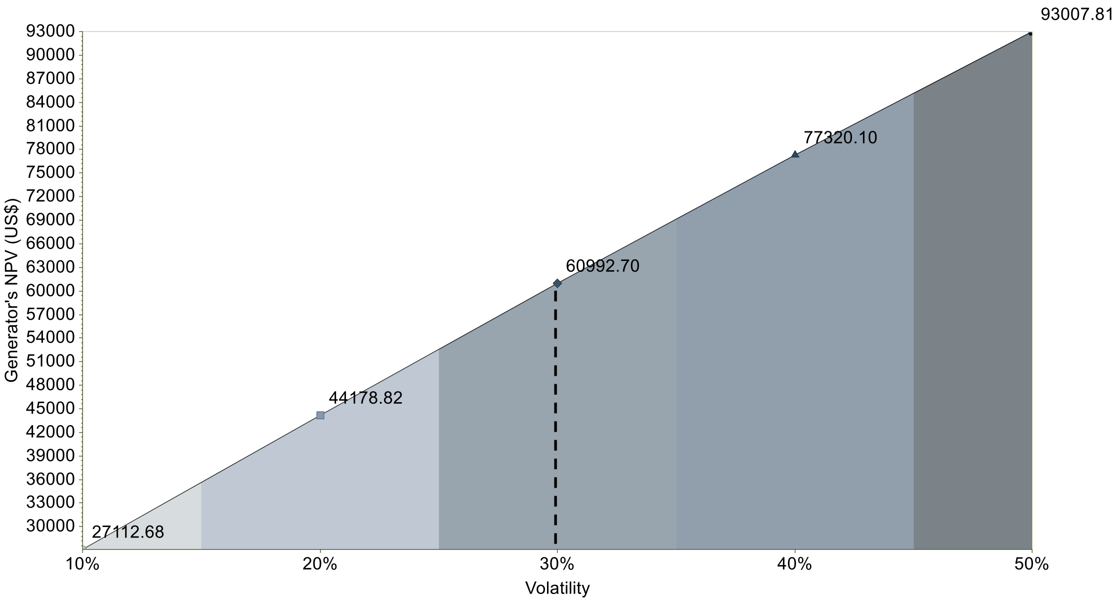

Figure 6 – Sensitivity Analysis of Volatility for Model II

We can observe that the generator's NPV can assume values between US$ 27,112.68 and US$ 93,007.81. Therefore, the generator's NPV increases as the volatility assumes larger values. This result is expected because the NPV in Model II is a convex function.

To evaluate the impact on the generator's NPV from variations in the marginal unit cost of entry to the platform, we consider that this parameter can assume values between US$ 1.00 and US$ 2.00, as shown in Figure 7.

