Vanderson Aparecido Delapedra da Silva

Investment appraisal of wind power projects in a mix of free and regulated market environments in Brazil

Brasília - DF

June 2021

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Thesis submitted to the Graduate Program in Business Management at University of Brasília in partial fulfillment of the requirements for the degree of Ph.D in Business Management.

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College of Economics, Business Management, and Accounting (FACE)
Graduate Program in Business Management (PPGA)
Finance and Quantitative Methods

Advisor: Herbert Kimura
Co-advisor: Paula Varandas Ferreira

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To my daughters Helena and Clarice

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"(...) que a miserável condição
da raça humana procurando o céu
levante a cabeça
e ao levantar por encanto
escorregue o seu véu."
O Condor, Música de Oswaldo Montenegro.

Abstract

The Brazilian electric sector is undergoing a structural transformation due to the expansion of the free energy market (ACL). The migration from the regulated market (ACR) to the ACL has led many electricity generation companies to seek profitable and less uncertain markets than the Short Term Market (STM), where differences between the generated and consumed amounts of electricity are negotiated. At the same time, the benefits offered to companies participating in the ACR market, such as priority access to transmission lines, contribute to the joint participation of companies in the ACR and ACL markets. Thus, models for the investment appraisal of electricity generation projects should take into account and incorporate the different characteristics of both markets. Considering the Brazilian potential for wind energy generation, this work studies the viability of wind energy projects that participate in these two electricity markets together. With this in mind, we carried out three studies focusing on the following: i) identification and analysis of recent publications on the financial evaluation of renewable energy projects; ii) economic evaluation of wind energy projects for different price scenarios using the traditional discounted cash flow approach complemented with Monte Carlo simulation; iii) viability analysis of wind energy projects assuming the possibility of postponing the investment from the year of the ACR market auction and using a real options approach. The reviewed literature showed that the traditional methods of evaluating projects, based on discounted cash flow, are very widespread in the evaluation of renewable energy projects. The research allowed also to conclude that the use of prices disclosed as a reference by the Brazilian authorities can signal important information for the economic evaluation of wind energy projects in the country. Finally, the results indicate that the volatility in the ACL market is not sufficiently high to indubitably justify a strategy of postponing the construction of the wind farm under the assumed future conditions.

Key-words: Renewable energy. Wind energy. Projects evaluation. Real options theory. Brazilian electrical system.

Resumo

O setor elétrico brasileiro está passando por uma transformação estrutural devido à expansão do mercado livre de energia (ACL). A migração do mercado regulado (ACR) para o ACL tem levado muitas empresas de geração de energia elétrica a buscarem mercados rentáveis e menos incertos do que o Mercado de Curto Prazo (MCP), onde são negociadas diferenças entre as quantidades geradas e consumidas de energia elétrica. Ao mesmo tempo, os benefícios oferecidos às empresas participantes do mercado ACR, como o acesso prioritário às linhas de transmissão, contribuem para a participação conjunta das empresas nos mercados ACR e ACL. Assim, os modelos de avaliação de investimento em projetos de geração de eletricidade devem ter em consideração e incorporar as diferentes características de ambos os mercados. Considerando o potencial brasileiro de geração de energia eólica, este trabalho estuda a viabilidade de projetos de energia eólica que participam desses dois mercados de eletricidade em conjunto. Nesse sentido, realizamos três estudos com enfoque nos seguintes temas: i) identificação e análise de publicações recentes sobre avaliação financeira de projetos de energias renováveis; ii) avaliação econômica de projetos de energia eólica para diferentes cenários de preços usando a abordagem tradicional de fluxo de caixa descontado complementada com simulação de Monte Carlo; iii) análise de viabilidade de projetos de energia eólica pressupondo a possibilidade de adiamento do investimento desde o ano do leilão de mercado do ACR e utilizando uma abordagem de análise de opções reais. A literatura revisada mostrou que os métodos tradicionais de avaliação de projetos baseados no fluxo de caixa descontado são muito difundidos na avaliação de projetos de energia renovável. A pesquisa permitiu também concluir que a utilização de preços divulgados como referência pelas autoridades brasileiras pode sinalizar informações importantes para a avaliação econômica de projetos de energia eólica no país. Por fim, os resultados indicam que a volatilidade no mercado de ACL não é suficientemente elevada para justificar indubitavelmente uma estratégia de postergar a construção do parque eólico nas condições futuras assumidas.

Palavras-chaves: Energia Renovável. Energia Eólica. Valoração de projetos. Teoria das Opções Reais. Sistema Elétrico Brasileiro.

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List of abbreviations and acronyms

ABEEOLICA	Associação Brasileira de Energia Eólica
ACL	Ambiente de Contratação Livre
ACR	Ambiente de Contratação Regulada
ADF	Augmented Dickey Fuller Test
ANEEL	Agência Nacional de Energia Elétrica
BEIS	Department for Business, Energy & Industrial Strategy
BP	British Petroleum
CO_2	Carbon Dioxide
CAPM	Capital Asset Pricing Model
CCEE	Câmara de Comercialização de Energia Elétrica
CER	Contratos de Energia de Reserva
CCEAR	Contrato de Comercialização de Energia Elétrica no Ambiente Regulado
CMSE	Comitê de Monitoramento do Setor Elétrico
CNPE	Conselho Nacional de Politica Energética
COE	Cost of Energy
CONER	Conta de Energia de Reserva
CUST	Contrato de Uso do Sistema de Transmissão
DCF	Discounted Cashflow
EPE	Empresa de Pesquisa Energética
EROI	Energy Return on Investment
GBM	Geometric Brownian Motion
GT	Gigatons
GW	Gigawatt

HOMER	Hybrid Optimization Model for Electric Renewables
IEA	International Energy Agency
IRENA	International Renewable Energy Agency
IRR	Internal Rate of Return
KV	Kilovolt
KWh	Kilowatt-hour
LCA	Life Cycle Assessment
LCOE	Levelized Cost of Energy
MAD	Marketed Asset Disclaimed
MARR	Minimum Acceptable Rate of Return
MCDM	Multi-criteria Decision-making
MCP	Mercado de Curto Prazo
MCS	Monte Carlo Simulation
MME	Ministério de Minas e Energia
MRM	Mean-Reverting Model
MW	Megawatt
MWh	Megawatt-hour
NPV	Net Present Value
NREL	National Renewable Energy Laboratory
NTN-B	Nota do Tesouro Nacional-Série B
O & M	Operational and Maintencance
ONS	Operador Nacional do Sistema Elétrico
PBP	Payback Period
PJ	Poisson Jumps
PLD	Preço de Liquidação das Diferenças
PND	Programa Nacional de Desetatização

RES	Renewable Energy Sources
RESEB	Projeto de Reestruturação do Setor Elétrico Brasileiro
ROA	Real Option Analysis
ROI	Return on Investment
SIN	Sintema Interligado Nacional
STM	Short-term Market
TFSEE	Taxa de Fiscalização de Serviços de Energia Elétrica
TPEM	Traditional Project Evaluation Methods
TWh	Terawatt-hour
WACC	Weighted Avarage Cost of Capital

Contents

Resumo Expandido

Avaliação de investimento de projetos de energia eólica em um mix de ambientes de mercado livre e regulado no Brasil

Nas últimas décadas, o fornecimento de recursos naturais tem sofrido pressão devido ao aumento da demanda decorrente do crescimento econômico e populacional acelerado. Atualmente, aproximadamente 70% da oferta mundial de energia vem de fontes não renováveis, como carvão e petróleo (IEA, 2020). Isso tem estimulado o surgimento de novas fontes de energia renovável, alternativas eficazes aos combustíveis fósseis (Lei et al., 2020). Uma dessas fontes, a energia eólica, é uma grande candidata para essa transição, dado seu potencial de redução significativa de custos (Maeda and Watts, 2019).

O Brasil já possui uma estrutura de geração de energia elétrica baseada em energia renovável proveniente das grandes hidrelétricas construídas na década de 1960 (Bradshaw, 2017). Além disso, o Brasil possui características favoráveis para o desenvolvimento de outras fontes renováveis, como a energia térmica obtida pela queima do bagaço da cana, além das fontes fotovoltaicas e eólicas.

Atualmente, a energia eólica é a fonte de energia de mais rápido crescimento no Brasil, isso ocorre pelo alto nível de ventos do país, favorável ao desenvolvimento de usinas eólicas. Além disso, seus baixos custos de produção tornam essa fonte de geração de energia elétrica uma opção ainda mais atraente (EPE, 2018).

As relações comerciais no setor elétrico brasileiro ocorrem basicamente em três ambientes de comercialização: Ambiente de Contratação Regulada (ACR), Ambiente de Contratação Livre (ACL) e Mercado de Curto Prazo (MCP), onde as diferenças entre os valores gerados com energia elétrica são contabilizadas e utilizam como referência o Preço de Liquidações de Diferenças (PLD). Os contratos no mercado de ACR são firmados entre agentes vendedores e compradores de energia que participam de leilões públicos. Porém, no mercado ACL, esses contratos são livremente celebrados entre os agentes. Os leilões no mercado ACR também podem ser categorizados em vários formatos; no entanto, os principais são os leilões de energia nova e energia de reserva. Até meados de 2018, esses dois tipos de leilões apresentavam diferenças significativas no formato de remuneração das empresas que pretendiam vender sua energia por meio de leilões.

Os contratos de energia de reserva remuneravam as usinas pela quantidade de energia vendida por elas para compor uma reserva de segurança do sistema elétrico brasileiro. Por outro lado, os contratos de energia nova possuíam um modelo de remuneração fixa para essas usinas até meados de 2018, e o preço estabelecido no leilão era utilizado como base para o preço de referência da energia disponível. Enquanto a modalidade dos contratos de energia reserva recebeu o nome de “modalidade por quantidade”, a modalidade dos contratos de energia nova recebeu o nome de “modalidade por disponibilidade”. Portanto, o risco de não geração nos contratos de energia nova era do comprador, e a análise de viabilidade desses projetos era menos suscetível aos riscos inerentes à variação da capacidade produtiva desses projetos.

Porém, a partir de meados de 2018, os contratos de leilões de energia nova passaram a assumir a modalidade “por quantidade” até então exercida apenas para contratos de energia reserva. Além disso, até 2017, as empresas que participavam de leilões de energia nova tinham que comprometer um mínimo de 70% de sua garantia física (energia comercializável) para o leilão de que participavam. Porém, a partir de 2017, esse compromisso mínimo passou a ser 30% da quantidade de energia qualificada, permitindo às usinas comercializar uma quantidade maior no mercado ACL de sua energia elétrica produzida.

Essa mudança trouxe uma nova dinâmica ao mercado de energia no Brasil, estimulando as empresas a ampliar sua participação no mercado de ACL. No entanto, como as relações comerciais nesse mercado são bilaterais e indisponíveis para consulta, a capacidade de construir diagnósticos a partir da viabilidade econômica desses projetos tornou-se mais complexa. Este cenário evidencia a necessidade de ferramentas capazes de estimar a viabilidade de projetos que desejam fornecer energia aos dois mercados simultaneamente. No entanto, estimar a viabilidade considerando duas fontes de receita requer o conhecimento do percentual de comprometimento do projeto com o fornecimento de energia para cada mercado em que participa.

Com base nisso, esta tese se concentrou em três estudos complementares. No primeiro estudo, foi realizada uma análise bibliométrica para identificar as características dos métodos utilizados para a análise financeira de projetos de energia renovável nos últimos anos. O primeiro estudo incluiu uma análise quantitativa e qualitativa de trabalhos publicados entre 2011 e 2020 e utilizou quatro grupos de interesse: (i) métodos tradicionais de avaliação de projetos, com métricas que avaliam a viabilidade dos projetos por meio do desconto dos fluxos de caixa: Valor Presente Líquido (VPL), Taxa Interna de Retorno (TIR), e *payback*; (ii) uma abordagem de análise de custos, representada pelo custo nivelado de energia (*Levelized cost of energy*); (iii) retorno sobre o investimento (ROI); e (iv) análise de opções reais.

Com a identificação da popularidade dos métodos baseados em fluxo de caixa descontado, foi iniciado o segundo estudo, que utilizou o VPL e a TIR para propor um procedimento de cálculo de viabilidade de usinas eólicas que participaram de leilões de energia em 2018 e 2019. O estudo calculou os resultados determinísticos e estocásticos usando o método de simulação de Monte Carlo para identificar a probabilidade de as taxas de retorno dos projetos serem superiores ao Custo Médio Ponderado de Capital (WACC) sugerida como referência pela ANEEL. Para tanto, foram utilizadas quatro premissas de preços para o mercado ACL.

Por fim, o terceiro estudo utilizou um dos quatro preços para o mercado ACL simulados no Estudo 2 para iniciar a simulação de preços no mercado ACL e calcular o valor da opção real de adiamento do investimento em projetos representativos dos leilões ocorridos em 2018 e 2019. Para isso, o estudo utilizou o método de simulação de Monte Carlo com incertezas nos preços de mercado do ACL e na quantidade de energia produzida para esse mercado ACL para identificar a volatilidade dos projetos. Em seguida, o estudo utilizou o método binomial para construir a árvore de decisão do projeto. O método das opções reais foi utilizado para identificar se os empreendimentos analisados teriam uma vantagem no atraso da construção da planta com base na volatilidade do preço encontrada na parcela do fluxo de caixa do mercado de ACL. A teoria das opções reais é utilizada como ferramenta em situações de incertezas, e pode ajudar a melhorar o processo de tomada de decisão sobre a viabilidade do projeto.

Os resultados sugerem que os preços médios do PLD divulgados pela ANEEL podem ser uma referência a ser considerada no momento da análise de viabilidade dos projetos que participam conjuntamente nos dois mercados ACR e ACL, conjuntamente. Além disso, foi constatado que a volatilidade encontrada nos preços do ACL não são suficientes para assegurar a existência de oportunidades futuras que justifiquem o atraso na construção da planta.

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Introduction

Thematic Considerations and the Research Problem

Over recent decades, the supply of natural resources has come under pressure due to increased demand from accelerated economic and population growth. Currently, approximately 70% of the world's energy supply comes from non-renewable sources such as coal and oil (IEA, 2020). This context has stimulated the emergence of new renewable energy sources (RES), which are effective alternatives to fossil fuels (Lei et al., 2020). One of these sources, wind energy, is a great candidate for this transition given its potential to significantly reduce costs (Maeda and Watts, 2019).

Brazil already has an electric power generation structure based on RES, which comes from the large hydroelectric plants that were built in the 1960s (Bradshaw, 2017). In addition, Brazil has favorable characteristics for the development of other RES, such as thermal energy obtained by burning sugarcane bagasse or photovoltaic and wind sources.

Currently, wind energy is the fastest growing source of energy in Brazil because the country's high level of wind is favorable for the development of wind power plants. Additionally, its low production costs make it an even more attractive energy option (EPE, 2018).

In 2019, wind energy in Brazil was the third most important RES, accounting for 8.3% of the total electricity generated in the country that year. This represented a 15.5% increase compared to 2018, reaching a total of 56 TWh (EPE, 2020). Currently, Brazil has more than 640 wind power generation plants, more than 7,700 generators, and the country reached an installed wind power capacity of 16.45 GW in 2020 (ABEEOLICA, 2020; ONS, 2020).

Despite current developments in Brazil's electrical system, its organization only started to gain importance at the beginning of the 20^{th} century. The global crisis of 1929 directly influenced Brazil's industrial structure. As a result, the national economic policies, which favored oligarchies of the coffee economy that prevailed at the time, began to shift toward large state owned companies and the massive investment into industrialization (Bennertz and Rip, 2018).

This scenario directly influenced the expansion and development of the country's electrical system, which assumed a more central and less regional role (Ramos-Real et al., 2009). In 1934, the federal government signed Decree No. 24,643, known as the water code, with the objective of regulating water use throughout the national territory. This combination of factors contributed to the exploitation of Brazil's great electric power generation potential from hydraulic sources. As in the case of most other Latin American countries, its potential is enhanced by its geography, which is characterized by extensive river systems (Lorenzon et al., 2017).

In the 1950s and 1960s, the Brazilian government focused on the electrical system´s regulation to consolidate the centralized planning of the sector (Junior and de Almeida, 2007). In 1960, the Ministry of Mines and Energy was created through Law No. 3,782, and in June 1962, Centrais Elétricas Brasileiras SA (ELETROBRAS) was officially created through Decree No. 1,178, with the mission of coordinating other companies in the electricity sector.

After the military regime that governed Brazil between 1964 and 1985, the development of the electric sector remained the task of the state. However, with the democratization of the country in 1985, as well as the rise of liberal governments from 1990, the electricity sector went through a period of change.

The promulgation of the 1988 Constitution ensured that the potential of hydraulic energy was considered a patrimony of the Brazilian state (in item VIII of article 20). In Article 21, the Constitution also ensured the competence of the Brazilian state in exploiting electric energy services and installations, as well as the use of water courses to produce energy directly or through authorization, concession, or permission.

