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Operating Model and Estimation of the Insurance Premium for an Energy Futures Clearing House in Brazil

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Abstract

Purpose – We propose and analyze a new operating model for an energy futures exchange that could be implemented in Brazil, where there is low liquidity for these contracts. The clearing house temporarily assumes the position of customers who fail to answer the margin call, instead of closing the position, as would normally be done under normal conditions.

Theoretical framework – The main theoretical bases were diffusion processes, with jumps and without jumps, and the pricing model developed by Merton (1976).

Design/methodology/approach – We developed a Monte Carlo simulation model, using diffusion processes, with and without jumps.

Findings – The results show that the proposed model and the insurance option generate relatively low-cost increments for the operation that could be easily absorbed by the clearing house.

Practical & social implications of research – This study will be especially useful for market agents who want to evaluate the implementation of a Brazilian energy exchange, which to date is not available.

Originality/value – The article proposes a new operating model for the Brazilian energy futures market and its results may encourage investment in the sector, which lacks an energy futures exchange.

Keywords: Electricity, futures markets, Monte Carlo simulation, clearing house.

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1 Introduction

A major overhaul of the Brazilian electricity sector began in 1997, when the first privatizations were initiated. The changes included the process of de-verticalizing electricity production, transmission, distribution and commercialization, part of the Brazilian electricity sector restructuring project. An environment for accounting and liquidation of electricity was also created, the Wholesale Energy Market, which is currently the Electric Energy Clearing House (*Câmara de Compensação de Energia Elétrica - CCEE*).

In 2004, the Free Contracting Environment (*Ambiente de Contratação Livre - ACL*) and the Regulated Contracting Environment (*Ambiente de Contratação Regulada - ACR*) were created. Before that, the free market had very low liquidity, and with the creation of the ACL, it started to see growth, but, even so, the futures market continued to feature bilateral trades and the over-the-counter (OTC) format. In 2005, the first trading session for energy contracts in the country was created by the Brazilian Mercantile and Futures Exchange (BM&F), which, due to low liquidity, was discontinued. In 2012, BRIX and BBCE (*Balcão Brasileiro de Comercialização de Energia*), two important electronic trading platforms, started operations, which brought more agility to the business and standardization of contracts. However, these are platforms that still operate in an OTC format.

During the overhaul of the Brazilian electricity sector, attempts were made to develop an energy exchange in which investors could trade futures contracts, but these failed, possibly due to the lack of an adequate methodology and technological tools that are available today, and due to characteristics of the market, such as the high volatility of electricity prices and the difficulty of establishing a mark-to-market consensus. The high volatility of energy prices in the Brazilian market is a characteristic that is difficult to change, as the Brazilian electricity matrix features hydraulic energy as its main source, which is extremely dependent on climatic factors, which are difficult to predict. Periods of drought or prolonged rain, for example, can cause a sharp rise or fall in short-term energy prices and the futures market.

The high volatility of energy prices undermines the process of securing multilateral guarantees and, today, some of the most sophisticated methods to deal with this issue are used in European and American energy exchanges. The main method is cascading, where futures contracts with longer periods expire on previously agreed dates and are replaced by shorter, equivalent contracts, promoting greater security and liquidity in the market. This methodology can be adapted to Brazilian specificities to provide less volatility and increase market liquidity.

Another alternative to increase the security and liquidity of the market, with the objective of making the operation of a Brazilian energy exchange viable, is to structure an operation in which the clearing house assumes the positions of clients that do not respond to the margin call, after the mark-to-market. As the purpose of the transaction is not speculative, in this model, the clearing house closes the positions it has taken as soon as possible. This strategy makes the existence of a symmetric order in the order book unnecessary to close the position of a client who does not respond to the margin call. In a highly liquid market, the manager would not need to take any position and would simply close the position of these clients using other clients' open orders, from the order book. However, in the Brazilian energy market, due to low liquidity, it would not always be possible to close the position immediately and it would be necessary, as a protective measure, to set up an operation in which the clearing house would, provisionally, assume the position of that client, removing them from the operation.

Recently, Souza et al. (2021) analyzed the economic preconditions for the Brazilian electricity market, perceptions, and expectations of agents about a specific future electricity market, through an exploratory study. In this study, questionnaires were applied to market agents to estimate the perception and expectation of the conditions for the implementation of an electricity futures exchange in Brazil. The study identified mostly positive perceptions about the economic preconditions for the creation of a future electricity market, which reinforces the importance of developing works that seek to build frameworks that help in the feasibility of an electricity futures exchange.

The objective of this work is to propose and simulate a model to enable the operation of an electricity futures exchange, adhering to the Brazilian reality of low liquidity and high volatility, where the clearing house assumes the positions of clients that do not respond to the margin call, after marking to the market, and generate relevant information for agents who are willing to create an enterprise of this type in Brazil. For the work, we produced simulations of a set of possible scenarios, including bullish and bearish shocks and different levels of liquidity. We also analyzed the sensitivity of returns in relation to the expected level of liquidity, given the characteristics of the Brazilian market, and we evaluated the option of taking out insurance to protect the clearing house. The insurance premium was calculated using a Monte Carlo simulation, a well-established and widely used method in studies of derivatives and futures markets, used in studies such as those of Irwin et al. (1996), Cortazar and Schwartz (1998), Abadie and Chamorro (2009) and Pelajo et al. (2019). The analysis of the simulation results and the insurance calculation are new and important information for market agents interested in the creation of a Brazilian electricity futures clearing house.