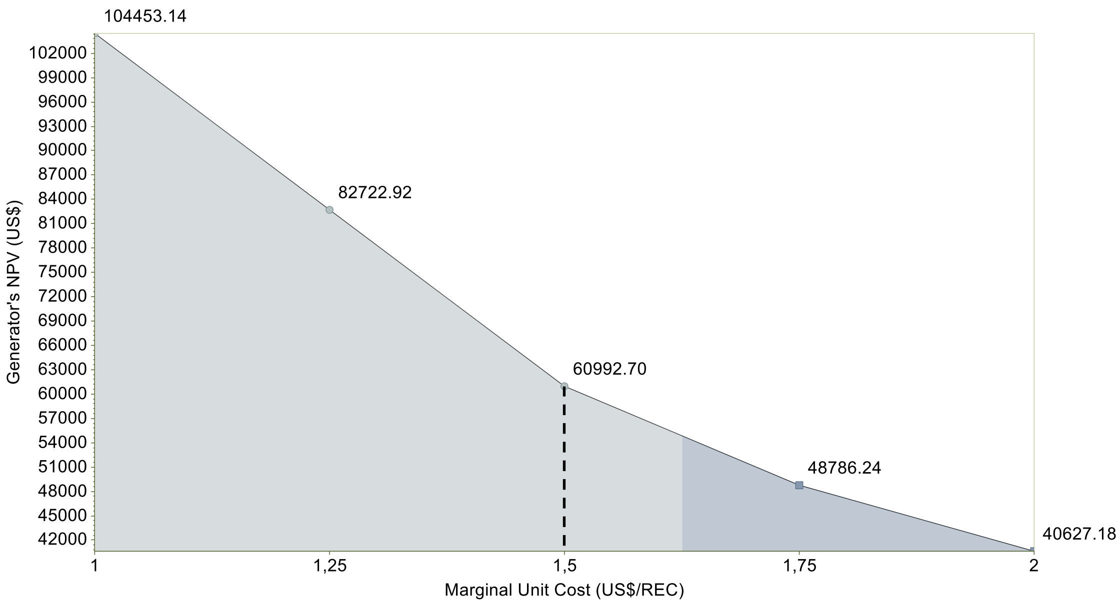

Figure 7 – Sensitivity Analysis of the Marginal Unit Cost of Entry for Model II

Note that the generator's NPV, in this case, varies between US$ 40,627.18 and US$ 104,453.14. In addition, observe that a 50.00% increase in the value of the parameter under analysis causes a 66.61% reduction in the generator's NPV; and, on the other hand, a reduction of 50.00% causes an increase of 71.26% in the generator's NPV.

5.3. Third Model Results Analysis

With the values of the initial shock (C_0) and the growth rate (α) presented in Table 1, we can determine the shock value in each quarter for the next three years, as shown in Table 3:

t	Shock (C_t)
1	1.05
2	1.10
3	1.16
4	1.22
5	1.28
6	1.34
7	1.41
8	1.48
9	1.55
10	1.63
11	1.71
12	1.80

Table 3 – Projection of Quarterly Shock

In this case, the investment in the platform is given by the marginal unit cost of input multiplied by the expected demand for the first eight quarters, shown in Table 4.

t	Expected Demand $E[D_t]$
1	15,750
2	16,538
3	17,364
4	18,233
5	19,144
6	20,101
7	21,107
8	22,162
Total	**150,398 MWh**

Table 4 – Expected Demand in the Base Case

When we define the total expected demand for RECs for the next two years, we find that the value of the generator's investment is equal to US$ 225,597.70. After that, we use the upside and downside values of the binomial tree (u = 1.35 and d = 0.74); we calculate the risk premium $(\zeta_D = 10{,}16\%\text{ a.t. or }47{,}26\%\text{ a.a.})$ using numerical methods, respecting the equivalence between the PVs; and, we determine the risk-neutral probabilities (p = 34.09% and 1-p = 65.91%).

To model the demand for RECs, which is the uncertainty in this model, we use the DPL software and incorporate the generator's revenue as the cash flow of the model, as shown in Figure A.5. Through this model, we find that the generator's NPV in the third protocol is negative and equal to - US$ 12,056.97.

Please note that we do not consider the generator option to delay your investment for one year. In order to include flexibility to the model, first, we consider that the investment of the generator, in the case of Deferral, increases to I_A = US$ 346,190.64, since the expected demand starts to assume the values presented in Table 5; and then we project the tree shown in Figure A.6.

t	Expected Demand *E[D_t]*
5	19.144
6	20.101
7	21.107
8	22.162
9	23.270
10	24.433
11	25.655
12	26.938
Total	**182.810 MWh**

Table 5 – Expected Demand in the Deferral Case

When considering the generator's option to defer its investment for one year, its NPV will be equal to US$ 5,357.52. In this case, the Deferral option promoted a growth of 144.44% in the generator's NPV.

5.3.1. Sensitivity Analysis

As in the other two models, we performed sensitivity analyzes on volatility and marginal cost of entry into the protocol. Figure 8 shows the first sensitivity analysis:

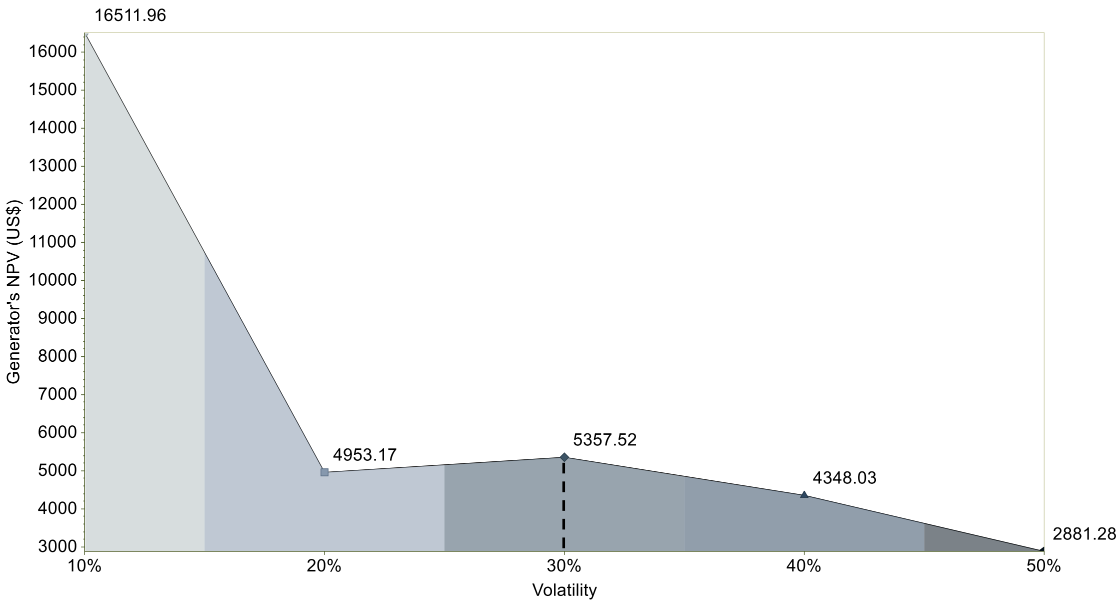

Figure 8 – Sensitivity Analysis of Volatility for Model III

Considering that the volatility can assume values between 10.00% and 50.00%, we evaluate the impact of this variation on the generator's NPV. Note that the generator's NPV increases as we decrease the volatility from 20.00% to 10.00%, as well as from 50.00% to 30.00%. This is explained by the fact that the NPV, in these intervals, is a concave function, as in Model I.

It is also important to note that the lack of monotonicity of this curve is explained by the fact that we incorporate the optimal demand, calculated from the First Order Condition, as an absorbing barrier in the stochastic process of uncertainty. If, considering this barrier, the sensitivity curve becomes concave for all the analyzed volatility values.

Finally, we evaluate the impact on the NPV from variations in the marginal unit cost of entering the platform. We assume that this parameter can assume values between US$ 1.00 and US$ 2.00, as shown in Figure 9.