In 1990, the government of President Fernando Collor implemented a policy of opening up imports, reducing the presence of the state, and expanding privatization programs. However, allegations of corruption culminated in the presidents´ impeachment and contributed to interrupting the national privatization plan (PND) (Campos et al., 2020). Even so, the two governments that followed this scandal, both the vice president who took office after the impeachment and the president elected after him, created an economic environment that was favorable to the privatization process.

The growing debt in the electricity sector, coupled with its low capacity for generating investments, made it difficult to attract foreign capital during this period. For this reason, the country began the process of a normative review of the sector with a focus on its preparation for receiving foreign investments and boosting the market (Campos et al., 2020). In this context, Law No. 9,491 from 1997 revised the terms of Law 8,031 from 1990 (which implemented the PND) and regulated the operational modalities to be used in the privatization process, including for electric power distributors owned by the federal government. In this sense, bids in the auction mode were regulated for several operational privatization modalities, such as concessions, permissions, or authorizations for public services.

The Brazilian electrical system has evolved as a result of the modernization of the sector's regulations. To illustrate the dynamics of this modernization, the regulatory environment can be classified into three periods: i) before 1995, ii) from 1995 to 2003, and iii) from 2003 to the present. As already mentioned, in the first period, the Brazilian electricity system was composed of a centralized structure and a state monopoly. In this context, the sector was publicly financed.

In the second period, we highlight the emergence of regulatory agencies responsible for the operationalization and management of the sector's privatization process. Examples of this context are the approval of Law No. 9,427 from 1996, which instituted the National Electric Energy Agency (ANEEL), Law No. 9,074 from 1995, which eliminated the exclusivity of electricity supply by new concessionaires to consumers with a load equal to or greater than 10 MW, served in voltage equal to or greater than 69 kV. These consumers began to contract their supply from an independent electricity producer, thus inaugurating the free energy market model in Brazil.

In 1998, Law 9,648 created a company called the National Electric System Operator (ONS), which assumed responsibility for carrying out activities to coordinate and control the operation of electricity generation and transmission in Brazil. Later, Law No. 13,360 of 2016 assigned ONS the action of load forecasting and planning the operation of systems that were not yet interconnected with the national electricity system.

The severe electrical crisis in 2001, as well as the rise of a new government in 2003, contributed to the emergence of a new phase in the sector's regulation. As of 2004, the legislation started to prioritize partnerships and covenants between state and private companies, in addition to creating management entities for these markets, such as the Electric Energy Trading Chamber (CCEE). The legal framework that opened this period was Law No. 10,848 from 2004, which created the CCEE and regulated the new electric energy trading model in Brazil.

The agents responsible for the structure of the Brazilian electrical system operate in different ways and at different instances. However, it is possible to establish a hierarchy among them that can delimit their areas of expertise. With this, at least two levels of performance can be selected: a first level that is more strategic, comprising of agents responsible for the regulation, concession, inspection, planning, and monitoring of the system, and a second more operational level, with agents responsible for carrying out the actions that support the electrical system.

At the strategic level, the first agent in this hierarchy is the National Energy Policy Council (CNPM), which was created by Law No. 9,478 of 1997. The CNPM plays a strategic role in proposing national policies and actions to the President of the

Republic to promote the rational use of the country's energy resources. The guidelines on energy policy in the country are the result of CNPM action. However, as it is a broad and strategic council, it not only addresses issues related to electric energy, but also to energy derived from fossil fuels and other sources.

With the guidelines of the national energy policy already established, the Ministry of Mines and Energy (MME) became responsible for the implementation of these policies. MME also monitors the development of activities for the generation, transmission, distribution, commercialization, and export and import of energy from different sources. Considering this, the Ministry is also responsible for assessing the supply conditions and security of supply for energy in the country. Its strategic characteristics also allow integration with other agents so that they can identify factors that affect energy security, which are linked to the expansion of energy supply across the country. Within this integration, the MME has a monitoring arm for the electric system (CMSE), a group that monitors and assesses the security of the electric supply in the national territory.

The formulation of studies and projections with the objective of subsidizing the planning and development of national energy policy is an attribution of the Energy Research Company (EPE), another agent linked to the MME and created by Law No. 10,847 of 2004.

In the strategic field, Law No. 9,427 of 1996 created the National Electric Energy Agency (ANEEL), an autarchy linked to the MME whose main purpose is to regulate and supervise the generation, transmission, distribution and commercialization of electric energy in Brazil. ANEEL's role is essential for implementing policies related to the exploitation of electric energy in the country and to administer bidding procedures for the contracting of public service concessionaires for the generation, transmission, and distribution of electric energy.

In the operational field, the two main agents responsible for executing actions and procedures focused on the management and improvement of the Brazilian electrical system are linked to ANEEL. The first is the National Electric System Operator (ONS), which, in addition to coordinating and controlling the function of the national electrical system, also conducts studies on the system and its agents to ensure the safety and supply of electricity throughout the country.

The second main agent in the operational field is the Electricity Trading Chamber (CCEE), which plays an important role in ensuring the security and viability of the electricity trading environment in the country. The CCEE is also responsible for accounting for electricity purchases and sale operations throughout the national territory and is constantly determining the differences between the amounts generated and those contracted or consumed by market agents.

Commercial relations in the Brazilian electricity sector were established in three commercialization environments: The Regulated Contracting Environment (ACR), the free contracting environment (ACL), and the Short-Term Market, where the differences between the amounts generated from electric energy started to be accounted for.

The contracts in the ACR market are signed between selling agents and buyers of energy that participate in public auctions. However, in the ACL market, these contracts are freely established between agents and are not public. The ACR market auctions can also be categorized into several formats; however, the primary ones are the auctions for additional energy and backup energy. Until mid-2018, these two types of auctions had significant differences between them in the remuneration of the companies that intended to sell their energy through auctions.

The backup energy contracts remunerate the plants for the amount of energy sold by them to compose a security reserve for the Brazilian electrical system. On the other hand, the additional energy contracts had a fixed remuneration model for these plants until mid-2018, and the price established in the auction was used as the basis for the reference price of available energy. While the modality of the backup energy contracts received the name "modality by quantity," the modality of the additional energy contracts received the name of "modality by availability". Therefore, the risk of non-generation in the additional energy contracts was with the buyer, and the viability analysis of these projects was less susceptible to risks inherent to variation in the productive capacity of these projects.

However, from the middle of 2018, the contracts for additional energy auctions started to assume the "by quantity" modality previously exercised only for backup energy contracts. In addition, until 2017, companies that participated in additional energy auctions had to commit a minimum of 70% of their physical warranty to the auction that they participated in, which in turn is the maximum amount of energy that can be used to prove cargo or for commercialization through contracts. However, as of 2017, this minimum commitment became 30% of the amount of qualified energy, allowing the plants to sell a greater amount of energy produced in the ACL market.

This change brought about a new dynamic to the energy market in Brazil, encouraging companies to expand their participation in the ACL market. However, since the commercial relations in this market are bilateral and not available for consultation, the ability to build diagnoses based on the economic viability of these projects has become more complex.

This scenario highlights the need for tools capable of estimating the viability of projects that want to supply energy to both markets simultaneously. However, estimating viability while considering two sources of revenue requires knowing the percentage of the project's commitment to the energy supply for each market in which it participates.

Therefore, this thesis focused on three complementary studies. In the first study[1], a bibliometric analysis was conducted to identify the characteristics of the methods used for the financial analysis of renewable energy projects in recent years. The first study included a quantitative and qualitative analysis of works published between 2011 and 2020 and used four groups of interest: (i) traditional project evaluation methods (TPEM) with metrics that evaluate the viability of projects by discounting cash flows: Net Present Value (NPV), Internal Rate of Retunr (IRR), and payback period; (ii) a cost analysis approach, represented by the levelized cost of energy (LCOE); (iii) return on investment (ROI); and (iv) real options analysis (ROA).

With the identification of the popularity of methods based on discounted cash flow, the second study[2] used the NPV value and IRR to propose a procedure for calculating the viability of wind energy plants that participated in energy auctions in 2018 and 2019. The study calculated the deterministic and stochastic results using the Monte Carlo simulation method to identify the probability of projects' rates of return being higher than the Weighted Average Cost of Capital (WACC) suggested as reference by ANEEL. For this, four price assumptions for the ACL market were used.

Finally, the third study[3] used one of the four prices for the ACL market simulated in Study 2 to calculate the value of the real option to defer the investment in representative projects of the auctions that took place in 2018 and 2019. For this, the study used the Monte Carlo simulation method with uncertainties in ACL market prices and in the amount of energy produced for that ACL market to identify the volatility of projects. Then, the study adopted the binomial method to build the project's decision tree. The real options method was used to identify whether the projects analyzed would have an advantage in the construction based on the price volatility found in the cash flow portion of the ACL market. The real options theory used as a tool in situations where there are uncertainties can help to improve the decision-making process about project viability.

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1 Study submitted to journal *Revista de Administração de Empresas (ISSN 0034-7590), status: submitted*

2 Study published in the journal *Energies (ISSN 1996-1073)*

3 Study to be submitted to journal *Business Strategy and the Environment (ISSN 1099-0836), status: to be submitted*

Objectives

To help decision makers invest in renewable energy, it is crucial to build reliable alternatives for analyzing the economic interest of these projects. In this sense, the main objective of this thesis is to contribute to develop a methodology for the economic evaluation of renewable energy projects participating in a mix of free and regulated market environments in Brazil, taking into account the underlying uncertainty of this strategy and considering the market dynamics between the supply and demand of electricity in the ACL market in Brazil.

To achieve this objective, the following specific objectives will be pursued:

- To review and critically analyze methods and performance indicators directed toward the financial assessment of RES projects. This analysis will assess how these methods are affected by RES development and will provide the context required for the research.
- To propose an economic evaluation of wind energy projects in Brazil with mixed participation in ACR and ACL markets considering the dynamics between energy supply and demand in the ACL market.
- To use Real Options methodology to evaluate the impact of market uncertainty on investment timing and assess the value of postponing the construction starting of wind energy projects in Brazil.

Justification

Although a significant portion of Brazil's electricity production is based on RES, it still has huge untapped potential to explore other sources of clean energy, mainly because of its access to sunlight and stable, abundant winds. With the development of these RES, the regulatory environment of Brazil's electricity sector is changing. Bill No. 2987 of 2015, for example, proposed expanding the range of consumers in the ACL market, thereby raising expectations regarding the generation of energy to meet market demand.

Another factor that reinforces the aspect of regulatory change in the RES sector in Brazil is the change in the format of participation through auctions in the ACR market. This effectively reduces the minimum percentage of electricity required of projects participating in auctions, which may contribute to the development of the ACL market.

However, for investors to be able to assess the projects assertively, the existence of good tools for the economic assessment of the viability of renewable energy projects is essential. Based on bilateral contracts and the low level of information disclosed in the ACL market, this feature makes the task more challenging.

The construction of a strategy that can analyze the viability of these projects based on the percentage of energy destined for each market (ACR or ACL) can facilitate this by adjusting the credit analysis of these projects to specific investment decisions. In addition, changes in the level of risk and volatility in the ACL market price can be easily adjusted using a mechanism that takes into account the contextual particularities of each market.

In this sense, the justification for this proposal is the need for a valuation mechanism of renewable energy projects in Brazil that is capable of meeting revenue and cost expectations from the two electric energy contracting environments (ACR and ACL). In addition, identifying reasonable prices to serve as a reference for these contracts in the ACL market is essential so that viability assessments can be more agile and automated. Finally, the use of real options is another important tool that can assist decision makers to deal with market uncertainty and even benefit from the flexibility on the investment timing.

Contributions

Given climate change, and the possibility of forecasting rainfall patterns becoming increasingly uncertain, an electrical system based on the generation of a large hydraulic source, as in the case in Brazil, is directly affected by the increased supply risk. In this sense, the emergence of new sources of renewable energy may become an important strategy to overcome the uncertainties related to the sustainability of electricity generation in Brazil. Wind is one of the most promising and rapidly growing energy sources in Brazil because of the country's generous wind regime, which is capable of providing enough constant energy.

Parallelly, the expansion of the ACL market has caused significant changes in the regulation of auctions since 2018. This allowed a greater supply of energy into the market, where prices are not public and are subject to the dynamics between the supply and demand of any commodity market. Therefore, a viability analysis that can identify these uncertainties and their relationship with joint participation in the two markets (ACR and ACL) can contribute to a more realistic look at the development of these plants in this new context. This thesis proposes mechanisms to evaluate the viability of wind energy projects in Brazil and demonstrated it for the case of 2018 and 2019 auctions. Although there is no public data on prices practiced in the ACL market, the study tested different scenarios and enabled an analysis based on the percentage of energy destined for each market.

Considering a minimum commitment of 30% of the electricity supply by the wind plant when they participate in ACR auctions, a credit agent or investor will be able to build a viability analysis of the company based on this chosen percentage by the plant. On the one hand, this analysis can help draw a minimum viability indicator for the company based on its market choice; on the other hand, it can also simulate these minimum profitability indicators, suggesting price limits for participation in the auction that do not compromise the company's viability.

The first study of this thesis contributes to a comprehensive analysis of the mechanisms used to evaluate the economic viability of renewable energy projects. With this, the results of the study can help investors identify the most widely used and the most appropriate assessment methods for some energy sources, as well as to identify where these methods can be applied. The study also contributes to an understanding of how the methods developed in different regions of the world over time.

The second study, in turn, makes practical contributions to the calculation of the viability of wind generation projects considering two sources of revenue (ACR and ACL). This study presents an evaluation proposal for the Brazilian case that allows the analysis of projects' viability based on the percentage of energy to be offered to each market. From the construction of a deterministic structure, the study performed a Monte Carlo simulation using 10,000 simulations from four price scenarios. This proposal is intended to help credit agents or financial advisors gain a more comprehensive view of the risks involved in the project from the moment they have information on the percentage of energy that the company allocates to each market. The uncertainties in the prices and quantities practiced in the ACL market are reflected in the adaptation of the model to simulate the results using the Geometric Brownian Motion or Mean Reversal process. They also reflect the microeconomic dynamics between supply and demand from five levels of price elasticities distributed over four five-year periods. Thus, in addition to capturing the uncertainties in prices in a market where prices are not public, the study also allows for possible changes in the relationship between supply and demand in the future market.

The third study allows the analysis of the plant's viability by considering its construction timing. Until they have to deliver energy for the contracts established in the auction, the investor can choose to start the plant construction immediately after the announcement of the result of that auction, or up to three years before this deadline, in order to fulfill the contract on time. To do this, this study uses the theory of real options to analyze the option of deferring the construction based on the volatility that ACL market prices can cause in project NPVs. This analysis can also help credit managers and financial advisors identify the best time to start construction. This analysis can contribute to the construction of credit solutions that facilitate this construction process, as well as creating mechanisms of financial incentives considering the best moment to begin construction. Finally, considering the possible development of Brazil's ACL market in the coming years, this proposal seeks to contribute to a better method of market analysis. This contribution includes practical elements of viability calculation and simulation scenarios that can facilitate decision-making.

Methodology and Structure

The three studies were organized based on a logic that could be integrated with the main objective of this thesis: to contribute to a better viability analysis of renewable energy projects in two different markets in Brazil.

The detailed methodology of the first part was based on a qualitative and quantitative bibliographic analysis of studies related to the financial evaluation of renewable energy projects. The objective of this study was to identify the most suitable methods to evaluate the performance of renewable energy projects, and to contribute to a clearer perception of these tools. The data collected in July 2020 was treated in five steps.

Step 1: Initial research carried out in the Scopus database with the keywords: "RENEWABLE ENERGY," its variation in the plural form, and the other keywords chosen as selection criteria; that is: i) "Net Present Value" OR "Internal Rate of Return" OR "Payback" OR "NPV" OR "IRR" OR "PBP"; ii) "Levelized Cost of Energy" OR "Levelised Cost of Energy" OR "levelized cost of electricity" OR "Levelised Cost of Electricity"; iii) "Return on Investment" OR "ROI" AND NOT "EROI" AND NOT "Energy Return on Investment"; iv) "Real Option."

Step 2: The selection of completed documents published in journals (in English) from 2011 to July 20, 2020.

Step 3: Detailed quantitative bibliometric analysis of the articles of each separately researched group, in addition to an analysis of the intersection of these articles.

Step 4: Qualitative analysis of the content of the five most relevant articles based on the number of citations.

Step 5: Critical analysis of the research.

In the second part, the methodology is based on the construction of a cashflow proposal that considers weighted revenues from the ACL and ACR market. For this, we used information from the 95 wind energy projects that participated in auctions 28, 29, and 30, which took place in 2018 and 2019, in addition to the identification and information about these projects. In the second step, a metric of the energy load generated and another one available in the ACR market were used to identify the energy percentage of each market. In the third step, we defined four possible price scenarios for the ACL market, and in the fourth step, the representative cash flows of each auction were calculated. Finally, we inserted assumptions of uncertainty into the price of the ACL in order to carry out a Monte Carlo simulation and identify the viability of projects in each scenario.