The article is divided as follows: the first chapter presents the theoretical framework of the work; chapter 2 presents the methodology used; chapter 3 discusses the simulation results; and chapter 4 presents the conclusions of the work.

2 Theoretical foundation

2.1 Central clearing houses

Central counterparty clearing houses (CCPs) are formed by companies that intermediate in operations in a market and operate in a structure in which they assume the credit risk of all parties, but as their net position is always zero, they do not assume the market risk (Bliss & Steigerwald, 2006). The CCP becomes the intermediary for all trades (Figure 1) between the members of a given market, converting all trades into symmetrical contracts between the parties involved and the CCP. Settlement of positions is made much easier with this model, as the position taker only needs to find a symmetrical position in the CCP's order book to close it. This eliminates the need for bilateral contract termination.

When contracts are centrally managed, there is a reduction in the need for collateral, as only the net positions of agents are considered, reducing risk when compared to a non-centralized structure (Cont & Kokholm, 2014). Another advantage of a CCP is the reduction of operating costs (when compared to bilateral contracts), transparency and the mitigation of default risk, as the CCP protects members against this type of risk (Nosal, 2010). The CCP is also responsible for marking the position of customers to the market and ensuring the transfer of amounts according to the result of the operation, associated with their contracts (Pirrong, 2009).

2.2 Energy futures: risk premiums and pricing

A classic approach to explaining commodity futures prices, where future price expectations are uncertain, is to assign an inventory carrying cost (such as inventory cost and depreciation) and a premium risk charged by the speculators, so that the futures price includes these components. By selling futures, asset holders get rid of the risk of future variations and pass them on to speculators, who are remunerated with a premium for the risk they assume. When we consider the cost of carrying inventory, it is possible to highlight an important component

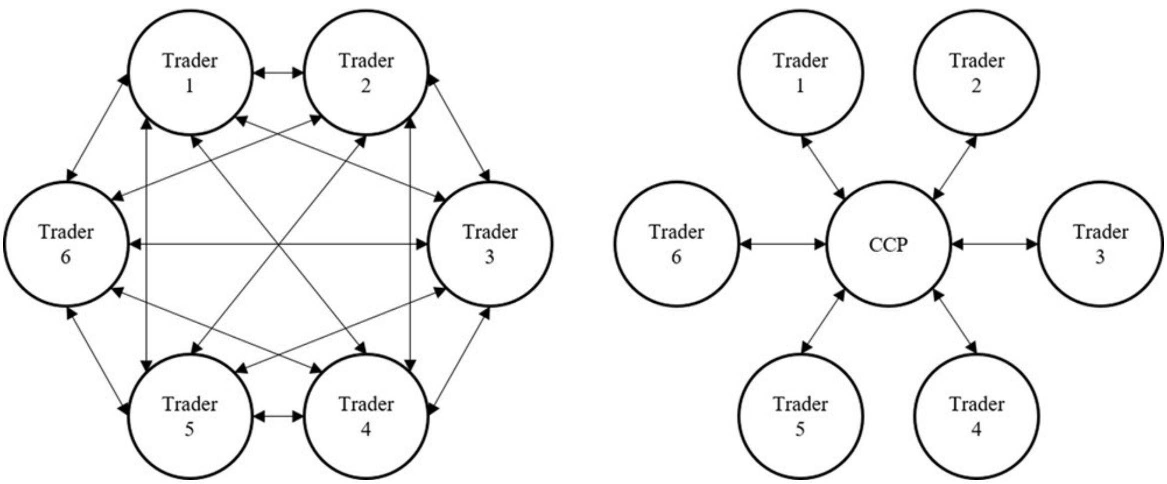

Figure 1. Over-the-counter OTC (L) and central counterparty clearing CCP (R)
Note: Adapted from Cont and Kokholm (2014).

that is considered separately in the models, which is the convenience fee. A convenience fee exists when the possession of a certain stock can be useful to its holder. For example, it may be useful for a producer to have inventory to meet unexpected demand (Fama & French, 1987; Kaldor, 1939). Algebraically, we can define the relationship between future price (PF), expected price (EP) and current price (CP) as a function of the interest rate i, the cost of carrying inventories c', the risk premium r and the rate of convenience q, as presented in Equation 1 (all terms are marginal):

$$EP - CP = i + c' - q + r \tag{1}$$

In markets where hedgers are future sellers, we have the following relationship, presented in Equation 2 and Equation 3:

$$FP - CP = i + c' - q \tag{2}$$

$$FP = EP - r \tag{3}$$

When the hedgers are future buyers, we can use Equation 4 and Equation 5 to describe the relationship relationship between future price (PF), expected price (EP) and current price (CP) as a function of the interest rate i, the cost of carrying inventories c', the risk premium r and the rate of convenience q:

$$FP - CP = i + c' \tag{4}$$

$$FP = EP - r + q \tag{5}$$

The market behavior, where the futures price falls below the expected future price and the futures price converges to the spot price, at maturity, from underneath, is known as normal backwardation. In general, the behavior of normal backwardation is associated with circumstances where there is a low level of supply and/or a low level of inventory. When the opposite occurs, that is, when hedgers are on the long end and speculators are on the short end, the situation is reversed, and futures prices converge to the spot price from above. This market behavior is known as contango. Contango behavior is usually associated with circumstances where there is an immediate abundant commodity supply (Benth et al., 2008).