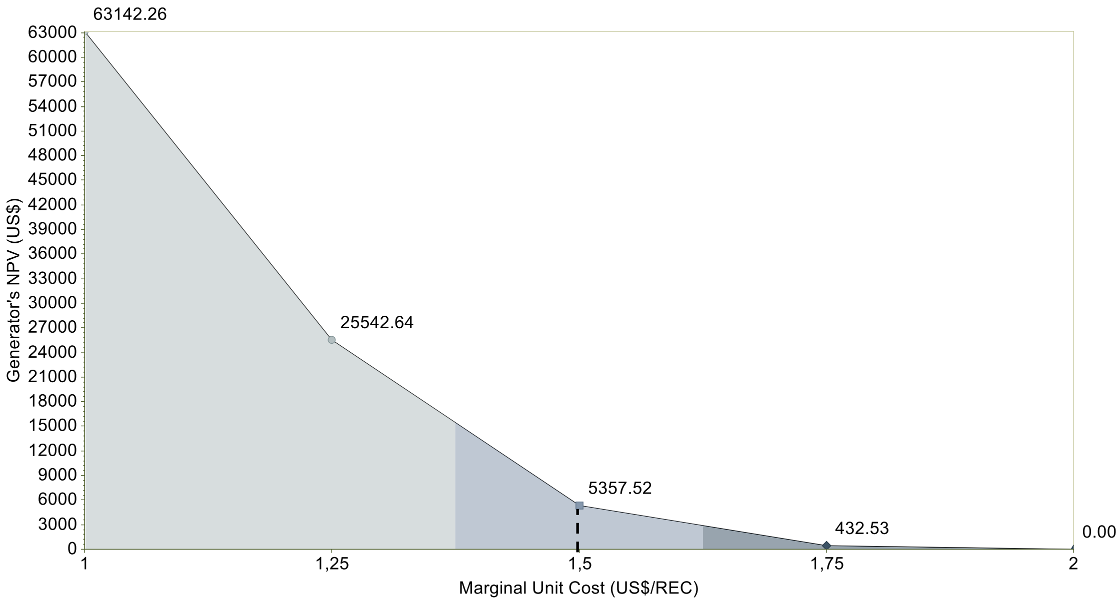

Figure 9 – Sensitivity Analysis of the Marginal Unit Cost of Entry for Model III

In this last analysis, the generator's NPV ranges from US$ 0.00 to US$ 63,142.26. It is important to note that a reduction of 50.00% in the marginal unit cost generates an increase of 1,078.57% in the generator's NPV. On the other hand, a 50.00% increase in the value of this parameter generates a reduction of 100.00% in the generator's NPV. Note that this sensitivity presents the most significant impact on the NPV.

5.4. Comparative Analysis

After evaluating the generator's NPV in each model, we can determine in which the generator should invest so that its decision making is optimal. When considering the parameters defined in Table 1 and comparing the NPVs of each model, we verify that the generator should invest in the second, since it is the one that provides the highest NPV (US$ 60,922.70).

In addition, it should be noted that even considering the sensitivity analysis on the marginal cost of entry into the platform, Model II remains the optimal model for the generator, as shown in Table 6:

Marginal Unit Cost (US$/REC)	NPV (US$)		
	Model 1	Model 2	Model 3
1.00	73,566.98	**104,453.14**	63,142.26
1.25	53,886.85	**82,722.92**	25,542.64
1.50	40,044.68	**60,992.70**	5,357.52
1.75	32,259.35	**48,786.24**	432.53
2.00	24,474.01	**40,627.18**	0.00

Table 6 – Sensitivity of the Marginal Unit Cost in the Choice of the Optimum Model

However, if we consider the sensitivity analysis on volatility, the result may change, as shown in Table 7:

Volatility	NPV (US$)		
	Model 1	Model 2	Model 3
10.00%	**57,467.75**	27,112.68	16,511.96
20.00%	**45,099.20**	44,178.82	4,953.17
30.00%	40,044.68	**60,992.70**	5,357.52
40.00%	33,836.54	**77,320.10**	4,348.03
50.00%	27,979.34	**93,007.81**	2,881.28

Table 7 – Sensitivity of Volatility in the Choice of the Optimum Model

It should be noted that when the volatility is lower than 20.00%, Model I becomes the optimal model for the generator. This result is mainly explained by the fact that the generator's NPV is a concave function in Model I and, in contrast, is a convex function in Model II.

6. Conclusion

In this work, we analyze the investment under uncertainty of the renewable energy generator, party interested in offering RECs, in three autonomous models of different issuance and sale of tokens based on RECs. In all three models, 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 blockchain.

Therefore, the main objective of this work is to evaluate in which of the three models proposed is optimal the generator to realize the investment. For this, we used the real options approach that allowed calculating the generator's NPV, considering both the uncertainty of each model and the managerial flexibility related to the option of Deferral.

In Model I, which follows a stable coin concept, the generator's NPV is equal to US$ 40,044.68. In Model II, where the price is a function of inverse demand subject to stochastic shocks, the generator's NPV is US$ 60.992.70. Finally, in the last model, which considers that the uncertainty derives from the demand for RECs, the generator's NPV is US$ 5,357.52.

In this sense, we can conclude that the generator must invest in Model II, since it is the one that provides the highest NPV. However, it is important to note that when considering the sensitivity analysis of the volatility of demand for RECs, we find that if σ <20.00%, the optimal model from the point of view of the generator becomes the first.

This work contributes to the understanding of the dynamics of the performance of digital products under uncertainty, as well as to 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 analyzes under investment uncertainty and flexibility the investment of the renewable energy generator in three different DAOs. This research also highlights that simple pricing methods of real options can aid in decision making when there is uncertainty and flexibility, making investment opportunities better evaluated.

The main limitation of this research is the fact that we have few data on the RECs transactions in the market. The history provided by the Instituto Totum has information only for the period between 2014 and 2018. In addition, in this study we consider only one uncertainty in each model, as well as only the managerial flexibility of Deferral. In future work, we suggest adding other uncertainties and analyzing different types of options, such as abandoning the platform.