In the third part, we used the reference price assumption identified in Chapter 2 to calculate the valuation of the representative projects for each auction in 5 steps.

Step 1) We calculated the NPV and the representative IRR for each auction considering the anticipation of plant construction.

Step 2) A stochastic analysis of price was carried out in the ACL market and the amount of energy offered to that market.

Step 3) We performed a Monte Carlo simulation to identify the volatility of the projects based on previous assumptions.

Step 4) We built the project binomial tree, calculating the up and down movements at each node in the tree.

Step 5) We built the project decision tree based on the results found in the binomial tree.

Figure 1 illustrates the construction of the adopted procedures.

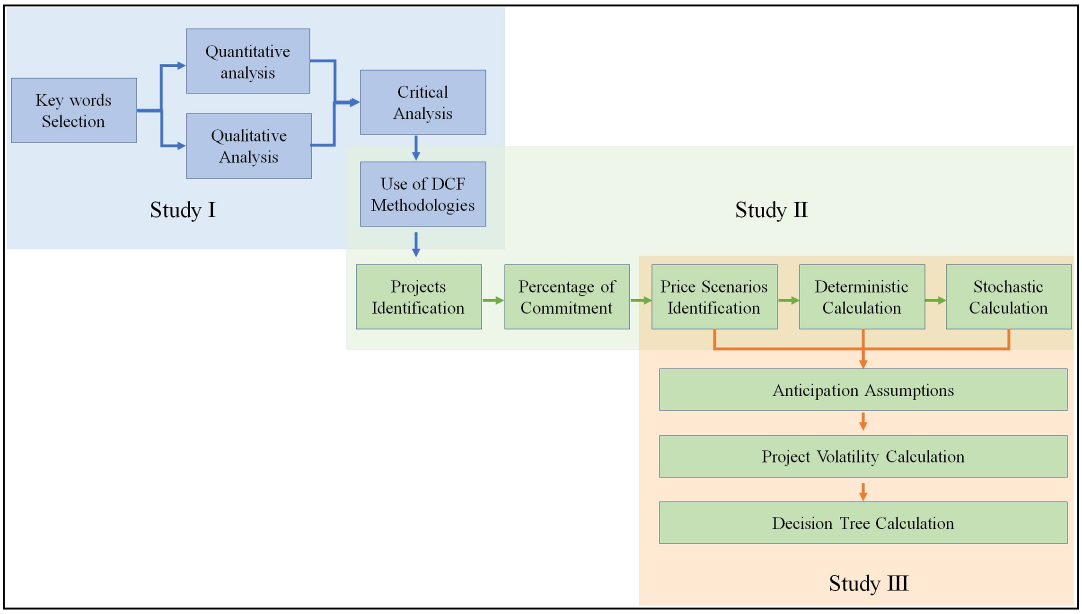

Figure 1 – Thesis operational procedures

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Part I

A Review of Financial Assessment Methods of Renewable Energy Projects

A review of financial assessment methods of renewable energy projects

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Abstract

The financial evaluation of renewable energy sources (RES) projects is well explored in the literature, but many different methods have been followed by different authors. It is important, then, to understand if and how these methods have been changing and what factors may have driven new approaches. Therefore, this part of the study aims to explore the publications on financial evaluation of RES projects from 2011 to 2020 and to present a critical analysis of the reviewed literature. The methods for evaluating RES projects were grouped into four categories: (i) traditional metrics based on net present value, internal rate of return, and payback period; (ii) levelized cost of electricity; (iii) return on investment approach; and (iv) real options analysis. A quantitative analysis was carried out considering aspects related to the relevance of the authors, productivity by country, and most relevant journals for each of these groups. Then, a qualitative analysis of the main characteristics of the five most cited articles in each group was conducted. The results show that the more traditional methods are still widely used for the financial evaluation of RES projects. However, indicators of cost of electricity and real options have been growing in importance to tackle the complex features of financial evaluation and comparison of RES projects.

1 Introduction

The accelerated economic and population growth in recent decades has put pressure on the limits of the planet's natural resources, emphasizing the need for a change in the current energy matrix (Lei et al., 2020). In 2014, the energy sector was responsible for around 35% of greenhouse gas emissions on the planet, and the electricity segment accounted for more than 70% of these (IPCC, 2014). After three years of stabilization, emissions from the energy sector increased in 2017 and 2018. However, in 2019, energy-related CO2 emissions decreased by around 33 gigatons (Gt) thanks to the growing role of renewable energy sources (RES) in developed economies (IEA, 2020b).

Currently, 72% of the energy supplied globally comes from nonrenewable sources, such as coal, oil, and nuclear energy (IEA, 2020a). The substitution of fossil fuels, responsible for the emission of a large volume of greenhouse gases, with RES has become an important strategy for sustainable economic development accompanied by a lower risk of energy interruption (United Nations, 2015, 2020).

BP (2019) indicated an average increase of more than 16% per year between 2008 and 2018 in non-hydro RES generation and 2.6% for hydro RES generation worldwide. The share of RES (including hydro) in the world electricity production reached 25% in 2018. Particularly remarkable is the growth of non-hydro RES, which in 2018 represented 9.3% of total generation, up from only 1.3% 20 years ago.

However, the intermittency and high fluctuation of renewable sources limit their development as an efficient alternative to nonrenewable sources. Considering their interaction with the transmission and distribution networks in addition to the storage systems, renewable sources require greater effort to develop solutions capable of guaranteeing their viability (Nian et al., 2019).

In addition, the viability of power-generation plants also depends on positive externalities linked to the availability of resources, technological environment, integration of the transmission network, and labor developed. Also, it is necessary a normative framework that promotes a safe environment for investments in renewable energy (Sovacool and Dworkin, 2015).

Despite the global increase in RES investments associated with economic and population growth (Ellabban and Alassi, 2019), few studies have presented a comprehensive evaluation mechanism for RES projects, mainly due to the multiplicity of variables capable of influencing the viability of these endeavors. Therefore, building models that allow an efficient and, at the same time, holistic measurement is a difficult task (Liu et al., 2018).

The development of tools for valuing renewable energy-generation projects are essential to encourage the undertaking of these initiatives. The study of RES represents a relevant field of research not only because of the foreseen technical developments but also because of the multidisciplinary approach needed to assess these projects from the social, environmental, and financial perspectives. The doubts about the viability of continuous investments in energy infrastructure based on fossil fuels have contributed to stimulating new frontiers for studies related to renewable energy projects (Li et al., 2013; Detert and Kotani, 2013).

Despite the specific characteristics of energy-investment projects, such as non-reusable assets and the high uncertainty in an increasingly liberalized market (Santos et al., 2014), the viability analysis of these projects follows the logic of exploring their financial capacity to generate returns that outweigh the amount invested in the business.

To help decision-makers invest in RES technologies, it is essential to have reliable indicators capable of measuring a project's total performance, comparing it with other alternatives. The optimal combination of risk and return can be used to assess the viability of investments in general. In terms of investments in renewable energy, externalities and environmental uncertainties tend to add risk to the investment, implying an increase in the required minimum rate of return (Salm et al., 2016).

Several tools are used to measure the viability of RES projects. For example, Ramadan et al. (2018) applied net present value (NPV) combined with an annual Return on Investment (ROI). NPV can also be used as a standalone tool or combined with the Internal Rate of Return (IRR) (dos Santos et al., 2016). Carneiro and Ferreira (2012) also explored the use of NPV associated with IRR and Payback Period (PBP) while Talavera et al. (2007) applied NPV with IRR and Levelized Cost of Electricity (LCOE).

Although most of the current studies on the viability of RES projects are based on the use of more than one indicator, the classic NPV is the most popular indicator for evaluating investments in general (Marchioni and Magni, 2018). The popularity of NPV is also reflected in its use in the evaluation of renewable energy projects (Shimbar and Ebrahimi, 2017). However, the long-term investment characteristic of RES projects can compromise the reliable application of traditional indicators to measure viability (Shimbar and Ebrahimi, 2017; Espinoza, 2014)

In a comparative analysis on the evaluation mechanisms of renewable energy projects, Menegaki (2008) presented four approaches: (i) economics based on well-being, (ii) financial options, (iii) ecological analysis, and (iv) economic analysis without the bias of well-being. The author underlined that the economic method based on well-being is the most appropriate for the assessment of RES projects when using economic valuation techniques. However, the importance of the financial assessment and, in particular, of deriving a financial value of the RES flexibility using real options theory is also recognized.

Based on the Life Cycle Assessment (LCA) concept as a model to quantify the environmental impacts of the energy sector supply chain, Kourkoumpas et al. (2018) presented a review of environmental and energy performance indicators for a holistic approach to RES technologies. According to the authors, these could be classified as (i) PBP; (ii) cumulative energy demand, expressing the necessary amount of energy invested in relation to the amount of delivered energy; (iii) gross energy requirement, indicating the energy inputs necessary to deliver a product/technology or service the point of interest; (iv) energy incorporated from the materials; and (v) global warming potential.

Another approach to measure the viability of RES projects is based on the perspective of cost analysis. In this approach, it is possible to identify the concepts of Cost of Electricity, also called Cost of Energy (COE) (Upadhyay and Sharma, 2016) or or Levelized COE (LCOE) (Bahrami et al., 2019), defined as the average cost ($) per KWh of energy produced by the system (Elkadeem et al., 2019). Aussel et al. (2018) claimed that the LCOE indicator is widely used for energy projects, and Siddaiah and Saini (2016) highlighted LCOE as the preferred indicator for minimizing the lifecycle cost of a project.

The ROI, defined as the annual cost saving over the invested capital (Elkadeem et al., 2019), or as the annual average net profit over the invested capital (Do et al., 2014), is also a common criterion used for analyzing the economic viability of RES projects (Elkadeem et al., 2019). Although ROI is strongly linked to NPV in investment valuation (Marchioni and Magni, 2018), some studies use these two indicators as complementary metrics (Do et al., 2014). Other papers highlight that the ROI parameters may not incorporate the time value of money (Jana and De, 2015) and, for this reason, the metric could be used as an independent financial parameter. A variation of ROI is the Energy ROI (EROI), defined as the proportion of the plant's usable energy over the energy invested in the plant (Weißbach et al., 2013), which will not be considered in this paper.

Given the need to value the managerial flexibility of projects in light of a future of uncertainty and change, some tools can be explored. Real options analysis (ROA), which seeks to price the future uncertainty of these projects, can be used as an indicator that complements traditional metrics based on a fixed cash flow (Kozlova, 2017). The real options theory has been applied with increasing frequency to the evaluation of RES projects (Martín-Barrera et al., 2016; Santos et al., 2014).

Methodologies that consider factors other than economic dimensions, such as environmental, technical, and social dimensions, can contribute to expanding the analysis beyond a traditional financial perspective. For instance, multi-criteria decision-making (MCDM) methods have been widely used for RES project assessment, allowing the analysis of problems involving conflicting and comprehensive criteria (Zhang et al., 2019). The issue of MCDM for RES analysis has been the focus of several reviews that highlight the role of MCDM in dealing with distinct criteria and the diversity of methods commonly used (Campos-Guzmán et al., 2019; Ilbahar et al., 2019; Siksnelyte-Butkiene et al., 2020).

Despite the existence of important research focused on the theory of evaluating RES projects (Schachter and Mancarella, 2016; Jeon and Shin, 2014), the literature does not fully explore a combined analysis of quantitative and qualitative elements or discuss the methodologies most used by a given technology or in a specific region. In addition, there are a few studies that focus on critical reviews on the evaluation of RES projects (Colla et al., 2020; Dranka et al., 2020), but the complementarity of the evaluation approaches and its relation to RES development still require further analysis.

To contribute to filling this gap, this paper will seek to answer the following research question: Is it possible to discern a change in the use of financial methods to assess the viability of RES investment projects over the last decade? Thus, this work will contribute to a better understanding of the methods and performance indicators directed towards the financial assessment of RES projects. The proposed financial perspective in this study will reveal important insights for investors. This study contributes to RES project practitioners to identifying the most used evaluation methods and those most suitable for their particular case. Moreover, the analysis contributes to a better understanding of the development of these methods over time and in different regions of the world. By doing this, we aim not only to present the state of art in what concerns the financial appraisal of RES projects but also to show how these methods are affected by the RES development and devise some possible paths for future research.

Though addressing other perspectives and dimensions is important, methods that go beyond the financial indicators (e.g., social or environmental criteria) are considered beyond the scope of this research. Specifically, the paper aims to review the so-called economic and financial efficiency measures for managerial purposes applied to the case of RES projects. An eventual multidimensional approach would be a major expansion of the proposed review and may be undertaken in a future research. Despite the relevance of MCDM models for the evaluation of RES projects, such models propose an analysis that frequently goes beyond the financial aspect, including technological, environmental, and social aspects which are not the focus of this work.

This paper is organized as follows: section 2 reviews the different project evaluation methods, providing a brief explanation of their calculation; section 3 presents the methodology used to obtain the paper database and its analysis; section 4 addresses what is coined as the quantitative analysis; and section 5 addresses the qualitative analysis of a set of papers. Section 6 presents the critical analysis of the results, and, finally, section 7 draws the conclusions and gives directions for further research

2 Evaluation Methods

Renewable energy production can contribute to not only combating climate change but also reducing energy price volatility when compared with nonrenewable sources, which are vulnerable to political instabilities, trade disputes, and embargoes, among others (Su et al., 2018).

Despite the existence of many methodologies for valuing projects or companies, Siziba and Hall (2019) emphasized three categories: (i) discounted cash flow (DCF)-based methodologies, (ii) non-DCF-based methodologies, and (iii) alternative methods. According to the authors, what distinguishes these three approaches is the way they deal with the time value of money and business uncertainty.

Aussel et al. (2018) classified the economic criteria for valuing projects in four groups: (i) NPV methods, (i) rate methods, (iii) ratio methods, and (iv) return methods. The first and second methods are linked to discount rates and return rates, respectively, while the third relates to the concept of ROI. The fourth method relates to the PBP. According to the authors, the choice of economic and environmental indicators for RES projects is made after the analysis of technical optimization based on the energy efficiency of these projects. In this context, economic and environmental indicators would assume the role of reinforcing their attractiveness.

Wu and Sun (2015) analyzed the case of wind energy projects and divided the valuation methods into five groups: (i) income methods, (ii) market methods, (iii) cost methods, (iv) real options methods, and (v) strategic value methods.

A more recent review from Dranka et al. (2020) called attention to the possibility of using traditional DCF methods or a combination of several indicators for the evaluation of RES projects. The authors also underlined the relevance of real options to deal with uncertainty and managerial flexibility.

This paper will discuss four groups of financial evaluation methods for RES projects in the context of a bibliometric analysis: (i) Traditional Project Evaluation Methods (TPEM), expressed by metrics that evaluate the viability of projects by discounting cash flows: NPV, IRR, and PBP; (ii) Cost analysis approach, represented by LCOE; (iii) ROI; and (iv) ROA. The proposed grouping ensures, on one side, that methods referred to in the literature are properly considered in this revision and, on the other hand, that their diversity is recognized, which should allow better establishing the changes in the use of these financial methods and their complementarity.

2.1 Traditional Project Evaluation Methods (TPEM - NPV, IRR, and Payback)

The indicators that form the group of tools named TPEM are rooted in a common characteristic: the reference to a project's cash flow (Chang and Starcher, 2019).

The NPV represents the total value of a project at current value, considering a discount rate that reflects the risk at which the investor demands to be remunerated (Žižlavský, 2014). NPV is considered the most theoretically reliable tool from a financial perspective since it measures value creation (Marchioni and Magni, 2018).

Along with cash-flow estimation, the discount rate emerges as a fundamental parameter for the NPV calculation. Failure to select an appropriate discount rate for a project can distort its viability (Hatata et al., 2019). According to Žižlavský (2014), the discount rate ranges from 10% to 15% for corporate projects and from 25% to 30% for investments in high-tech companies.

However, Hatata et al. (2019) argued that this rate varies depending, for example, on the inflation rate for each region or country where a project is developed. They suggest that this rate generally varies between 5% and 12% for small hydro-power plants. Also, Thornton and Pipeline (2018) shows how the discount rate is affected by the hosting country and its market characteristics. In contrast, Oxera (2011) report on discount rates for RES technologies supports that the maturity level of deployment of a technology may be the most important factor for the risk perception with significant impact on the discount rate. The NPV formula can be represented by equation (2.1).

$$NPV = \sum_{i=0}^{N} \left(\frac{CF_i}{(1+k)^i} \right) \tag{2.1}$$

where:
CF_i = Cash Flow in year i
k = Annual discount rate
N = Project lifetime, in years.

In the field of RES projects, NPV has great popularity and is being used in various studies focusing, for instance, on (i) analysis of the viability of small hydro plant projects (Hatata et al., 2019), (ii) investigation of the viability of renewable energy on domestic systems (Frangou et al., 2018), or (iii) analysis of renewable energy systems in rural areas (Arranz-Piera et al., 2018).