In another very popular approach to explaining the behavior of commodity futures prices, the price of the futures contract is divided into two components, one component related to the forecast of spot prices of the commodity for the future date and another related to the risk premium. The risk premium in this case would be related to the ability of a restricted subset of speculators to better predict the futures price than other market participants and futures contract prices would be unbiased predictors of the futures price. This theory is known as forecasting theory and its advocates argue that there would be no clear price movement trend in futures markets and that the proportion of profits relative to contango or normal backwardation would be zero (Lee & Zhang, 2009).

Lee and Zhang (2009) examine the characteristics of the price movements of 29 markets and present evidence of the validity of the mechanisms explaining the prices of futures contracts proposed by the two theories, simultaneously showing that, depending on market conditions, one theory is dominant to explain the behavior of prices. The common view that two theories are mutually exclusive is replaced by an interpretation that they complement each other and, in a way, compete. It is observed that the presence of normal backwardation, contango or forecasting is related to the specific characteristics of each market and, according to its specificities, one type of mechanism can become dominant.

The electricity markets are part of the commodity markets, and are characterized by the limitation in storing electricity, which directly influences the behavior of spot prices for electricity and derivatives, which futures and forward markets are part of. The price behavior differs from other commodities, where it is possible to wait, increasing storage, for the most opportune moment to offer them to the market. Without this option, arbitrage arising from storage capacity is extremely limited and prices are expected to be highly dependent on demand and specific local conditions, such as weather conditions and the level of local economic activity (Lucia & Schwartz, 2002). Models based on storage capacity thus have limited power to explain prices in electricity markets.

In electricity markets where hydroelectric generation with reservoirs is predominant, there is evidence that the theory of inventory cost and convenience rate is relevant, as the reservoirs of hydroelectric plants work to store electricity. Empirical results from Nord Pool, one of the most important in Europe and with contracts traded in more than 14 countries, show that, for weekly futures contracts, hydrological conditions have a great influence on market behavior. The convenience rate is positive (normal backwardation) when reservoir levels are low, in the first half of the year, and negative (contango) when levels are high, in the second half of the year. On average, the observed convenience rate is negative and spot prices tend to be below the prices of futures contracts, in contango, with risk premiums having a negative sign over the analysis period, from 1996 to 2006 (Botterud et al., 2010).

2.3 Diffusion processes with jumps and asset pricing

Distributions of returns on some assets traded in an exchange environment, such as stocks, have thick tails (a leptokurtic format) when compared to the normal distribution. This phenomenon can be caused by the presence of price jumps, which are infrequent and large-scale movements (Yan, 2011). The energy market has well-known characteristics of asset price behavior, such as mean reversion, high volatility and the presence of jumps, and the models developed need to consider these characteristics.

A classic modeling of this type of process, where there is a discontinuity in the pattern of movements, with the presence of jumps, was developed by Merton (1976). This approach allows the calculation of the option value (insurance) in the presence of a jump, which was not possible until then, with the diffusion model developed by Black and Scholes (1973).

This approach proposes two components that explain the variation in the price of the asset, one linked to a normal variation, with marginal effects, such as adjustments between supply and demand or changes in interest rates; and the other based on important and completely new information to the market, which causes more than marginal effects on prices. The first component, with marginal effects, is governed by the Wiener process and the second is modeled as a Poisson process, where the event is the arrival of new information on the market about a given stock. New information arrives independently and is evenly distributed. The differential stochastic equation representing stock returns is presented in Equation 6:

$$\frac{dS}{S}=\left(\alpha-\lambda\kappa\right)dt+\sigma dz+dq \qquad (6)$$

where S represents the asset price, dS is the price change, α is the expected instantaneous return, σ is the instantaneous volatility of the returns, dz is the Gauss-Wiener process, and dq is the Poisson process. Processes dz and dq are independent. The average amount of new information (number of hops) per unit of time is represented by λ. κ is the expected value of (Y-1), a random variable that represents the percentage change if the Poisson event occurs. If λ, κ and σ are constant, the returns on stock prices over time t can be described according to Equation 7:

$$\frac{S(t)}{S}=exp\left[\left(\alpha-1/2\sigma^2-\lambda\kappa\right)t+\sigma z(t)\right]Y(n) \qquad (7)$$

When Y(n) is a lognormal distribution, $\frac{S(t)}{S}$ also assumes a lognormal distribution. Merton (1976) demonstrates that the European option value can be defined according to Equation 8:

$$F(s,t)=\sum_{n=0}^{\infty}e^{-\lambda t}\left(\lambda t\right)^n\left[\varepsilon_n\left\{w\left(sx_n and^{\lambda\kappa t},t;E,\sigma^2,r\right)\right\}\right] \qquad (8)$$

where $\varepsilon_n\left\{w\left(sx_n e^{\lambda\kappa t},t;E,\sigma^2,r\right)\right\}$ represents the value of the option according to the Black-Scholes formula for the exercise price E and risk-free rate r.