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Appendix

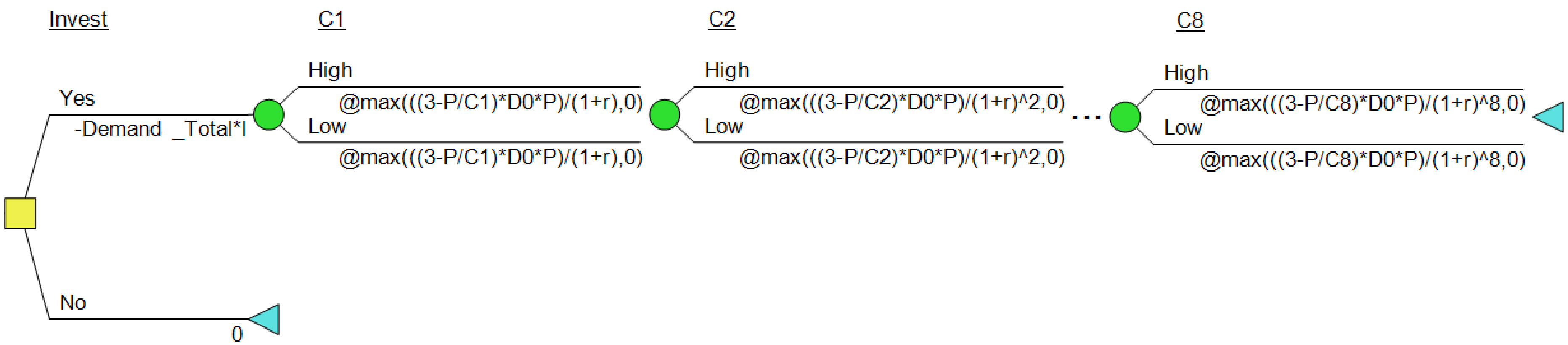

Figure A.1 – Binomial Tree of Model I

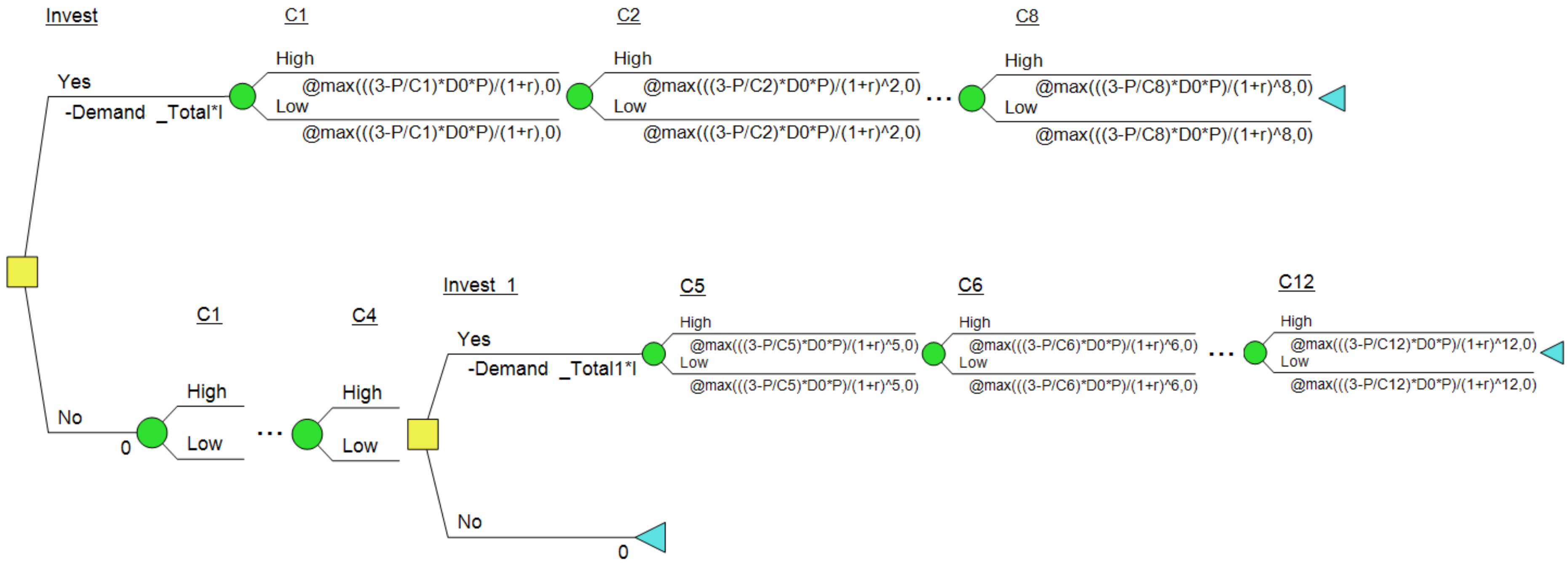