Another indicator widely used in RES projects is the IRR, expressed by the interest rate for which a project's NPV is zero. When the future cash flows of a project are discounted using the IRR, the present value of cash outflows equals the present value of cash inflows (McAllister, 2013). IRR is generally used with the NPV in the evaluation of projects (Arranz-Piera et al., 2018). Mellichamp (2017) discussed the IRR and argues that, joint with NPV, it represents the second measure of project profitability. It is based on a nondimensional scale while NPV represents a monetary quantity. The IRR can be obtained solving the equation figure (2.2).

$$0 = \sum_{i=0}^{N} CF(1 + IRR)^{-i} \tag{2.2}$$

where:
CF = Cash Flow in year i
N = Project lifetime, in years.

Despite considering the value of money over time, IRR has some disadvantages in being used as a sole indicator. IRR lacks the information on monetary project values and may be hard to calculate when cash flows are not conventional Belyadi et al. (2019). The advantages and limitations of IRR are extensively discussed in the literature, such as by Mellichamp (2017).

Finally, the PBP is an indicator that aims to express the time to recover the investment in a project. The PBP is the number of years or months necessary for the gross value of the inputs and outputs to be equal (Talavera et al., 2007). PBP can be used with or without considering the time value of money. When this is considered, the method is called the Discounted PBP; otherwise, it is frequently called the Simple PBP. Despite its easy understanding and usability, PBP disregards existing cash flows after investment is recovered and is a very limited tool for decision-making Cucchiella et al. (2018). The discounted payback can be obtained with equation (2.3).

$$PBP = \frac{I}{\sum_{i=1}^{Np} \left(\frac{CF_i}{(1+k)^i} \right)} \tag{2.3}$$

where:
I = Initial investment
CF = Cash Flow in year i
k = Annual discount rate
Np = Number of years until the investment is recovered.

Regardless of its limitations, the PBP method is widely used to analyze different types of RES projects. Chang and Starcher (2019) used this mechanism to evaluate wind energy projects in the USA, estimating an average time of 13 years when tax incentives are used. Uhunmwangho et al. (2018) used PBP to support the viability of different types of hydroelectric turbines in Nigeria whereas Cucchiella et al. (2018) explored this indicator as an auxiliary tool to evaluate different sizes of biogas plants.

According to de Andrés et al. (2015), despite the preference of using NPV in the academic area, practitioners prefer to use such tools as PBP and IRR to analyze project viability. Although, as discussed by Galli (2020), NPV has superior characteristics over IRR and PBP, their different rationale justifies the inclusion of all these metrics in a bibliometric analysis.

2.2 Levelized Cost of Electricity (LCOE)

The viability of RES projects can also be analyzed from a lifecycle cost perspective. LCOE is a comparative measure widely used for this purpose (Aussel et al., 2018).

Basically, the objective of LCOE is to identify the unit COE over the life of a project, dividing all costs generated by the energy system by the amount of energy produced by that system (Aldersey-Williams and Rubert, 2019). LCOE can be represented by equation (2.4).

$$LCOE = \frac{Lifecycle\ Cost}{Lifetime\ Energy\ Production} \tag{2.4}$$

This indicator is a measure of performance evaluation used in several RES projects, such as wind energy (Bahrami et al., 2019), solar energy (Gürtürk, 2019), biomass-based energy (Abdelhady et al., 2018), among others. While some authors consider LCOE to be estimated at the present value of all costs incurred during the life of a project (Abdelhady et al., 2018), others consider that the indicator is composed of the annualized cost of the project (Lai and McCulloch, 2017).

Aldersey-Williams and Rubert (2019) highlighted that these two approaches reflect two distinct views, one suggested by the Department for Business, Energy and Industrial Strategy (BEIS, UK) based on the present value of costs and the other proposed by the Department of Energy's National Renewable Energy Laboratory (NREL, USA) relying on annual energy cost.

Although several studies adopt the present value view of project costs, Loewen (2019) demonstrated that LCOE represents not a discounted metric but, rather, an undiscounted metric. Moreover, the author argues that the present value approach of costs excessively penalizes projects with a longer lifecycle. However, LCOE remains a fundamental metric widely disseminated among the energy industry, academics, and organizations (see, for example: (IRENA, 2020a; IEA, 2019)).

2.3 Return on Investment (ROI)

Despite the similarities between NPV and ROI, there are important differences that justify their inclusion in different categories. More specifically, in NPV, future cash flows are discounted by a discount rate that reflects the opportunity cost of capital. This mechanism of adjusting a project to a risk rate is not used in the ROI metrics (Žižlavský, 2014).

Copeland Thomas et al. (1994) compared the ROI and the indicators based on the DCF. Although the DCF-based indicators were important tools, companies adopting this method could postpone the expenses of capital to improve its cash flow in the short term, making it impossible to reliably portray project performance. In this context, financial indicators like ROI could provide a more reliable panorama, helping to set short-term goals and evaluating a project or company over time.

According to Siziba and Hall (2019) ROI has increasing importance as a mechanism of capital budgeting techniques and is used especially in the United Kingdom, USA, South Africa, and India. ROI is considered a complementary method for analyzing the viability of different types of RES projects.

The ROI rate can be defined by the percentage ratio between the annual net profit (net cash flow) over the life of a project and the total capital investment in the project Jana and De (2015), and can be represented by equation (2.5).

$$ROI = \frac{Annual\ Return}{Investment} \times 100 \tag{2.5}$$

According to Gamel et al. (2016), ROI is one of the most important investment criteria adopted to analyze investments in RES projects. ROI can be identified in studies focused on the economic viability of energy generation by biomass plants (Do et al., 2014; Jana and De, 2015), wind power plants (Ederer, 2016), photovoltaic systems (Elkadeem et al., 2019), among others.

2.4 Real Options Analysis (ROA)

In the traditional analysis of investments through DCF, decisions are assumed to be fixed, not allowing managers to expand or retract investments beyond the initial project estimate (Kozlova, 2017).

The term “real options” is used to express the options embedded in investment opportunities, such as suspending, postponing, or abandoning the investment, and reducing or expanding the scale of operations (Lambrecht, 2017). The real option is a tool focused on finding solutions to the uncertainties found in a project, contributing to the identification of present and future investment opportunities(Zhang et al., 2014).

A real option gives the right, but not the obligation, for a company to undertake a strategy depending on a given future scenario. Thus, a real option has to be included as part of the investment cost. Real option theory has been applied with increasing frequency in the evaluation of RES projects (Martín-Barrera et al., 2016).

For instance, in wind power generation, in addition to the intrinsic uncertainties due to variation of wind levels and direction (Martinez-Cesena and Mutale, 2012), some studies explore uncertainties arising from changes in product prices (Munoz et al., 2009) and costs of producing energy (Wesseh and Lin, 2016).

Kozlova (2017) pointed out that 40% of the studies related to real options applied to wind power generation are concentrated in a single source of uncertainty, most frequently the price of electricity. However, other uncertainties may be considered. For example, Barroso and Iniesta (2014) used real options to analyze investment in wind power generation in the German market. The authors modelled the primary uncertainties that affect a project besides cost including investment, electric power produced, and consumer price index.

In a case study, Martinez-Cesena and Mutale (2012) highlighted the need to improve the valuation of wind energy projects. The existing uncertainties in this sector should motivate the use of real options theory as a tool for improving the valuation of energy projects. The authors concluded that, in most scenarios, the use of real options theory results in greater value for wind energy projects.

Gazheli and van den Bergh (2018) also explored real options to investigate three cases with investment possibilities between wind and photovoltaic energy. The authors concluded that the uncertainties regarding future prices and energy costs indicate that the most viable strategy is to invest only in one source of energy due to the initial costs and the learning rates of each technology. In this case, the authors suggested that diversifying a project using different energy sources could be the wrong strategy.

The use of ROA has been expanding with application to different RES projects and considering different uncertainties due to different market organizations or resource conditions. Several studies addressed these issues—for instance, in Brazil (Dranka et al., 2020), Portugal (Santos et al., 2014), and the USA (Maeda and Watts, 2019). The ROA formula can be represented as follows in equation (2.6).

$$NPV_{expanded} = NPV_{Deterministic} + NPV_{Flexibility} \tag{2.6}$$

where:

$NPV_{Determistic}$ = Tradicional NPV

$NPV_{Flexibility}$ = Uncertain cash flow value to be added, due to the existence of a real option within the project.

Finally, ROA is considered a complementary tool in analyzing project viability. Santos et al. (2014) compared the traditional NPV method to the expanded NPV method that considers the flexibilities of a specific project. The authors concluded, as expected, that the value of NPV using ROA is greater than the traditional calculation since a real option gives flexibility and then adds value to the project.

3 Methodology and data

According to Haddaway and Macura (2018), a literature review needs to generate some relevant scientific evidence, which goes beyond the collection of studies and their respective syntheses. In this sense, this study brings elements capable of assisting decision-makers in the valuation of RES projects, highlighting the main uses and limitations on the methodologies used in this field and where they would more suitably be applied.

Some limitations may be assigned to a literature review study, such as (i) lack of detailed methods enabling reproducibility, (ii) inclusion of studies based on authors' familiarity, and (iii) different decisions based on the individual options of the reviewers, among others (Haddaway and Macura, 2018). This work seeks to overcome these limitations by presenting a detailed method of analysis based on four specific groups using a systematic and replicable approach.

3.1 Quantitative analysis

The quantitative analysis of the articles follows a bibliometric approach. There are at least two main procedures in building a bibliometric analysis. The first, performance analysis, seeks to evaluate groups of authors and the impact of their activities. The second, scientific mapping, aims to express the cognitive structure of a study, presenting its structural and dynamic aspects (Zupic and Čater, 2014; Cobo et al., 2011).

The most influential authors in a research area can be identified using indicators that measure their influence on a given theme from the amount of published works. The h index proposed by Hirsch (2005) is defined by the largest number h of papers by an author that received at least h citations. The h index considers both the number of publications and their impact on individual authors' performance measurement, summarizing citations and publications into a single reference number (Alonso et al., 2009; Schreiber, 2010).

However, the difficulties in capturing the contribution of authors with common names, the existence of differences between research fields in the typical values of h, as well as their insensitivity in situations where articles are rarely placed or very frequently cited, have contributed to the proposal of new alternative metrics (Alonso, S., Cabrerizo, F. J., Herrera-Viedma, E., Herrera, 2010; Egghe, 2006). For instance, the g index proposed by Egghe (2006) and the hg index proposed by Alonso et al. (2009)

sought to improve the performance measurement of the authors in publications of a particular field of research.

The g index is an indicator that expresses the most cited articles by an author in a rank of articles arranged in descending order with the most cited g-articles having at least g^2 citations altogether (Egghe, 2006). However, these indicators focused on the authors' performance analysis, besides their relations in a certain thematic field, have little analytical scope in terms of the performance of the research fields themselves, in a conceptual way (Cobo et al., 2011). The thematic analysis requires, then, the identification of keywords that express the structure of relationships among the researched themes.

In addition, Lotka's law, which indicates an inverse exponential scale of the number of articles per author, can be used to further measure scientific productivity. Few authors tend to publish a large number of articles in a given area of knowledge while most authors publish a small number of papers (Henrique et al., 2020). Potter (1981) pointed out that, when there is a coverage period of 10 years or more, Lotka's law can be a useful metric.

3.2 Qualitative analysis

The qualitative analysis of the study was based on the four main groups of financial evaluation methods, previously identified (TPEM, LCOE, ROI, and ROA). The discussion presents the main sources of RES studied in the most relevant studies of each group. It will also discuss a regional view, indicating the main authors' affiliation, as well as a temporal approach, addressing the years in which these works were published.

Following the example used by Geng et al. (2017), the frequency of keywords in each group was analyzed. With this, it was possible to identify the most important topics in the field of the financial evaluation of RES projects. It was also possible to identify the focus of the most relevant papers in what concerns the most used methodologies and even the RES cases/technologies addressed. For the four groups of methods, a critical analysis of the five most relevant works, selected as those with higher number of citations, was undertaken to better understand the use of financial project appraisal methods and the combination of these methods. The geographical coverage of the studies and their technical focuses were also analyzed to discuss the alignment of scientific studies with market conditions.

3.3 Research Method

The data for this research were collected in July 2020 using a five-step approach:

Step 1: Search was conducted in the Scopus database with the keyword "Renewable Energy," its plural variation, and the keywords chosen as selection criteria for this research, detailed in Table 1.

Step 2: In the step 2, filters considered only articles in English, finalized, published in journals, in the period from 2011 until the date of the search (07/20/2020). In addition, conference papers, editorials, books, and reviews were excluded.

Step 3: Within the database selected in step 2, a detailed quantitative bibliometric analysis of the articles in each researched group was performed separately. This step also included an intersection analysis of the reviewed papers.

Table 1 – Group of Keywords

Groups	Keywords
TPEM	"Net Present Value" OR "Internal Rate of Return" or "Payback" OR "NPV" OR "IRR" OR "PBP"
LCOE	"Levelized Cost of Energy" OR "Levelised Cost of Energy" OR "levelized cost of electricity" OR "Levelised Cost of Electricity"
ROI	"Return on Investment" OR "ROI" AND NOT "EROI" AND NOT "Energy Return on Investment"
ROA	"Real Option"

Step 4: The five most relevant articles were selected based on the papers most cited for a qualitative analysis of their content.

Step 5: Based on both quantitative and qualitative analysis, a critical analysis of the research is proposed. The operational procedures are summarized in figure 2.

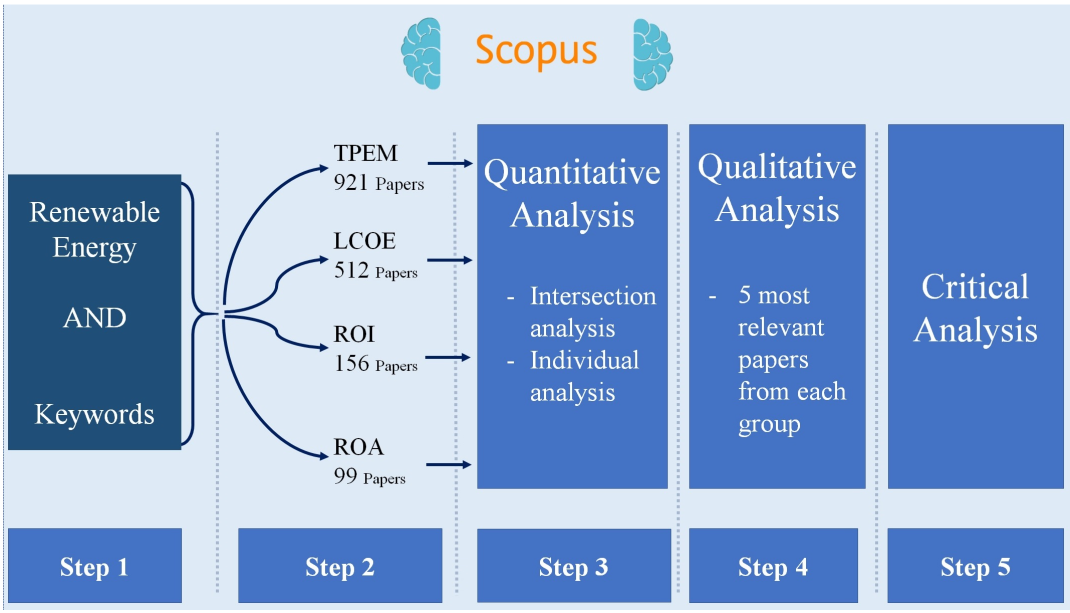

Figure 2 – Operational procedures

These operational procedures ensure, then, that this study is transparent in the sense that all activities are reported, it may be reproducible, the reviewed papers were included according to their relevance for the field of study, and the eligibility choices are based on a priory protocol from the definition of keywords selected according to a previous analysis of the literature.

4 Results ans Discussions

4.1 Quantitative Analysis

Following the proposed methodology, this section will present the main results of the quantitative analysis, including the analysis of the intersections of articles included in the four groups of financial evaluation methods for RES projects and the individual analysis of the papers included in each group. For the individual study, we focused on the annual rate of publication and analysis of most preeminent authors, institutes, countries, and journals in terms of publications and citations.

4.1.1 Intersection analysis

The analysis was carried out without excluding any article from each group. Therefore, due to their scope, articles may appear in different groups, as shown in figure 3.