3 Methodology

3.1 Simulation model of the clearing house

For the simulation of the electricity futures clearing house operation, we used the contract and financial volume data from the Brazilian Electricity Trading Agency (BBCE) referring to January 2020 (Appendix A. Supplementary Data 1 – Monthly Volumes), obtained from the company's website (Balcão Brasileiro de Comercialização de Energia, 2020). The volume of contracts traded by BBCE in January 2020 was 6,245 contracts, through which a financial volume of BRL 4.2 billion and 17,446,000 MWh of energy were traded, representing a weekly average of 1,419 contracts, BRL 954.5 million in financial volume and 3,965,000 MWh. The settlement of differences price (SDP) is determined on a weekly basis, considering the load levels of each submarket of the Brazilian electrical system. Monthly traded contracts and financial volume data are not normally made available to the market. This is private and difficult to access information. We obtained the data from a news item on the company's website and therefore used them as an estimate. However, there is no data available for other months and the use of the January

2020 volume for the other months is the best estimate that was possible for this work.

We obtained the weekly volumes through the daily average of the total volume transacted through BBCE in January and the rate of new contracts considered in the model is constant over the weeks. Seasonality is not considered in the rate of new contracts. The choice of a constant rate of creation of new contracts was due to the absence of information on monthly volumes for BBCE. Future works may include this feature if necessary and if the data to support the choice of seasonality in the rate of new contracts are available.

The choice of BBCE data as a basis for volumes is due to it being the most important OTC for electricity futures contracts in Brazil. Thus, it is an excellent reference of volume for simulating the clearing house. We inserted the weekly volumes in the model considering the selling and buying ends and therefore the number of positions is twice the number of contracts.

To perform the calculations and generate the graphs, we developed a Python code (Appendix A. Supplementary Data 2 – Python Code) in version 3.8 64-Bit and the following packages: numpy version 1.18.1; pandas version 1.0.1; matplotlib version 3.1.3; IPython version 7.12.0; and ipywidgets version 7.5.1. The technical terms of this work are presented in Chart 1.

3.2 Simulation of contract price trajectories and weekly returns

As the electricity futures market in Brazil continues to trade bilaterally and in the OTC format, information on futures market trading prices is not reliably available,

Chart 1
Technical Terms

Term	Description
Over-the-Counter (OTC)	The OTC market is a decentralized market in which market participants trade instruments directly between two parties and without central counterparty clearing.
Central Counterparty Clearing House (CCP)	A CCP is a company that intermediates in operations in a market and operates in a structure in which it assumes the credit risk of all parties, but as its net position is always zero, it does not assume market risk.
Bearish Shock	This occurs when prices fall further than expected, changing the pattern of variation.
Bullish Shock	This occurs when prices rise more than expected, changing the pattern of variation.
Monte Carlo Simulation	The Monte Carlo method is a computerized mathematical technique that allows researchers to quantitatively account for risk in forecasting and decision-making. It uses random samples of parameters to explore the behavior of a complex system.
Insurance Premium	An insurance premium is the amount paid for an insurance policy.
Market Liquidity	Market liquidity is a market feature whereby an individual or firm can quickly purchase or sell an asset without causing a drastic change in the asset's price.
Real Option	A real option is an economically valuable right to make or abandon some choice that is available to the managers of a company, often concerning business projects or investment opportunities.
Weighted Average Cost of Capital (WACC)	The weighted average cost of capital (WACC) is the average rate that a business pays to finance its assets, calculated by averaging the rate of all the company's sources of capital (both debt and equity), weighted by the proportion of each component.
ANEEL	National Electric Energy Agency.
EMBI+BR	Emerging Markets Bond Index. The emerging markets bond index (EMBI) is a benchmark index for measuring the total return performance of international government and corporate bonds issued by emerging market countries that meet specific liquidity and structural requirements. The EMBI+BR is related to the Brazilian market.
Backwardation	This is a market behavior where the futures price falls below the expected future price and the futures price converges to the spot price, at maturity, underneath.
Contango	This is a market behavior where the futures price falls above the expected future price and the futures price converges to the spot price, at maturity, overhead.
Wiener process	The Wiener process is a real-valued continuous-time stochastic process.
Poisson process	A Poisson process is represented by a series of discrete events where the average time between events is known, but the exact timing of events is random and the arrival of an event is independent of the event before.

as it does not come from a liquid and transparent market, with public information. This information is available to a very limited extent.

Today there is a private company (DCIDE) that consolidates some information and expectations of market participants to sell periodical bulletins containing, among other information, the forward curve projected by it. However, the data used are neither public nor complete.

On the other hand, energy spot price paths are public and reliable, as are spot price forecasts, which rely on a robust methodology and forecast models fully available to market agents. It is to be expected, therefore, that in a future operation of an energy exchange the forward already includes all market information regarding prices and expectations and that future variations result only from the inclusion of new information.

The presence of jumps can occur, as these are also the result of the arrival of new information to the market. Thus, we assume that the jump diffusion process is the best representation for the movement of prices in the futures market. The use of another process to represent the price variation of futures contracts, such as an autoregressive model, could go against the non-arbitrage argument, which is valid in a highly liquid and transparent environment.