Figure A.2 – Binomial Tree of the First Model with Deferral Option

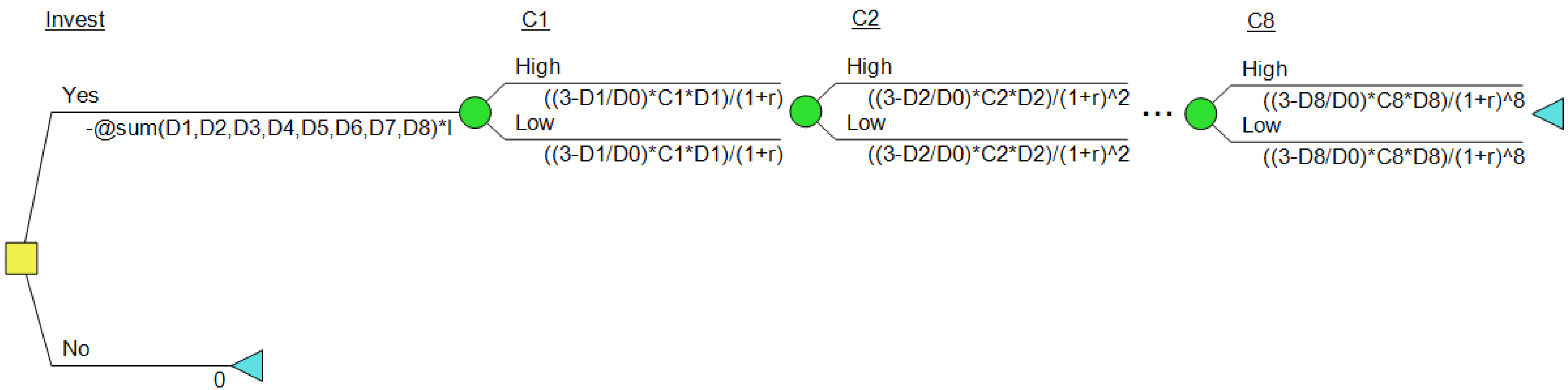

Figure A.3 – Binomial Tree of Model II

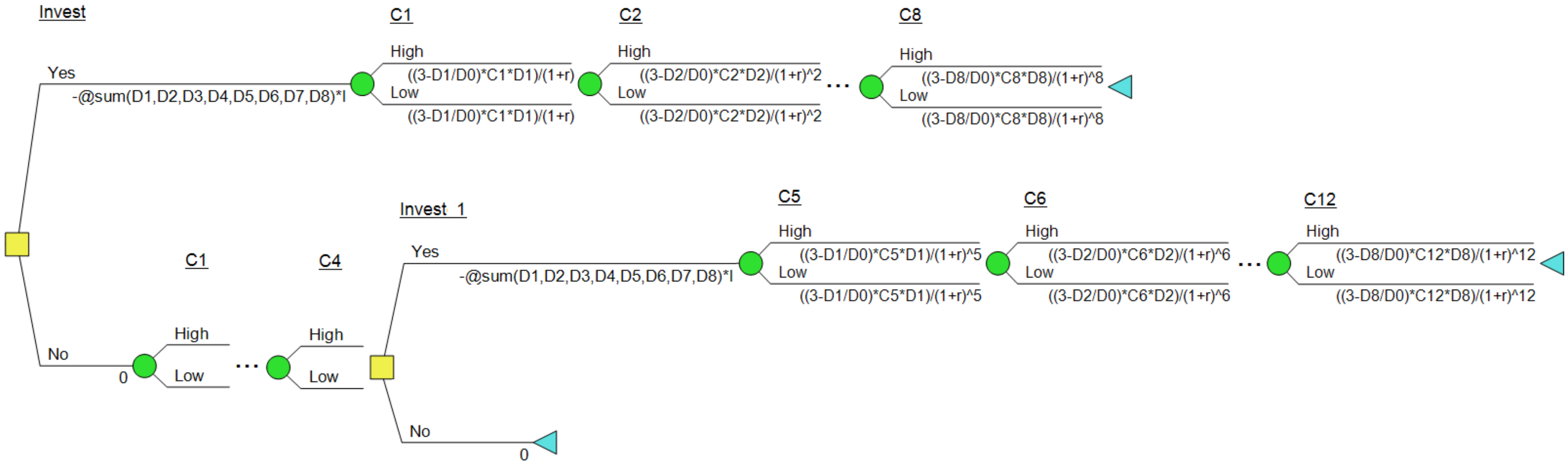

Figure A.4 – Binomial Tree of Model II with Deferral Option