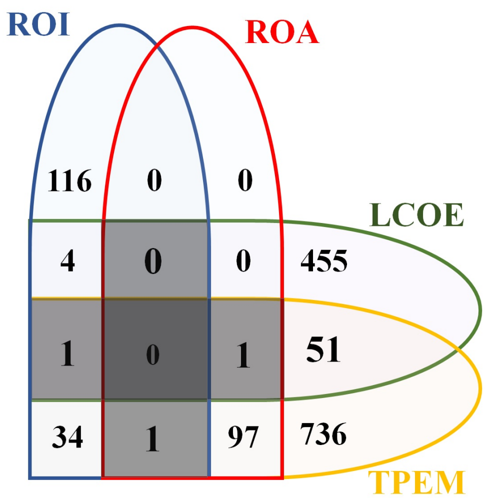

Figure 3 – Intersections of articles in different groups

Figures 2 and 3 show that LCOE and TPEM represent the two most important categories of papers including close to 85% of the papers included in step 2.

Figure 3 highlights the intersection of different groups, which may be seen as a proxy for the complementarity assessment of the different methods. The following points can be derived from the intersection analysis:

- ROI is frequently used independently of other methods. The initial search identified 156 paper using ROI for RES evaluation, and, of those, only one was combined with TPEM, four were combined with LCOE, one included both LCOE and TPEM, and one included both ROA and TPEM.

- The initial search identified 512 papers for LCOE. Of those, 455 did not include other methods for financial evaluation, but 51 were combined with TPEM, four with ROI, one with both ROA and TPEM, and one with both ROI and TPEM.
- The initial search identified 921 papers for the TPEM, but, of these, 185 combined these methods with ROA (97), LCOE (51), ROI (34), both ROA and LCOE (1), both ROI and LCOE (1), or both ROI and ROA (1).
- ROA is never used independently. All papers are always combined with TPEM either alone (97) or with both TPEM and LCOE (1) and with both TPEM and ROI (1).

Figures 2 and 3 demonstrate the importance of TPEM as independent metrics or as metrics that support other analysis. In particular, and as expected, the articles in the ROA and TPEM group should have a certain type of intersection. In this case, all articles in the ROA group were also inserted in the TPEM group; this is explained by the fact that the theory of real options can be seen as a complementary (or extended) approach to the traditional NPV, as previously demonstrated in equation 6.

4.1.2 Individual analysis

4.1.2.1 TPEM

The annual production of this category of articles had an annual growth rate of 18.8% in the analyzed period. In 2019, the total number of articles published was 185. The fall in publications in 2020 refers to the date of this search, which was conducted before the end of the first semester. Figure 4 shows, then, that, although based on traditional and well-recognized methods, the use of DCF approaches in scientific papers addressing RES project evaluation has not declined or even slowed during these 10 years.

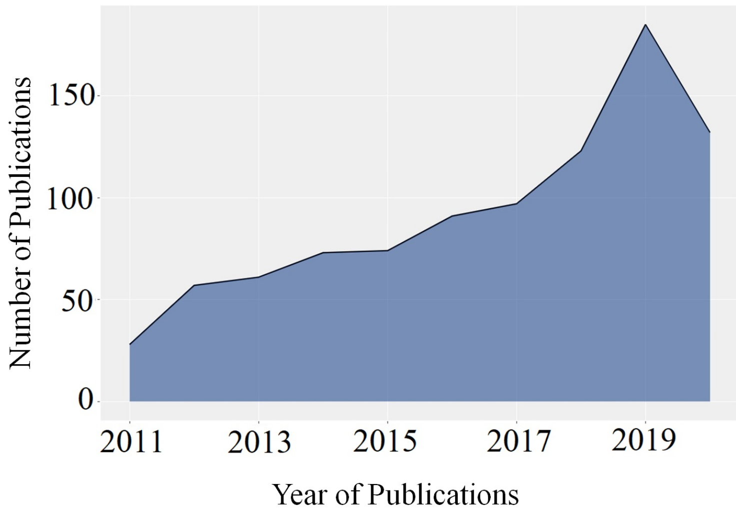

Figure 4 – Annual Scientific Production (TPEM)

In table 2, it is possible to identify the 15 most relevant authors in the group. The list of authors was ordered based on the h index; however, it is possible to verify that the g index also tracks the relevance of authorship in the researched field and presents a similar trend.

Table 2 – Authors Impact (TPEM)

Author	h_index	g_index	NC	Year*
Cucchiella F.	9	11	305	2014
Gastaldi M.	6	8	123	2015
Zhang X.	5	8	103	2012
Gheewala H.	5	5	77	2013
Manan A.	5	5	53	2012
Li J.	4	6	54	2013
Li X.	4	6	38	2014
Fleten S.	4	5	218	2012
Kleme J.	4	4	44	2015
LI H.	4	4	115	2016
Wan Alwi Sr.	4	4	69	2015
Li Z.	3	5	72	2014
Zhang Y.	3	5	34	2016

Table 2 – Authors Impact (TPEM)

Author	h_index	g_index	NC	Year*
Madlener R.	3	5	25	2014
Hagspiel V.	3	4	19	2018

NC = Number of Citations, July (2020)

* = Year of the first publication on the topic

Among the articles in this category, various common words were found, representing the intersection of topics and interests among the papers, i.e., investment, renewable energy, economic analysis, and alternative energy. Considering the 15 most frequent words, an analysis was carried out focusing on referenced energy sources.

Words related to solar energy are more frequent than those related to wind energy. These two sources of energy were the only ones found among the 15 most frequent words. It is worth mentioning that words related to the same source (e.g., solar energy, photovoltaic, etc.) were grouped under the word "solar." In the 15 most frequent words, words related to both solar and wind energy appeared 479 times, as shown in Figure 5.

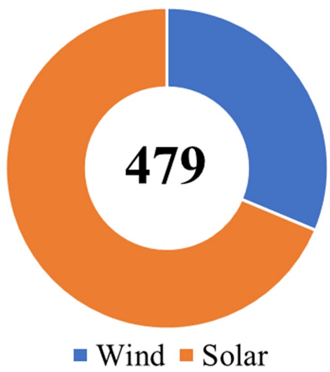

Figure 5 – Occurrence of "wind" and "solar" in Most Frequent Words (TPEM)

Regarding the most cited articles in the dataset, only 2 of the 15 most cited publications were not published between 2011 and 2015, which was to be expected, since the longer since the article was published, the greater the period to accumulate citations. Table 3 lists these most cited articles.

Table 3 – Most Cited Papers (TPEM)

Author	Year	Citations
Espinosa et al. (2012)	2012	345
Şengül et al. (2015)	2015	182
Bradbury et al. (2014)	2014	168
Boomsma et al. (2012)	2012	157
Schelly (2014)	2014	122
Jouny et al. (2018)	2018	110
Beal et al. (2015)	2015	114
Dincer and Zamfirescu (2012)	2012	104
Blum et al. (2011)	2011	98
Ju et al. (2016)	2016	92
Gude et al. (2012)	2012	91
Daud et al. (2013)	2013	87
Arnold and Yildiz (2015)	2015	85
Erb et al. (2012)	2012	81
Harder and Gibson (2011)	2011	78

Regarding the most relevant publication outlets, Table 4 reveals that, among the 15 main journals, *Renewable Energy*, *Energy*, *Applied Energy*, *Energies*, and *Energy Policy* contain 30.5% of all papers in the sample of 921 papers.

Table 4 – Papers by Source (TPEM)

Sources	Articles
Renewable Energy	75
Energy	67
Applied Energy	52
Energies	45
Energy Policy	42
Journal of Cleaner Production	40

Table 4 – Papers by Source (TPEM)

Sources	Articles
Energy Conversion and Management	36
International Journal of Renewable Energy Research	22
Solar Energy	19
Energy and Buildings	18
Sustainability (Switzerland)	17
Energy Economics	13
Applied Thermal Engineering	10
International Journal of Hydrogen Energy	10
Journal of Energy Storage	10

Figure 6 depicts the geographical distribution of the scientific production in this group, defined by the first author's affiliation country. Considering the 15 most relevant countries, the leader is the USA with 15.6% of scientific production followed by China, 12.6%; Italy, 8.6%; the UK, 7.4%; and Spain, 7.0%. Altogether, these five countries accounted for half of the total scientific production of the 15 countries

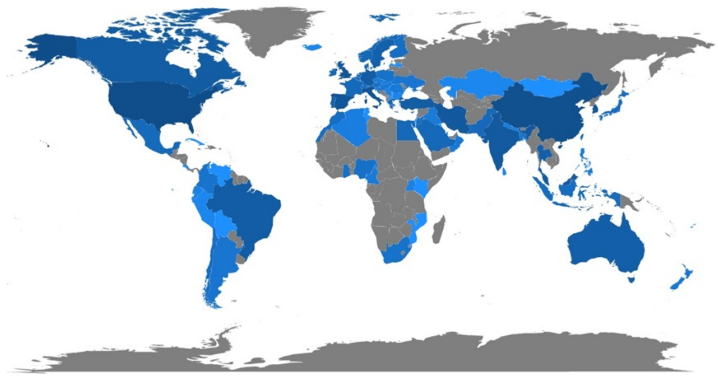

Figure 6 – Country Scientific Production (TPEM)

Table 5 shows a geographical analysis of the most cited papers, defined also by the first author's affiliation country, it is possible to see that outside Europe, only USA and China are among the five most cited countries. On the European continent, the most cited papers come from the UK, Italy, and Turkey.

Table 5 – Most Cited Countries (TPEM)

Country	Total Citations
USA	1329
UK	658
Italy	612
Turkey	581
China	525
Korea	511
Germany	498
Canada	410
Denmark	391
Spain	347
Austria	230
Brazil	216
Greece	211
Hong Kong	207
Malaysia	182

Despite being the main countries for producing scientific articles, China and Spain occupy lower positions when analysis focuses on the quantity of citations with USA leading these values.

4.1.2.2 LCOE

In the LCOE group, the annual production of articles had an annual growth rate of 37.7% in the period under analysis. In 2019, the total number of articles published was 147. Literature on specific metrics for analyzing the cost of electricity related to LCOE had a more expressive growth than the literature on traditional financial metrics grouped in the TPEM category. This growth rate also reflects the very low number of articles in the beginning of the analyzed period and a remarkable number of publications in 2019.

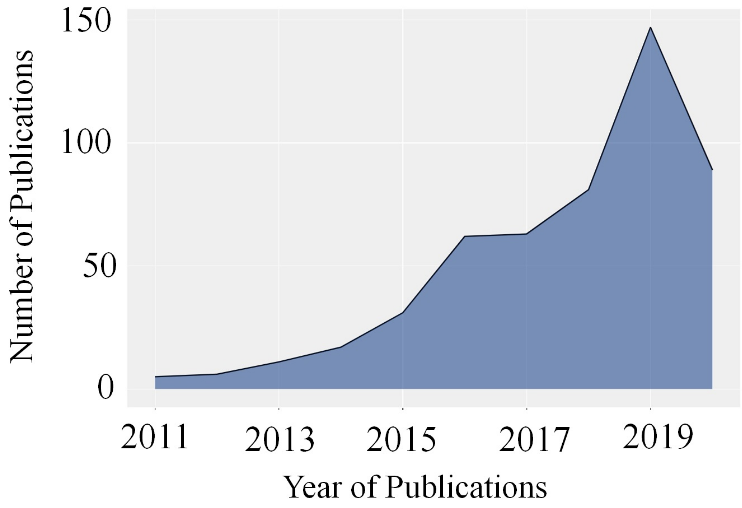

Figure 7 – Annual Scientific Production (LCOE)

The most influential authors in this group are listed in Table 6. Results show that 60% of the most relevant authors published their first paper on the topic in 2017 or 2015. This evidence reflects another difference when comparing the LCOE and TPEM groups with this last one showing that, for most authors, the first publication included in this analysis dated from 2014 or before. Although a well-recognized method in the industry, LCOE academic literature is more recent, and results suggest the topic is still gaining attention in scientific studies about energy projects.

Table 6 – Authors Impact (LCOE)

Author	h_index	g_index	NC	Year*
Breyer C.	15	23	537	2015
Bogdanov D.	14	20	500	2015
Aghahosseini A.	7	13	218	2017
Gulagi A.	5	6	191	2017
Adaramola MS.	4	4	233	2014
Goel S.	4	4	33	2016
Ghenai C.	3	4	60	2018
Zhang X.	3	4	57	2015
Caldera U.	3	4	56	2017
Taylan O.	3	4	39	2017
Wang S.	3	4	31	2019

Table 6 – Authors Impact (LCOE)

Author	h_index	g_index	NC	Year*
Zhang Y.	3	4	29	2015
Child M.	3	3	141	2018
Kim J.	3	3	36	2017
Kumar A.	3	3	24	2017

NC = Number of Citations, July (2020)

* = Year of the first publication on the topic

In the 512 articles included in the LCOE group, common words that represented the intersection of interests, such as renewable energy resources, renewable energies, economic analysis, and electricity generation, were also identified. When the 15 most frequent words were analyzed, "wind" and "solar energy" were also identified with 323 occurrences, as detailed in Figure 8. Within this group, no other source of energy has been identified.

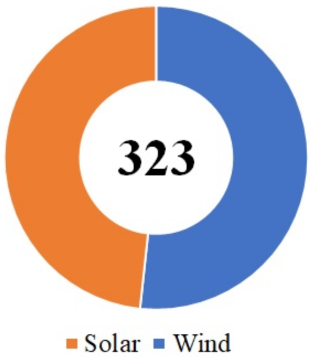

Figure 8 – Occurrence of "wind" and "solar" in Most Frequent Words (LCOE)

Table 7 shows the list of articles most cited in the LCOE set. Again, this highlights that these publications tend to be more recent than those included in the TPEM group. For the TPEM group, the years of publication were distributed over the analysis period while, in the LCOE group, most of the most cited papers were published between 2014 and 2017.

Table 7 – Most Cited Papers (LCOE)

Author	Year	Citations
Ueckerdt et al. (2013)	2013	209

Table 7 – Most Cited Papers (LCOE)

Author	Year	Citations
Darling et al. (2011)	2011	188
Zamalloa et al. (2011)	2011	182
Li et al. (2013)	2013	138
Dalla Rosa and Christensen (2011)	2011	127
Ouyang and Lin (2014)	2014	124
Adaramola et al. (2014b)	2014	102
Halabi et al. (2017)	2017	95
Maheri (2014)	2014	88
Malheiro et al. (2015)	2015	86
Adaramola et al. (2014a)	2014	73
Ramos et al. (2017)	2017	71
Breyer et al. (2018)	2018	70
Barbosa et al. (2017)	2017	66
Isa et al. (2016)	2016	61

Regarding the most relevant sources, table 8 reveals that, among the 15 main journals, Energy, Renewable Energy, Applied Energy, Energy Conversion and Management, and Energies represent 39.1% of the 512 papers.

Table 8 – Papers by Source (LCOE)

Sources	Articles
Energy	51
Renewable Energy	50
Applied Energy	38
Energy Conversion and Management	32
Energies	29
Energy Policy	21
International Journal of Renewable Energy Research	14

Table 8 – Papers by Source (LCOE)

Sources	Articles
Renewable and Sustainable Energy Reviews	13
Solar Energy	11
International Journal of Hydrogen Energy	10
Journal of Cleaner Production	10
Sustainability (switzerland)	10
Energy Strategy Reviews	8
Environmental Progress and Sustainable Energy	6
Applied Thermal engineering	5

Figure 9 presents the scientific production by country, considering the first author's affiliation. The leader is the USA with 20.6% of the scientific production among the 15 most relevant countries followed by China, 9.6%; Germany, 8.9%; India, 8.6%; and Spain, 7.1%. Altogether, these five countries accounted for 54.8% of the scientific production of these 15 most relevant countries.

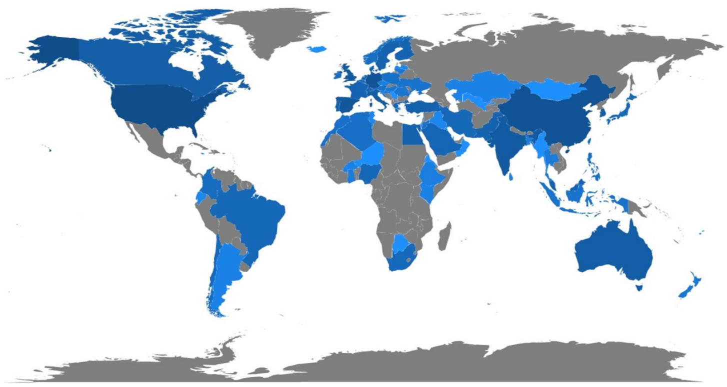

Figure 9 – Country Scientific Production (LCOE)

Table 9 presents the ranking of the most cited countries, considering first author's affiliation. In this analysis, among the 15 most cited countries, the five main countries represent 64.4% of citations, namely, the USA, Finland, Germany, China, and Australia. It is important to note that, for the LCOE group, both Italy and the UK are less representative in terms of citation when compared to TPEM.

Table 9 – Most Cited Countries (LCOE)

Country	Total Citations
USA	680
Finland	468
Germany	404
China	346
Australia	208
Belgium	190
Denmark	181
Canada	156
Italy	132
UK	112
Korea	106
Spain	77
Chile	76
Sweden	72
Brazil	63

4.1.2.3 ROI

In the ROI group, article publication had an annual growth rate of 11.2% in the period. In 2019, the total number of articles published was 21. Unlike the TPEM and LCOE groups, the ROI group showed a floating trend throughout the years.