The price trajectory modeling was based on the model proposed by Merton (1976); however, we forced the jumps associated with the Poisson process, in the proposed modeling, to occur in two of the three scenarios of the simulated operation for 1 year. This is because it is important to assess the financial impact when the jump in prices occurs throughout the year, compared to the scenario where the jumps do not occur. Thus, we modeled three price trajectories, using the Brownian geometric movement to represent the returns. In the base scenario, we evaluated the operation in a year where there are no jumps. The other two scenarios evaluate the operation where there is a jump of 50% positive and 50% negative, respectively, in one of the randomly chosen weeks in each price trajectory (Appendix A. Supplementary Data 3 – Price Trajectories).

The SDP has a maximum and minimum value, which for 2020 was set at BRL 559.75 and BRL 39.68, respectively (Câmara de Comercialização de Energia Elétrica, 2020). However, for futures contracts, we do not impose this price restriction, as risk premiums may be applied, depending on the behavior of the market, causing prices to have to be adjusted and, eventually, they may exceed these legal limits of the spot market.

We started from the premise that there is no type of convenience fee for holding a futures contract. We made this choice since the behavior of the risk premium can change due to several factors, including hydrological ones, as seen in the Nord Pool market (Botterud et al., 2010). Market behavior can also change according to market hedging needs and speculators' positioning. Although some studies such as those of Luz et al. (2012) and Costa (2018) identified the presence of contango in the Brazilian forward market, the data used for the studies are quite limited and scarce, because the forward market is in the OTC format, without information transparency and full standardization. Thus, inferring a premium in the behavior of price paths would be premature. Therefore, we consider the drift to be zero, so that only the component of the Wiener process has an influence on the price variation.

Below, we show Equation 9 of returns (R_t), used in the base scenario, where there are no jumps and which follows a stochastic Wiener process (S_t), where α is the drift, t is the time and σ is the deviation pattern. Eliminating the drift and using $\Delta t = 1/52$, the return at t is according to Equation 10, in which $\in$ are independent Gaussian variables with a mean of 0 and variance of 1. Prices at t+1 are as according to Equation 11. The calculated weekly returns are in Appendix A. Supplemental Data 4 – Weekly Returns.

$$R_t = \alpha dt + \sigma dz \tag{9}$$

$$R_t = \sigma \in \sqrt{\Delta t} \tag{10}$$

$$P_{t+1} = P_t * and^{R_t * 1} \tag{11}$$

3.3 Calculation of positions taken by the clearing house

In the proposed model, the clearing house assumes the position of clients that do not respond to the margin call. To calculate the positions provisionally assumed by the clearing house, it is necessary to calculate the probability of customer default. The assumption adopted is that the clearing house works with a maximum probability of default of 1%, referring to a weekly variation of 100% (positive or negative). To represent this behavior, we chose the default percentage function $d_{\%}$ defined as $\sqrt{|r_t|}$, in Equation 12, where $d_{\%}$ is the percentage of default for the absolute percentage return $|r_t|$ that week. Note that for a 100% variation from one week to another, the default percentage is 1% ($d_{\%} = \sqrt{|1|} = 1$). For a weekly return of

50%, the default percentage is 0.71% ($d_{\%} = \sqrt{|0.5|} = 0.71$). This function generates a default percentage that varies according to the weekly return. When the weekly return is small, the number of customers in default is small for that week. When the weekly return is large, the number of customers in default increases.

$$d_{\%} = \sqrt{|r_t|} \tag{12}$$

The number of positions (x_t) taken by the clearing house, given the weekly volume of 3,965,000 MWh (7,930,000 MWh considering both ends, but only one end that is called margin), is given by Equation 13, where the variable side is assigned as -1 for negative returns and 1 for positive returns.

$$\begin{aligned} x_t &= \sqrt{|r_t|} * 3,965.00 * side \\ side &= \{-1, for\ r_t \langle 0\ 1, for\ r_t \rangle = 0 \end{aligned} \tag{13}$$

The positions opened weekly, based on BBCE's January 2020 data, are as follows:

- 1,419 new contracts per week.
- 1,419*2 = 2,838 open contracts (considering both ends).
- 3,965,000 MWh traded weekly (7,930,000 considering both ends).

3.4 Clearing house

The total net position depends not only on volatility, but also on the time it takes to close positions. We define the liquidity ratio L as the average time it takes the clearing house to dispose of contracts. The scenario of greater liquidity is associated with the index L=1 period and the scenario of less liquidity is associated with the index L=4 periods. The position is given by Equation 14, which represents the sum of positions assumed and not yet closed, in period t for the liquidity ratio L.

$$X_t = \sum_{k=1}^{L} x_{tk} \tag{14}$$

3.5 Scenarios

Twelve scenarios were analyzed, obtained based on three price levels (neutral, bullish shock and bearish shock) and four liquidity levels, represented by the number of periods for the clearing house to dispose of the position (1, 2, 3 and 4 weeks). We simulated the bullish and bearish shocks as follows: a week is randomly chosen in the year for a bullish or bearish shock of 50%. The distribution of the binary variable is uniform, so that for each trajectory, each week of the year has an equal probability of being selected for the occurrence of the shock. The bullish or bearish shock is a regime change that is represented in the model according to Equation 15:

$$r_t = \sigma \in \sqrt{\Delta t} * \left(1 \pm 0.5 * I^t_{\{0.1\}}\right) \tag{15}$$

where σ is the standard deviation, ϵ are independent Gaussian variables with a mean of 0 and variance of 1, Δt is the time interval and $I^t_{\{0,1\}}$ is the binary variable that assumes the value of 1 when regime change occurs and 0 when it does not. The objective is to simulate the occurrence of stress, which can be caused, for example, by a sudden drop in domestic consumption, as occurred recently due to the pandemic caused by covid-19.