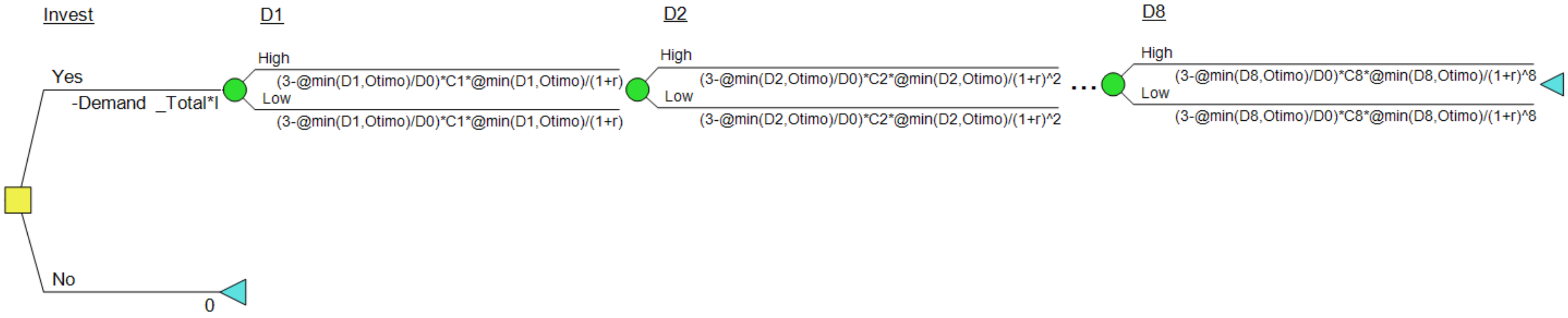

Figure A.5 – Binomial Tree of Model III

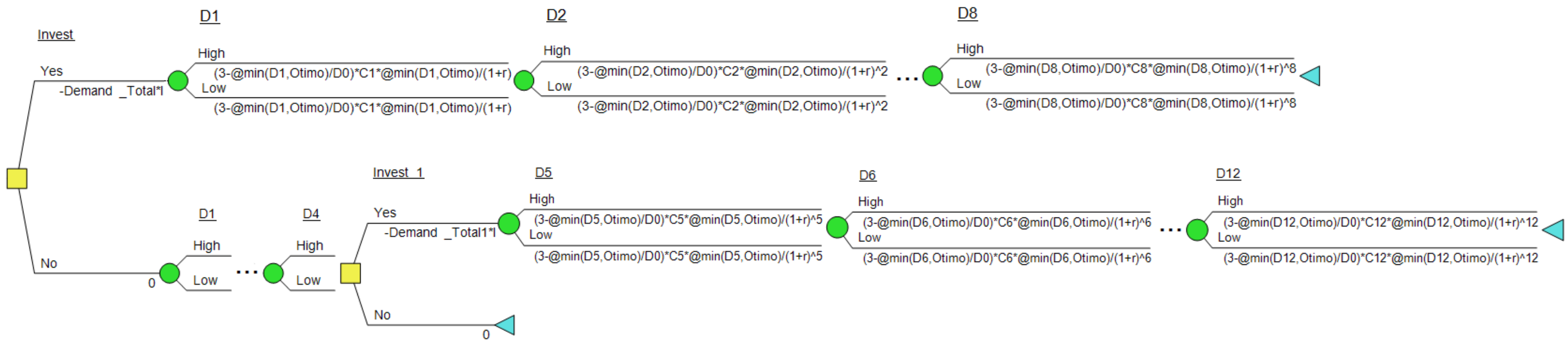

Figure A.6 – Binomial Tree of Model III with Deferral Option