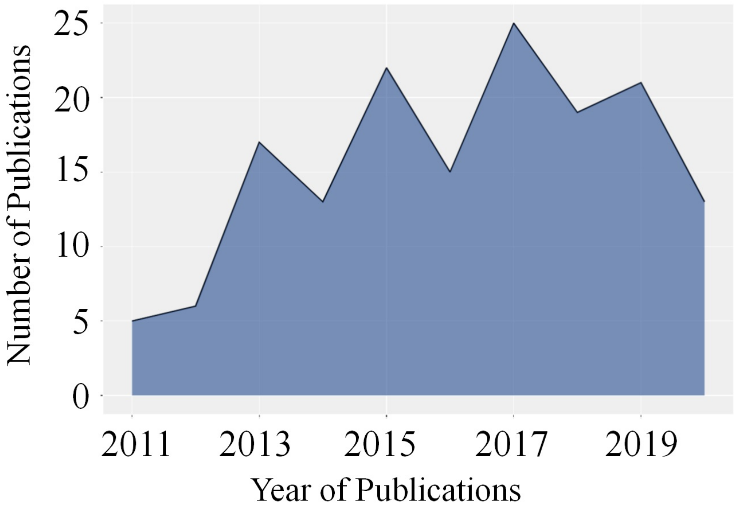

Figure 10 – Annual Scientific Production (ROI)

The most influential authors in this group are listed in Table 10. The results show that 53.4% of the 15 most relevant authors published their first papers in 2014 or 2017, in equal shares.

Table 10 – Authors Impact (ROI)

Author	h_index	g_index	NC	Year*
Do, T. X.	3	3	56	2014
Lim, Y. I.	3	3	56	2014
AL Shariff S	2	2	15	2013
McMeekin S. G.	2	2	115	2011
Stewart B. G.	2	2	115	2011
Li Y.	2	2	58	2017
Jokisalo J.	2	2	57	2017
Kosonen R.	2	2	57	2017
Niemelš T.	2	2	57	2017
Yeo H.	2	2	40	2014
Yang J.	2	2	31	2014
Radzi M. A. M.	2	2	27	2015
Liu X.	2	2	24	2015
Atieh A.	2	2	15	2013

Table 10 – Authors Impact (ROI)

Author	h_index	g_index	NC	Year*
Ali D.	2	2	6	2013

NC = Number of Citations, July (2020)

* = Year of the first publication on the topic

In the ROI group, words that represented the intersection of interests, such as "renewable energy resources," "renewable energies," "economic analysis," and "electricity generation," were also identified. Among the 15 most frequent words, the only expressions related to energy sources were "wind power" with 24 references and "Photovoltaic Cells" with 19. However, despite being in the 16th and in the 17th position among the most cited words, the group of expressions "Photovoltaic Cells," "Solar Power Generation," and "Solar Energy," when added together, result in a total of 50 references.

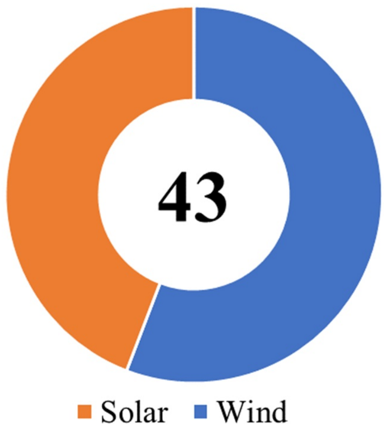

Figure 11 – Occurrence of "wind" and "solar" in Most Frequent Words (ROI)

The 15 most cited papers for the ROI group are listed in table 11. In the analysis, 60% of these were published in 2013 or 2015.

Table 11 – Most Cited Papers (ROI)

Author	Year	Citations
Jenner et al. (2013)	2013	156
Schelly (2014)	2014	128
Eriksson and Gray (2017)	2017	84

Table 11 – Most Cited Papers (ROI)

Author	Year	Citations
Cherrington et al. (2013)	2013	83
Muhammad-Sukki et al. (2011)	2011	66
Calvert et al. (2013)	2013	51
Li, Y., Wu, M., Li (2018)	2018	49
Muhammad-Sukki et al. (2014)	2014	49
Barsanti and Gualtieri (2018)	2018	44
Jacobs et al. (2013)	2013	42
Niemelä et al. (2017)	2017	37
Hou et al. (2017)	2017	36
Tokunaga et al. (2015)	2015	36
Al Garni et al. (2018)	2018	34
Salm et al. (2016)	2016	34

The 15 most relevant sources can be seen in table 12. In this list, the five top journals represent 30.8% of all 156 papers in the sample.

Table 12 – Papers by Source (ROI)

Sources	Articles
Energy Policy	11
Energies	10
Renewable and Sustainable Energy Reviews	10
Renewable Energy	10
Energy Conversion and Management	7
Joural of Cleaner Production	6
Energy	5
Sustainable Cities and Society	5
Applied Energy	4
Solar Energy	4

Table 12 – Papers by Source (ROI)

Sources	Articles
Biomass and Bioenergy	2
Energy and Buildings	2
Energy Research and Social Science	2
Environment Systems and Decisions	2
IET Renewable Power Generation	2

The most productive countries in terms of first author's affiliation are listed in figure 12. The leader is the USA with 29.5% of the scientific production among the 15 most productive countries, followed by the UK with 12.9%. As for China, it represents 7.6%. Altogether, these three countries accounted for 50% of the publication of these top 15 countries.

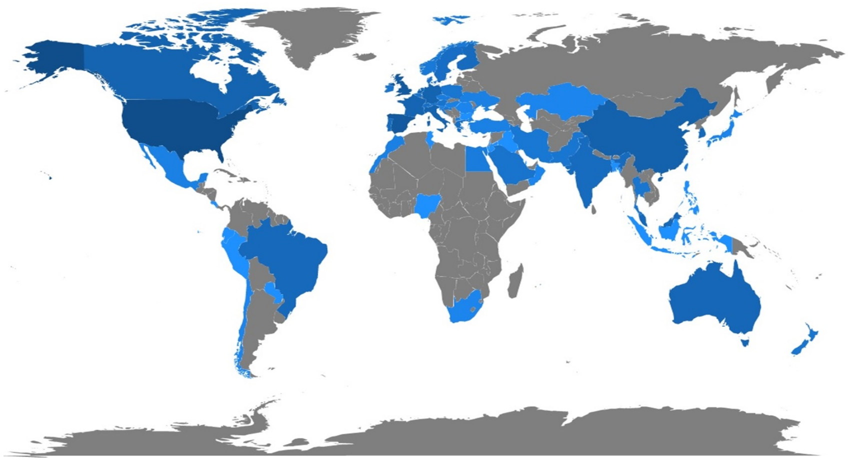

Figure 12 – Country Scientific Production (ROI)

Table 13 presents the most cited countries, considering first author's affiliation. In the sample with the 15 most cited countries, the five top countries represent 69.6% of these citations. Moreover, half of the citations are related to authors affiliated in American and British institutions.

Table 13 – Most Cited Countries (ROI)

Country	Total Citations
USA	318
UK	271

Table 13 – Most Cited Countries (ROI)

Country	Total Citations
Germany	183
Canada	126
Australia	84
Korea	75
Finland	67
Brazil	49
China	44
Italy	44
Spain	39
Denmark	36
Switzerland	34
Turkey	31
Netherlands	30

Table 13 shows that some of the countries that are very representative in terms of productivity can be less cited. China, for example, is the 3^{th} country in terms of publications but is 9^{th} in terms of citations.

4.1.2.4 ROA

The annual production of articles in the ROA group presented an average yearly growth of 23.12% in the period. Unlike all other groups, the number of papers published in the ROA group in 2020 is already higher than in each of the three preceding years, which seems to indicate an increasing interest in this method.

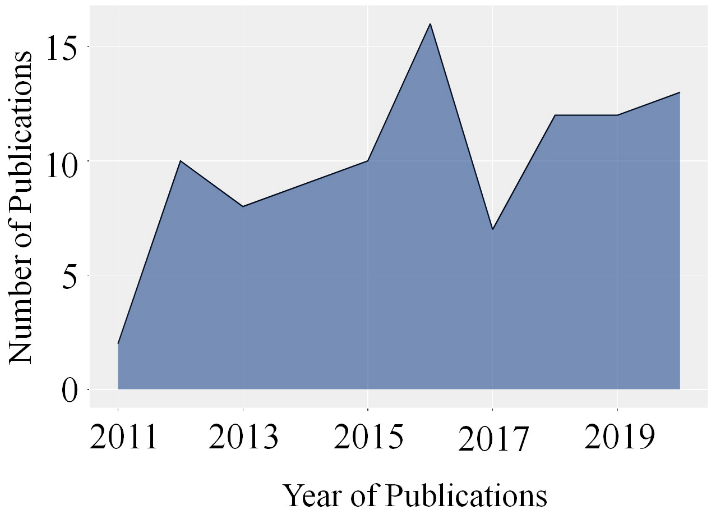

Figure 13 – Annual Scientific Production (ROA)

Considering the more influential authors, the most frequent year of the first publications on the topic was 2014 with 33.3% of the publications, as indicated in table 14.

Table 14 – Authors Impact (ROA)

Author	h_index	g_index	NC	*Year
Fleten S. E.	4	5	218	2012
Hagspiel V.	3	4	19	2018
Madlener R.	3	5	25	2014
Boomsma T. K.	3	3	205	2012
Zhang M. M.	3	3	107	2016
Linnerud K.	3	3	85	2014
DI Corato L.	3	3	35	2011
Ferreira P.	2	3	64	2014
Fuss S.	2	2	135	2012
Bartolini F.	2	2	40	2012
Gazheli A.	2	2	24	2013
Barroso M. M.	2	2	22	2014
Iniesta J. B.	2	2	22	2014
Ashuri B.	2	2	19	2015

Table 14 – Authors Impact (ROA)

Author	h_index	g_index	NC	*Year
Glensk B.	2	2	5	2019

The analysis of the most frequent words in the ROA group also demonstrated that wind energy was the only source with occurrences among the 15 main keywords with 25 occurrences. The most cited papers included in the ROA group are listed in Table 15. Results indicate that 53.3% of these listed studies were published in the years 2015 and 2016.

Table 15 – Most Cited Papers (ROA)

Authors	Year	Citations
Boomsma et al. (2012)	2012	157
Fuss et al. (2012)	2012	68
Reuter et al. (2012)	2012	67
Zhang et al. (2016b)	2016	54
Wesseh and Lin (2016)	2016	53
Ritzenhofen and Spinler (2016)	2016	53
Santos et al. (2014)	2014	49
Monjas-Barroso and Balibrea-Iniesta (2013)	2013	48
Jeon et al. (2015)	2015	45
Zhang et al. (2016a)	2016	43
Wesseh and Lin (2015)	2015	41
Kim and Lee (2012)	2012	41
Bruno et al. (2016)	2016	36
Hach and Spinler (2016)	2016	35
Detert and Kotani (2013)	2013	35

Table 16 shows the most relevant journals for this set of articles. The five main journals concentrate more than 47% of the publications of all 99 works in the sample.

Table 16 – Papers by Source (ROA)

Sources	Articles
Energy Policy	11
Applied Energy	10
Energy Economics	10
Energies	8
Energy	8
Renewable Energy	5
European Journal of Operational Research	3
Journal of Cleaner Production	3
International Journal of Greenhouse Gas Control	2
Journal of Construction Engineering and Management	2
Agricultural Finance Review	1
Aims Energy	1
Biomass and Bioenergy	1
Canadian Journal of Agricultural Economics	1
Chinese Journal of Population Resources and Environment	1

Figure 14 describes the scientific production for the top 15 publishing countries. The authors affiliated with Chinese institutions account for 21% of these publications. Germany lies in second with 9.1% followed by Norway, South Korea, and the UK, all of them representing 8.1% of these publications.

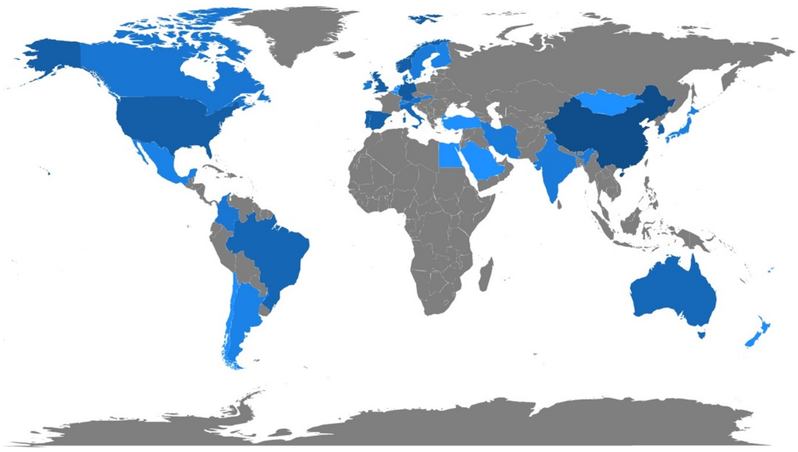

Figure 14 – Most Cited Countries (ROA)

Table 17 shows that China is also a relevant country when it comes to articles cited by authors linked to their institutions. In this group, the USA has no leadership either in the production of articles or in citations.

Table 17 – Most Cited Countries (ROA)

Country	Total Citations
UK	296
China	168
Austria	143
Germany	140
Korea	130
Spain	101
USA	80
Portugal	49
Brazil	40
Italy	40
Japan	35
Iran	27
Sweden	26
Canada	23
Denmark	20

4.2 Qualitative Analysis

For the qualitative content review, the five most cited studies from each of the four groups previously analyzed were addressed.

4.2.1 TPEM

In the most cited articles in the TPEM group, Espinosa et al. (2012) combined PBP with LCOE to evaluate simplified photovoltaic cells. The authors proposed a polymer solar cell technology capable of generating very low-cost solar energy, capable of being paid for during a day of use; in this sense, the PBP is considered an indicator to assess the daily payback of the investment. The authors highlight the scalability factor as a preponderant to guarantee a scale production to the point that the generation is sufficiently compensable to this one-day payback.

Şengül et al. (2015) used PBP as a criterion for the classification of renewable energy supply systems in Turkey. However, the use of the traditional PBP method is only peripheral and is set as one of the criteria included in the proposed MCDM approach.

Bradbury et al. (2014) applied the IRR indicator to assess the economic viability of implanting different energy-storage systems responsible for the greater stability and efficiency of the renewable energy system. The authors concluded that, among the storage systems compared in the study, the most viable are Pumped Hydro Storage, Sodium Nickel Chloride batteries, and compressed air energy storage.

Boomsma et al. (2012) examined the sources of uncertainty related to the choice of support schemes, namely, feed-in tariffs, and negotiation of renewable energy certificates. Although addressing TPEM, the focus of this paper is related to real option analysis, and it cites NPV as a starting point.

Schelly (2014) presented an empirical study to identify the factors that motivate the residents of Wisconsin (USA) to adopt residential solar electric technology. The author points out that PBP, considered a popular way of referring to ROI, is an important economic calculation tool capable of contributing to decision-making by investing in residential photovoltaic energy projects.

An important outcome of the works most cited in this TPEM group is the presence of studies combining two or more tools for economic evaluation. For example, Espinosa et al. (2012) combined the LCOE and PBP methodologies to price the manufacture of simplified photovoltaic cells. In this case, LCOE was mostly related to the evaluation of the project while the PBP demonstrated that the scalability of the photovoltaic cell production line can support its viability. Schelly (2014) also referred to PBP and ROI to demonstrate ways of valuing RES projects. Also remarkable is the use of these metrics as part of MCDM studies showing the importance of TPEM individually but also as part of more integrated approaches for project evaluation or energy planning.

4.2.2 LCOE

In the LCOE group, it is possible to identify that the tool is also widely used for the economic valuation of RES projects. However, Ueckerdt et al. (2013) highlighted some weaknesses in this methodology. According to the authors, LCOE does not capture the variability and integration between energy sources, which are common in the field of renewable energy. Therefore, Ueckerdt et al. (2013) proposed a new metric system based on LCOE that handles variability and integration and used the example of wind energy.

Darling et al. (2011) also emphasized the misuse of LCOE as a method of comparing electricity-generation technologies. According to the authors, the use of LCOE as a deterministic parameter can reveal an unfounded and potentially misleading sense of certainty. Instead, the authors proposed considering input parameter distributions based on available data so that an LCOE distribution can more accurately reflect the cost uncertainty associated with renewable-energy projects.

Other applications for economic evaluation of RES projects can also be used in the most cited articles of the LCOE group. Zamalloa et al. (2011) combined the use of LCOE with other traditional valuation metrics and proposed a lower-cost alternative to produce energy using microalgae as a raw material.