We considered volatility of 17.03%, obtained from Argento (2020), who analyzed weekly forward contract returns data from 2012 to 2019, obtained from DCIDE. Volatility was obtained by applying the Markov-switching variance model. Even though the data are from the OTC market, these data are the best reference available for the simulation. The value of 17.03% is conservative for the purpose of this work and refers to the volatility of contracts maturing in one month (M1). The volatility of contracts with longer maturities is lower. As the volume segregated by maturity is not known, the choice of the highest volatility, in this case, is the most appropriate and conservative, to represent the possible variation for the set of contracts. For each scenario analyzed, we simulated 10,000 return and exercise paths for the insurance option. We simulated a period of 52 weeks, representing 1 year of operation. Table 1 summarizes the 12 scenarios analyzed.

3.6 Definition of financial result of the operation

The financial result π_t for the proposed operation, between a period t and another t-1, is given by Equation 16 and the accumulated result Π_t in the period is given by Equation 17:

$$\pi_t = (P_t - P_{t-1}) * X_t \tag{16}$$

$$\Pi_T = \sum_{t=0}^{T} \pi_t \tag{17}$$

Table 1
Scenarios analyzed

Returns/liquidity	1 Period	2 Periods	3 Periods	4 Periods
Bearish Shock	Scenario 1	Scenario 2	Scenario 3	Scenario 4
Neutral	Scenario 5	Scenario 6	Scenario 7	Scenario 8
Bullish Shock	Scenario 9	Scenario 10	Scenario 11	Scenario 12

where X_t is the total net position, defined in Equation 14, and P_t and P_{t-1} are, respectively, the prices of the contracts at times t and $t-1$.

3.7 Insurance

We performed the insurance premium calculation using the Monte Carlo simulation, where, for each trajectory of returns, the insurance cover helps the clearing house to recover financially from any loss at the end of the 52-week period. The amount received from the insurance contract, when insurance cover is necessary, is equal to the absolute value of the accumulated loss. In the case of positive returns, at the end of the period, the clearing house does not trigger the insurance and the amount received from the insurance company is zero.

Insurance for the clearing house can then be modeled as a put with strike=0. The payoff α_s of the option, at the end of the period T, is given by Equation 18:

$$\alpha_s = max\left(-\Pi_T^s, 0\right) \tag{18}$$

The payoff for the average of the S scenarios is given by Equation 19:

$$\alpha = \frac{1}{S} * \sum_{s=1}^{S} \alpha_s \tag{19}$$

At time T=0, the present value p of the option brought at the risk-free rate is given by Equation 20:

$$p = \quad * e^{-T*r_f} \tag{20}$$

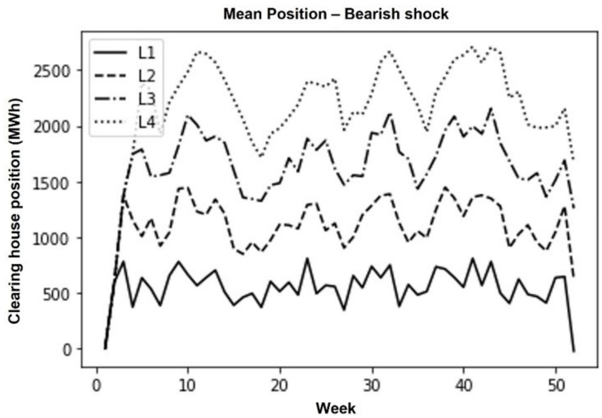

Figure 2. Mean position - bearish shock (MWh)

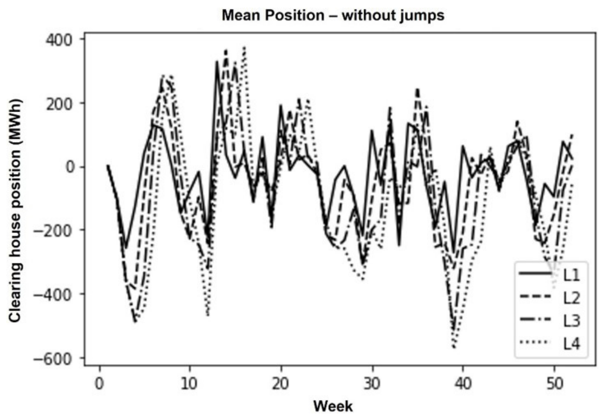

Figure 3. Mean position - bullish shock (MWh)

4 Results

We ran the simulation model for the 12 scenarios (Appendix A. Supplementary Data 5 – Average Clearing House Position). Below we present the graphs representing the results of the four liquidity levels, for the bearish shock (Figure 2), neutral (Figure 3) and bullish shock (Figure 4) price regimes. As expected, we observed that the lower the liquidity, which in practice translates into a longer time for the clearing house to dispose of positions, the greater the average size of the clearing house's positions. This behavior is observed for the three regimes (bearish shock, neutral and bullish shock).

Figure 5 below presents the three graphs on the same scale for comparison purposes. It is possible to observe that, in the neutral regime, the positions vary less compared to the other two regimes, which was an expected result, since there is a sudden variation of 50% in the price in all the bullish and bearish shock simulations.

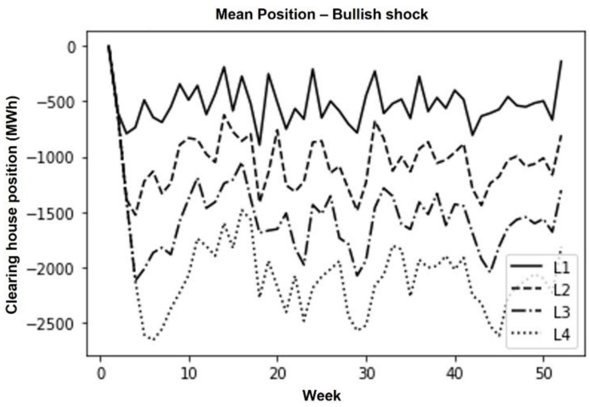

Figure 4. Mean position - neutral (MWh)

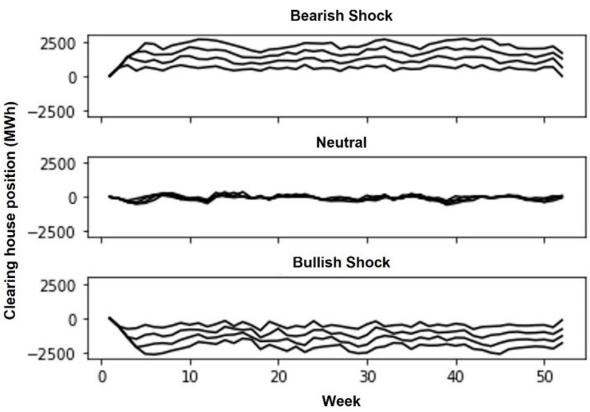

Figure 5. Results for the three price scenarios (MWh)

4.1 Calculation of cumulative returns

The clearing house operation generates, at the end of the period, an accumulated result that will be positive or negative, but it is expected to be close to zero or not significant in relation to the total volume transacted. The purpose of the operation is not to make a profit, but to enable a market that has low liquidity. For this work, we calculated the accumulated returns of each of the trajectories for each scenario (Appendix A. Supplementary Data 6 – Accumulated Returns). The average of the returns, for each scenario, is presented in Table 2, where we can observe that the higher the liquidity level, the higher the modulus of average return is. The neutral scenario is the one with the lowest accumulated values, in absolute terms. The values, however, are slightly negative, but very small in relation to the total amount transacted in the 52 weeks, of BRL 49.63 billion (BRL 954.5 million weekly). The fact that there is a floor for the SDP, which cannot be negative, generates slight asymmetry in the profile of returns, since the SDP, when it reaches zero, can only assume positive values. The same does not occur for very high SDP values, when there is always the possibility that they will continue to rise.

For scenarios where there is a 50% bearish shock, there is a greater volume of long positions that need to be taken over by the clearing house and, for the same reason as above, generate a positive return. Similarly, when there is a bullish shock, the clearing house must take on a large volume of short positions and the return tends to be negative. When there is a bearish or bullish shock, the values, whether positive or negative, are higher in absolute terms than in the neutral scenario, but they are still very small when compared to the financial volume traded in a year.

For the same type of returns (bullish shock, neutral, or bearish shock), the lower level of liquidity is related to greater risk, with an increase in the positive and negative values of the accumulated returns.

Considering that the clearing house's revenue would be 0.5% of the total contracts and both ends, it would have a revenue of BRL 496.36 million and the average loss, in the worst scenario, would represent only 0.19% of the revenue, which appears be quite reasonable in terms of cost, given the importance of the operation to the viability of the electricity futures clearing house.

4.2 Calculation of the risk-free rate

We calculated the risk-free rate following the methodology adopted until 2020 by ANEEL (Agência Nacional de Energia Elétrica, 2020) to calculate the weighted average cost of capital (WACC) of generation, transmission, and distribution projects, where the fixed income bond used is the US Treasury Bond type "USTB10," to estimate the risk-free rate. We obtained the series of annual data on the price of this security from the period from January 1995 to December 2012, and we calculated the arithmetic average, obtaining an average annual interest rate of 4.59%.

Country risk, of 3.52%, is calculated using the median referring to the EMBI+BR from January 2000 to December 2012. We estimated American inflation using the average of the period from 1995 to 2012, obtaining the value of 2.47% per year. Considering this inflation, the real interest rate is 2.07%, which, added to the country risk, results in a risk-free rate of 5.59% per year for Brazil.