Li et al. (2013) carried out a techno-economic viability study of a hybrid and autonomous energy system combining wind and photovoltaic sources with an energy storage system in a residence in Urumqi, China. For the case study, the authors concluded that the autonomous hybrid system is economically more interesting than systems that use only one of the sources associated with storage.

Dalla Rosa and Christensen (2011) also used LCOE as a methodology for calculating energy efficiency applied to homes. In view of the high demand for electricity for heating systems in regions in northern Europe, the authors demonstrated that heating systems based on RES are reliable in supply security for users in Denmark. LCOE was used to show that investment costs represent up to three quarters of total expenditure over a 30-year period.

The use of LCOE is recurrent for the viability analysis of domestic renewable energy systems for both electricity and heat generation. This factor may be related to the use of software specialized in this type of approach and which uses LCOE as an indicator of viability of the projects, such as the HOMER software (Hybrid Optimization Model for Electric Renewables) (see for example Sen and Bhattacharyya (2014)). The simplicity of the method allied to the industrial acceptance to compare energy technologies must be underlined. Regardless of the criticisms, the reviewed papers demonstrated the relevance of the metric and opened routes for possible extensions and improvements.

4.2.3 ROI

Jenner et al. (2013) used ROI as a dependent variable in a panel data model to confirm that policies to support renewable energy are important tools to drive capacity development in this sector in Europe. The authors found that incentive policies drive RES investments via the effect on the expected ROI.

The work of Schelly (2014) addressed ROI in general terms for assessing the rationale and economic impacts of residential solar electricity adoption. Eriksson and Gray (2017) reviewed the transition to electricity for transportation including battery and fuel cell electric vehicles. The authors' critical analysis is focused on the integration between hydrogen energy technologies and hybrid energy systems. When referring to ROI, the authors encompassed several economic metrics with the main objective of showing the need to evolve and give way to more comprehensive mechanisms with a holistic view including environmental and social considerations.

Cherrington et al. (2013) analyzed the impact of the revisions of solar photovoltaic tariffs in the UK. They applied a financial analysis for two installations to identify the impact of these tariff cuts on the ROI and simple PBP of the photovoltaic system. The authors concluded that, even with a lower tariff, micro-installations for photovoltaic power generation can still be viable. However, they highlighted the need for these investments to focus on more efficient modules while considering the costs related to the disposal of materials at the end of their useful lives.

Likewise, Muhammad-Sukki et al. (2011) also analyzed the deployment of electric power photovoltaic systems for both domestic and nondomestic uses in Japan and computed ROI and the simple PBP. The authors also considered the impacts of the implementation of a new tariff model in the country, which includes specific prices for solar photovoltaic installations. The authors concluded that, given the new model of renewable energy incentive tariffs, any nonresidential installation with a size of 100 KW in Japan could have an ROI of 7.43% per year, exceeding the return on value in European countries.

The studies addressing ROI showed that the term is frequently used under a broader view to assess the economic viability of an investment. As for the studies applying ROI metrics, we should highlight the simplicity of the approach as most of them rely on non-discounted approaches frequently based on accounting profit metrics and metrics combined with simple PBP.

4.2.4 ROA

In the most cited articles of the ROA group, it is possible to identify examples of applying real options to support the decision-making process. As mentioned before, Boomsma et al. (2012) analyzed the behavior of investment in renewable energy in the face of tariff support and renewable energy certificates. In view of the sources of uncertainty existing in these investments, the authors focused their analysis on a Nordic case study based on wind energy and concluded that, as the investment is made, the trade in renewable energy certificates creates incentives for larger projects.

Fuss et al. (2012) highlighted the role of uncertainties in the decision-making process for investments based on renewable energy. Considering the probability of the occurrence of certain events, the authors used the real options model to optimize the decisions for these investments.

Reuter et al. (2012) used the theory of real options to analyze the decisions of an electric energy producer to invest in a new generation capacity. This mechanism was used based on the uncertainty related to future energy prices and environmental variables. The authors pointed out that the uncertainties existing in this type of project affect the distribution of profits and demand mechanisms such as incentive rates to make investments viable and enable the entry of new investors.

Zhang et al. (2016b) used the concept of real options to evaluate an investment in renewable energy considering the existence of uncertainty in factors such as the price of CO2, the cost of non-renewable energy, the market price of electricity and the cost of investment. The authors applied the ROA to a photovoltaic solar power generation project in China and concluded that the high volatility of electricity and CO2 prices makes the country's market unfeasible to attract immediate investments in these projects. The authors also pointed out that greater subsidies and greater market stability are factors that can overcome these barriers.

Finally, Wesseh and Lin (2016) used the concept of real options to evaluate an investment in renewable energy considering the existence of uncertainty in factors such as the price of CO_2, the cost of nonrenewable energy, the market price of electricity, and the cost of investment. The authors applied the ROA to a photovoltaic solar power-generation project in China and concluded that the high volatility of electricity and CO_2 prices makes the country's market unfeasible to attract immediate investments in these projects. The authors also pointed out that greater subsidies and greater market stability are factors that can overcome these barriers.

The works using ROA confirm the close relation of this approach with TPEM as it can be seen as an important extension of traditional discounted cash-flow metrics. ROA can support the risk analysis of the RES projects in light of the market changes and technological advancements and can help assess and quantify the managerial flexibility of these projects. However, it is also obvious that this is still considered a complex approach that requires more data and more sophisticated mathematical models. If, on one hand, this poses important challenges for industrial acceptance, on the other hand, it also shows the promising potential of the applied academic studies.

4.3 Critical Analysis

The geographical coverage of the papers shows the dominant role of publications from the USA, China, and Europe. This is not an unexpected outcome and also reflects the development of RES in these countries/regions, which altogether represented 63% of the total installed RES power in the world in 2019 (IRENA, 2020b,a). Particularly remarkable is the case of China, which represented 30% of the total installed RES power in the world in 2019 against 19% 10 years ago. This somehow justifies the increasing number of papers coming from China and the number of citations particularly evident for LCOE and ROA groups. As for the USA, although showing a growth rate of almost 7% per year, it still lags behind China and Europe in installed RES power. Nevertheless, the number of papers and citations shows a promising interest from the USA scientific community in the topic of RES project evaluation.

Regarding technology concerns, wind and solar are still the main paper targets. Once more, this may be explained by the increased adoption rate of these technologies globally between 2011 and 2019, reaching more than 13% per year for wind power and more than 30% for solar power. The growth in China must be highlighted with almost 70% per year for solar power. In fact, solar power has been growing significantly for all countries, and the low initial values (with 2011 as a reference) justifies this high growth rate, especially in China, the USA, and Canada. Both LCOE and TPEM address both technologies, but it is still wind that captures most attention of the reviewed papers for ROA. This may be due to the perceived variability of the wind power output and of the market conditions that calls for further studies allowing the integration of uncertainties on the financial project appraisal.

China assumes a more influential position in both scientific production and citations on ROA. This may be linked to concerns about the uncertainties related to the expansion of the electricity system based on RES, the increasing interest of the academy in dealing with risk and managerial flexibility in project evaluation, and increasing importance of RES for Chinese investors in different countries.

In summary, some critical points can be highlighted based on the study and should contribute to answering the research question:

- The scientific studies seem to be well aligned with the RES growth with the reviewed papers reflecting a high interest in well-established RES technologies and in countries or regions with high RES share.
- Traditional models based on DCF still play a dominant role in the scientific community. Although the studies recognize the limitations and discuss, in particular, the importance of the assumed discount rate, the use of NPV, PBP, and IRR still seem to guide most investment decisions.
- The use of LCOE is far from universal, but that did not reduce its interest from the scientific community. The viability analysis of residential projects focused on distributed generation is a good example of the extensive LCOE application, and specialized software in these studies contributed to the high popularity of this indicator.
- As for ROA, the results suggest that this methodology is yet not as popular as might be expected for authors in American institutions. However, its popularization among authors from institutions located in Europe, where renewable energy systems are more developed, as well as among authors from institutions located in China, where there is a great potential for the development of this sector, can demonstrate its usefulness as a tool to analyze the viability of projects, albeit in a complementary way. The ROA does not replace the NPV but, rather, improved it by explicitly accounting for risk and managerial flexibility.
- Both LCOE and ROA papers demonstrate the need to bring together industrial practitioners and the academic community by turning simpler metrics into scientifically robust ones and disentangling complex approaches to respond to industrial needs.
- Regarding the methodology, the use of a revision based on previous established groups allowed for a better understanding of the methods and how they relate to different countries and technologies. The proposed intersection analysis also showed how different methods are related and may complement each other, which is also evident in the reduced set of journals that concentrate most of the publications. As for this last aspect, it is important to highlight that this revision included only articles that illustrated the application of financial evaluation methods for RES projects, and, as such, review articles were excluded, which may have limited the inclusion of papers from journals dedicated to reviews.

5 Conclusion

This article contributes to a better understanding of tools that support the economic evaluation of RES projects by presenting the results of a review based on scientific production on the subject. The study identified that, in the context of scientific papers, the most widespread RES projects are related to wind and solar energy.

The most traditional tools used to evaluate RES projects are more popular in solar energy than wind energy while more complex mechanisms such as ROA are more widespread in studies related to wind energy. The dissemination of instruments and techniques to measure the uncertainties related to the incidence of winds can explain this empirical evidence.

From a geographical point of view, looking at author affiliations, the most traditional techniques are more common in publications from countries such as the USA, Italy, Spain, and Germany while Asian countries, such as China and South Korea, have higher scientific production involving the technique based on real options.

The critical analysis provided some future research directions. Future research could analyze how these RES evaluation techniques vary and how they can be associated with other techniques to build more reliable and effective performance indicators. In fact, only about 23% of the reviewed studies seem to show some interlinkage between studies with the others somehow overlooking the complementarities of these indicators. In particular, the use of TPEM with ROA is well established, but LCOE is still frequently used as an independent metric that could benefit from integration in more holistic studies, for example addressing uncertainties of the energy markets and technology development.

Although the linkage between the financial studies and well-established RES technologies is evident, additional research is required to address promising new RES technologies or emerging enabling technologies.

For these innovative projects, risk and flexibility-related approaches are particularly relevant, and ROA can bring important insights. However, the use of ROA is still limited, which may derive from the perceived complexity of application and interpretation. As such, future studies should focus on identifying factors that prevent greater dissemination and usability of more complex techniques and even promote a “user-friendly” approach to these methods.

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Part II

Economic evaluation of wind power projects in a mix of free and regulated market environments in Brazil

Economic evaluation of wind power projects in a mix of free and regulated market environments in Brazil

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Abstract

The electricity market in Brazil is basically organized under two parts: the regulated market (ACR), where energy is traded through auctions, and the free market (ACL), where agents freely negotiate the price and quantity of electricity. Although ACR's revenues tend to be lower than ACL's, the auction shows that investors still value the lesser uncertainty and additional benefits brought by the regulated market. At the same time, it is possible to see a growing interest in the ACL since the price of electricity tends to be higher. This study investigates four ACL market price scenarios to analyze the expected return for investors given the uncertainty of this market. We used the traditional discounted cash flow approach complemented with Monte Carlo simulation to assess this viability. The study breaks new ground by capturing the weekly fluctuations and including the price elasticity of demand of the ACL market. The results indicate that the disclosure of the ceiling and floor price limits for the spot price can signal important information about the agents' price expectation in the ACL and can be used for the project evaluation. Furthermore, additional revenues related to the possibility of anticipating electricity supply and sales should not be disregarded.

1 Introduction

Currently, 72% of the world's energy supply comes from non-renewable sources (IEA, 2020). The environmental consequences of this exploitation have led to a steady growth in the use of renewable sources of energy over the last few years (BP, 2019; United Nations, 2020).

In addition, the pressure to reduce carbon dioxide emissions in the electricity generation process, caused mainly by burning coal, may hasten the replacement of non-renewable energy sources by renewable energy sources (RES) in the coming years (de Queiroz, 2016; United Nations, 2020).

In Brazil, almost 50% of the power generated in 2019 came from large-scale hydro plants, followed by thermoelectric plants (25%) heavily relying on biomass obtained from large sugar cane plantations, and wind power plants (nearly 13%) (ANEEL, 2020b). Even so, Brazil still has enormous potential to generate energy from other renewable sources, which needs to be explored. To achieve this, significant regulatory and technological innovations are needed.

Although wind power is not the main RES technology in Brazil, in 2020, its installed capacity reached 16 GW (ABEEOLICA, 2020). Thus, wind power is one of the most promising technologies in the country, especially in the northeastern region, mainly due to the favorable wind conditions (de Jong et al., 2017). Brazilian winds are characterized by positive factors related to stability, little variation in direction, and good intensity, which results in a high-capacity factor. In Brazil, the average capacity factor is nearly double that of the world average (ABEEOLICA, 2020).

The wind power generation sector in Brazil has grown exponentially and become an important alternative source of energy that can help reduce the environmental impact with low production costs. Another important advantage of wind power relates to the existence of more favorable winds during periods of drought, which warrants using wind farms in complement with the hydroelectric plants (EPE, 2018a). In addition to the reduced taxes by the government and the possibility of additional revenues in the negotiation of the carbon market, the high supply capacity of wind power due to the emergence of new technologies with more efficient turbines has made wind generation increasingly competitive in Brazil (da Silva et al., 2013; Pereira et al., 2012).

Wholesale electricity trading in Brazil is based on two markets schemes: Regulated Market (ACR) and Free Market (ACL), both are expressed in the Portuguese abbreviation. In ACR, the purchase and sale of energy is formalized through auctions by contracts between the generating agents and distributors. In ACL, the agents are free to negotiate bilateral contracts to agree upon the volumes of energy and prices between themselves (CCEE, 2019).

Until 2018, renewable energy supply contracts in the ACR market were subject to the availability concept. Then, the company that won the auction would receive a fixed remuneration for supplying energy, regardless of the amount generated. As of the second half of 2018, companies started to be remunerated according to the amount of energy they were able to supply. However, companies accepted in the auction are required to allocate at least 30% of the electricity production capacity of the project to the ACR.

The 2018 regulatory change tends to increase the risk in these projects as no fixed remuneration for availability is foreseen. Moreover, if the plants are unable to supply the amount of energy agreed upon at the auction, they need to cover the difference by buying energy at a spot price (PLD, in Portuguese) that is higher than the values in the ACR (CCEE, 2019).

Although the ACR tends to offer lower prices than the ACL, the auction results show that companies remain interested in participating in the auction and allocating the required minimum generation share to the ACR. This is because of the other benefits offered to participants, which go beyond selling electricity. For example, companies participating in auctions enjoy the benefit of using transmission lines granted by government plans (Dalbem et al., 2014).

The lower remuneration offered by the ACR is expected to be compensated by electricity sold under contracts in the ACL market, which usually results in higher revenue. It is, therefore, worth exploring how companies can operate in both ACR and ACL markets and what the expected return of such a strategy will be. Accordingly, this study seeks to better understand the premises that lead producers to invest in the wind power industry under this mixed free-regulated market environment in Brazil.

This paper presents and illustrates a methodological procedure for investment analysis of wind power projects that considers the possibility of selling energy in both markets. We argue that although lower prices in the ACR market can make participation in the auctions less interesting, a guarantee of revenue from that market associated with additional transmission line access benefits for auction participants should maintain the interest of companies in that market. We used the Difference Settlement Price (PLD) as a proxy for the ACL market prices and assessed whether the price limits released by the Brazilian regulatory agency in the sector (ANEEL) can be used as a reference to estimate the economic viability of the projects.

The main objective of this study is to estimate the viability of wind energy projects in Brazil that participate in both markets (ACR and ACL) considering the dynamics between energy supply and demand in the ACL portion. In addition, the study seeks to present evidence on the best use of price scenarios to estimate the viability of projects in the ACL Market, since bilateral and non-public contracts between agents in this market do not allow the analysis of historical price series.

This study used information from the last three wind energy auctions in Brazil that occurred in 2019 and the second half of 2018. For this, the traditional Net Present Value (NPV) and the Internal Rate of Return (IRR) indicators are used for a deterministic analysis. Then, for a more comprehensive evaluation, a stochastic analysis is performed using Monte Carlo Simulation (MCS) in a weekly price period that follows a Brownian Motion. Then, we calculated the annual average of these simulations for the construction of the annual cash flows of the projects.

The paper is organized as follows. Section 2 presents a review of evaluation of renewable energy projects. Section 3 provides a brief literature review about the wind energy sector in Brazil. Section 4 presents the material and methods. Section 5 describes the main economic assumptions. Section 6 presents the results and discussion, and lastly, Section 7 establishes the main conclusions of the paper and provides some insights for future research.

2 Evaluation of renewable energy projects

In addition to combating climate change, renewable energy production contributes to reducing energy price volatility as compared to the non-renewable sources, which are vulnerable to political instabilities, trade disputes, and embargoes, among others (Su et al., 2018). Thus, identifying ways of evaluating renewable energy projects is crucial to better assess the more efficient mechanisms in this environment.