4.3 Insurance premium calculation

We used the real options methodology to calculate the insurance premium, where the insurance premium is calculated as a put option. We calculated it for the 12 scenarios, with the put value following the methodology presented in sections 2.6 and 2.7. The put represents the option to sell the insurance at the value of Π_T^s (the result of the operation) when it is less than zero at the end of the 52-week period. The value is obtained by bringing the average payoff at the risk-free rate to the present value. Table 3 below shows the calculation of the average payoff, in BRL, for each of the 12 scenarios:

Table 4 shows the percentage of simulations in which the insurance was activated. Note that the value is high (close to 50%), which is understandable given that the generation of prices follows a geometric Brownian motion (GBM) and that the only restriction is that prices cannot go below zero. Values slightly below 50%, similarly to what happens with returns, are justified by the restriction of negative prices, which impose a barrier to falling prices, a restriction that does not exist for positive values.

Considering the payoffs and the risk-free rate of 5.59% per year, we calculated the insurance value for each of the scenarios. The insurance calculation results are shown in Table 5.

Table 2
Accumulated returns for 52 weeks (BRL)

Prices/Liquidity	1 Period	2 Periods	3 Periods	4 Periods
Bearish Shock	231,369.96	400,853.01	615,791.92	837,066.17
Neutral	-113,536.15	-142,096.15	-154,850.71	-175,348.16
Bullish Shock	-276,514.78	-539,550.52	-733,045.02	-887,398.66

Table 3
Average payoffs in BRL for the 12 scenarios

Prices/Liquidity	1 Period	2 Periods	3 Periods	4 Periods
Bearish Shock	1,155,485.50	1,570,661.12	1,800,629.69	1,952,360.92
Neutral	1,594,821.36	2,202,501.27	2,676,045.19	3,073,308.72
Bullish Shock	2,157,544.80	3,110,220.91	3,822,222.31	4,422,000.43

Table 4
Percentages of simulations that triggered the insurance

Prices/Liquidity	1 Period	2 Periods	3 Periods	4 Periods
Bearish Shock	45.48%	42.59%	40.40%	39.35%
Neutral	47.63%	44.43%	42.62%	40.65%
Bullish Shock	47.78%	44.13%	42.42%	40.21%

Table 5
Insurance calculation in BRL for the 12 scenarios

Prices/Liquidity	1 Period	2 Periods	3 Periods	4 Periods
Bearish Shock	1,092,666.02	1,485,270.08	1,702,736.11	1,846,218.27
Neutral	1,508,116.81	2,082,759.41	2,530,558.50	2,906,224.28
Bullish Shock	2,040,247.06	2,941,129.69	3,614,422.20	4,181,592.60

As, in the model, the insurance is annual, the values of the average payoffs are close to the value of the insurance itself. The amounts for the insurance of the operation are also small when compared to the total volume transacted, of BRL 49.63 billion. Considering billing of BRL 496.3 million, according to the rationale already presented, the maximum insurance value of BRL 4.2 million represents only 0.84% of the projected revenue, a value that could possibly be incorporated without major problems to the operation.

5 Conclusions

In this work, we proposed an operating model for a clearing house for trading electricity futures that would adhere to the Brazilian reality, marked by high volatility in energy prices and low liquidity of futures contracts. In the proposed model, the clearing house provisionally assumes the positions of clients that do not respond to the margin call, after marking to market, thus avoiding contract default. This strategy allows the clearing house to manage default risk even in a market with low liquidity, removing customers who do not respond to the margin call from the operation. The model can be used in conjunction with cascading, which can provide the market with increased liquidity, as higher value contracts, as they approach the expiration date, transform into several smaller, more accessible contracts that adhere to other customers.

We performed the simulations to reflect normal operating conditions and bullish and bearish shock scenarios in spot prices. These shocks need to be considered in the model due to the Brazilian electricity matrix, where there is a predominance of hydraulic sources, and the price formation mechanism based on marginal costs. We modeled the financial returns of the positions as a GBM, associated with the constraint of positive prices. We demonstrated that the average returns, for different levels of liquidity, generate a total return in 52 weeks that, in absolute terms, is small compared to the revenue and volume transacted. The worst average return occurred for the bullish shock scenario and liquidity associated with 4 days to dispose of the position, where the average return was BRL -0.89 million, compared to BRL 49.64 billion traded in the period of 52 weeks.

We also calculated the insurance value for each scenario, for the case in which the clearing house does not want to assume the risk of unexpected returns. The insurance needs to cover the most unlikely events and therefore its calculated value, for all scenarios, is above the average value of the clearing house's returns, however, it protects it against all negative results. Even so, the value of the maximum insurance, in the bullish shock scenario and with 4 days to close the positions, is BRL 4.18 million (0.84% of estimated revenue), an apparently reasonable value in terms of cost, considering the importance of the operation.

This work therefore showed that this operating model, where the clearing house assumes customer positions, generates relatively small additional costs and they may be easily absorbed by the clearing house. Even the insurance option presented small values for each scenario and compared to the total volume of the operation and projected billing. These data are of great use to agents interested in opening a venture of this type in Brazil, which still lacks an electricity futures exchange.

Among the limitations of the study, we highlight the non-availability of detailed data on volumes and values of contracts traded. As the market is private and in the over-the-counter format, the volume of operations of the main OTC markets is not available and the contracts are bilateral. Therefore, we used constant contract volumes, without considering any type of seasonality in the volume of futures contracts.

For future work, we suggest a search for more accurate data on contract volumes from the main companies that provide the over-the-counter market in a way that makes it possible to build a model with seasonalized volume data. Another suggestion is to adapt the model to a market where contango or normal backwardation predominates.

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