There are many methodologies used to evaluate investment projects or companies. However, Siziba and Hall (2019) emphasizes that they can be classified into three main groups: (i) discounted cash flow (DCF)-based methodologies, (ii) non-DCF-based methodologies, and (iii) alternative methods. According to the authors, these three categories are distinguished by two concepts: the value of money over time and the uncertainty of the business. DCF-based methods assume the value of money over time, as opposed to non-DCF-based methodologies like Return on Investment (ROI). The alternative methods such as real options analysis (ROA) incorporate concepts of time value of money and business uncertainty.

According to Kim et al. (2018), the DCF has been used as an important tool for analyzing the economic viability of energy projects. In this methodology, most investment projects use a weighted average cost of capital (WACC) approach, which assumes using the Capital Asset Pricing Model (CAPM) to obtain a minimum acceptable rate of return (MARR) for investors (Brandão and Dyer, 2005). Indicators such as NPV, IRR, and Payback Period are included in this category. According to de Andrés et al. (2015), these three indicators can efficiently express the degree of viability of projects. Since there is a wide acceptance of DCF-based methods in the literature, this paper will use the indicators NPV and IRR as the main measure of viability analysis.

Moreover, it should be noted that the correct valuation of renewable energy projects depends on numerous factors that are not always exclusively linked to the economic analysis of the project. Factors such as environmental impacts and non-use value, which is based on the fact that people enjoy living in a cleaner atmosphere as a result of reduced emissions from fossil fuels, are also worth considering in such projects (Tsukamoto et al., 2006). As Lai and Locatelli (2021) discussed, the evaluation of energy projects can follow a policymaker's perspective and include these social benefits, or an investor's perspective and examine the monetary value of the project.

In addition, many variables used for valuing renewable energy projects are subject to uncertainties of different natures. Some examples include the uncertainty related to wind variability (Onar and Kılavuz, 2015), the price of energy (Balibrea-Iniesta et al., 2015), the investment costs (Zhang et al., 2016), or the market regulation (Eissa and Tian, 2017; Eryilmaz and Homans, 2016). In response to this, MCS techniques may be employed to assess the risk by using probabilistic approaches to combine different variables and analyze the projects under different scenarios.

Some recent examples include the use of MCS for valuing renewable energy projects. Fleten et al. (2016) examined the behavior of the investor in hydroelectric projects in Norway, for this, the authors used the NPV as a measure to verify the viability of the investments. Given the uncertainty of electricity prices in their study, the authors applied the MCS method to assess the expected value of real options in the project. Aquila et al. (2020) studied the viability of wind energy investments in Brazil by using the MCS method to complement the deterministic analysis of the results. Carvalho et al. (2020) also analyzed the viability of Brazilian wind and photovoltaic projects, while also analyzing the risk associated with anticipating or delaying projects in the Brazilian energy market. The authors used the NPV method for a deterministic evaluation and the MCS for a stochastic evaluation of the results.

DCF methodologies have been very important in guiding investment decision-making. However, its deterministic nature is not capable of capturing future uncertainties related to the projects. Thus, the complementary use of tools capable of working with these uncertainties, such as MCS, are fundamental to appropriately analyze the viability of projects. Without incorporating these uncertainties and presenting probabilistic scenarios, the viability analysis is compromised and subject to events that can render the projects unfeasible, even if their viability analysis has been positive.

This representative analysis of previous papers showed that the use of traditional DCF and MCS for renewable projects evaluation is well established, but to the best of the authors'knowledge, its use on the complex mixed regulated-free market environment to support investors decision making is still an open field for discussion. That is the case of Brazil which will be briefly presented in the following section.

3 The Brazilian electricity system

3.1 Electricity market organization

The Brazilian electric system gained importance in the 1960's with large hydraulic constructions and large transmission and interconnection systems for hydroelectric power, which enabled increased efficiency and cost reduction (Bradshaw, 2017).

However, the characteristics of state monopoly regarding the country's electricity sector began to change in the second half of the 1990's. In August 1996, the government implemented the RESEB Project (Restructuring of the Brazilian Electric Sector), as it sought to ensure the economic efficiency of the sector and inviting investments to expand the energy supply. This project was the basis for the new model of the electric sector that would appear in 2004 (de Souza and Legey, 2008).

The energy crisis that hit the country in 2001 prompted the Brazilian government to implement a new regulatory framework for the sector (Juárez et al., 2014). With the enactment of the "Law of the new electric sector model" (Law nº 10,848/04), the electricity market was segregated into the following segments: generation; transmission; distribution; and marketing/commercialization. This disentangled the activities of the companies operating in the electricity sector (Brazil, 2004).

The new regulation of the sector also created the electricity trading system with two main markets: the ACR and the ACL. In addition, it authorized creating the Electric Energy Trading Chamber (CCEE), to make the sale of electricity more efficient, among other functions.

As previously mentioned, in the ACR market, auctions for the purchase and sale of electricity were characterized by contracts that remunerated producers with a fixed revenue regardless of the quantity of energy offered. As of 2018, these contracts started to remunerate the companies considering the amount of energy offered by them. The new remuneration format started to follow a rule described by Equation (3.1).

$$RV_{i,m} = \left[\left(\frac{Pot_{delay_{i,m}}}{Pot_{Total_i}} \right) \times P_{delay_{i,m}} + \left(1 - \frac{Pot_{delay_{i,m}}}{Pot_{Total_i}} \right) \times SP_{i,m} \right] \times CE_{i,m} \tag{3.1}$$

Where:

$RV_(i,m)$ = Revenue of the plant i, calculated in the month m for the ACR market
$CE_{i,m}$ = Contracted energy of the plant i in MWh, in the month m

$Pot_{delay_{i,m}}$ = Installed power referring to generating units committed to the contract, which are not in commercial operation after the respective expected dates of granting the power plant i, ascertained in the month m
Pot_{Total_i} = Installed power referring to the complete motorization of the plant i, in the plot committed to the contract
$SP_{i,m}$ = Sale price for the plant i, in the month m, defined in auction
$P_{delay_{i,m}}$ = Resale price, defined according to normative resolution n. 595/13 or another rule that will replace it, in the month m

Table 18 describes the electricity contracting models in Brazil and compares the main characteristics of ACR and ACL markets.

Table 18 – Electricity contracting models in Brazil

Characteristics	ACL	ACR
Participants	Generators, traders, free and special consumers	Generators, distributors,
and traders		
Contracts	Free negotiation between buyers and sellers	Energy auctions promoted by CCEE, delegated by the regulatory agency (ANEEL)
Kind of Contract	Freely established agreement between the agents	Regulated by ANEEL. Called Electric Energy Trading Contract in the Regulated Environment. (CCEAR)
Price	Freely agreed between the agents	Given in the auction

Whenever the producer is unable to supply the contracted amount to the ACR, it will need to resort to the short-term market (STM) or differences market, to comply with the purchase and sale agreement. The prices of this STM are established by the CCEE and are coined as Difference Settlement Price (PLD). The price of energy in the STM tends to be higher than the prices established by agents at the auction, which leads to higher costs for the non-compliant producer CCEE (2019).

It is notable that although CCEE calculates the PLD, the maximum and minimum limits for the price are defined by regulations. Between 2015 and 2019, the ANEEL normative resolution N. 633/14 defined these limits.

The main criterion adopted to classify the winners in an auction in Brazil is based on the principle of the lowest bid price per MWh of electricity to ensure reasonable tariff rates. In the recent past, the values of wind energy prices offered in auctions showed a relative downward trend. Concomitantly, the growth of ACL in the country has attracted the attention of many power producing companies.

Figure 15 shows the evolution of the bid prices in wind energy auctions from 2017 to 2019. In the figure, the auctions with the sign A-6 (A minus 6) represent a deadline for delivery of the contracted energy within six years of the auction. Similarly, A-3 and A-4 follow the same logic and have a contractual delivery deadline of three and four years, respectively. The quotation of values in US dollars followed the exchange rate average exercised in the auction year. Auctions 2018 (A-6), 2019 (A-4), and 2019 (A-6) are called auctions 28, 29, and 30, respectively, and are used as a database for this study.

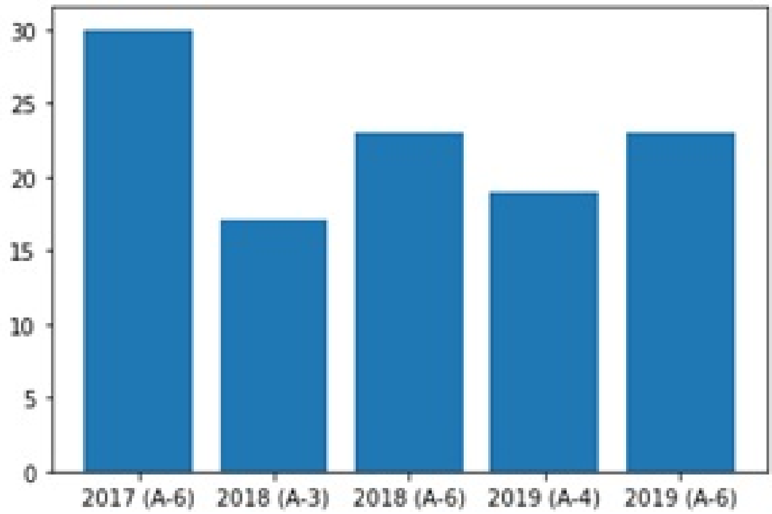

Figure 15 – Average Bid prices in Brazilian auctions (US$/MWh)

The average price established in the auctions, that included 95 projects, was 23.46 US$/MWh. The average value was 23.31 US$/MWh for Auction 28 (2018 – A-6), 19.32 US$/MWh for Auction 29 (2019 – A-4), and 23.85 US$/MWh for Auction 30 (2019 – A-6).

The Brazilian electricity system is highly influenced by hydropower plants. As such, the PLD is calculated using mathematical models that seek an optimum balance between hydroelectric plants and the thermal energy usage when rainfall is scarce. Thus, factors related to the demand for electricity, prices of fuels used in the generation of thermal energy, and the emergence of new projects and transmission lines influence the determination of an optimal price for the system, as specified by submarkets. The location distribution of submarkets of the electrical system in Brazil across 4 regions:

North (N), Northeast (NE), Southeast and Midwest (SE/CO) and South (S). The PLD prices are updated weekly for each regional submarket.

Figure 16 shows the location distribution of submarkets of the electrical system in Brazil across 4 regions: North (N), Northeast (NE), Southeast and Midwest (SE/CO) and South (S).

Figure 16 – Regions of the Brazilian electrical system
source:CCEE (2020a)

Figure 17 shows the evolution of PLD price using monthly averages.

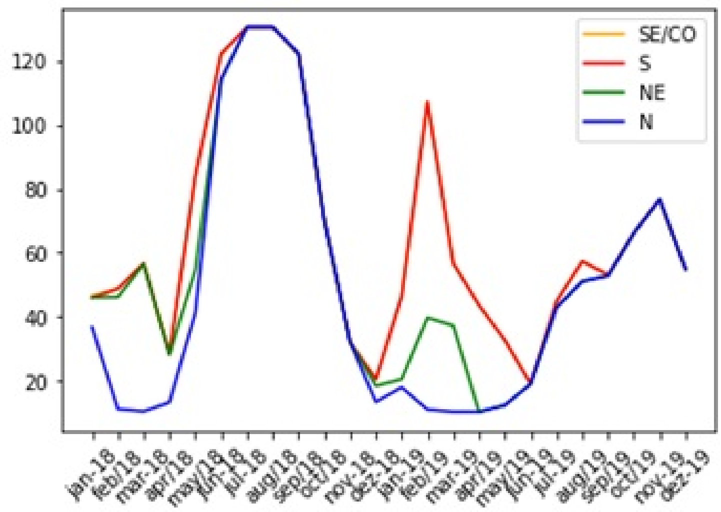

Figure 17 – PLD Price in Brazilian Market (US$/MWh)
source: CCEE (2020c)

The prices stipulated for the SE/CO and S submarkets are overlapping in Figure 17.

The internal restrictions of each region are not considered for the PLD calculation. However, energy transmission restrictions between regions are accounted for in the PLD calculation model (ABEEOLICA, 2020), which results in different prices for each region. For example, in January and February 2019 the prices in the S and the SE/CO regions peaked, which was due to the forecast of deteriorating water inflows for the system in the region. In contrast, the combination of lower consumption and higher rainfall in the N region maintained PLD at lower values. In 2018, the price values in the N region also followed the rising trend of the other regions due to the shortage of rainfall for all markets and delay in commencing the Belo Monte hydroelectric plant's operations, which is the fourth largest hydroelectric plant in the world. This market splitting requires a regional adjustment of the expected revenue of the projects as PLD will be used as a proxy for the price in the ACL. Given that the projects that won auctions 28, 29 and 30 were all located in the NE region, the PLD for the NE will be considered in the analysis.

3.2 Wind power in Brazil

The environmental impacts generated by the energy sector in Brazil have been a concern since the 1970s, which has boosted the development of research and new technologies aimed at generating renewable energy (da Silva et al., 2013; Pao and Fu, 2013).

In 2019, the supply of electricity in Brazil reached a total of 651.3 TWh and registered an increase of 2.3% as compared to 2018. The share of renewable energies in Brazil's electric matrix reached 83% in 2019, and in this total, wind energy occupied the third place in the order of importance, representing 8.6% of the total electric production matrix (EPE, 2020).

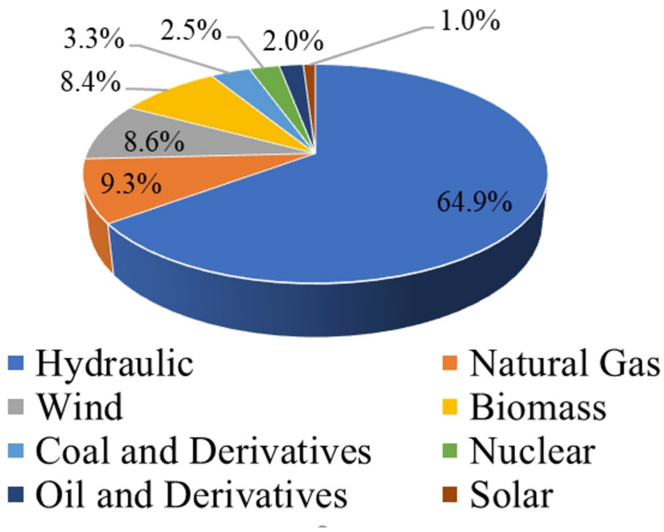

Figure 18 – Brazilian electricity production matrix 2019
source: (EPE, 2020)

The wind energy industry in Brazil has grown considerably since 2009, becoming a highly attractive Latin American market for this type of investment (Simas and Pacca, 2014). In 2019, Brazil generated 56 TWh of electricity from wind energy, a 15.5% growth as compared to 2018 (EPE, 2020). By 2029, the expansion of installed wind power capacity in Brazil is expected to be approximately 163% of the total recorded in 2019 (EPE, 2019).

Figure 19 shows that installed capacity of wind power in Brazil has grown steadily since 2010, surpassing 15GW in 2019, representing an expansion of 6.9% as compared to 2018.

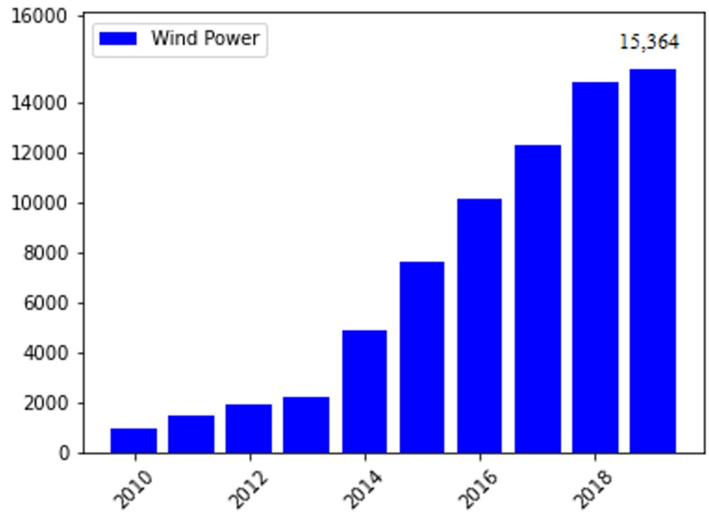

Figure 19 – Brazilian wind power installed capacity (MW)
source: (IRENA, 2020)

The large majority of Brazil's wind power capacity is installed in the Northeast region due to the high energy generation potential of the region. In 2019, Brazil had more than 7,000 generators distributed in 601 wind farms and 80% of them were located in the Northeast (Abraceel, 2019).

In addition, the Brazilian Ministry of Mines and Energy (MME) estimated that by 2029, the total installed capacity of wind power in Brazil will reach 39,475 MW (EPE, 2019). The development of wind energy in Brazil is considered one of the most promising options by the Ministry of Mines and Energy, which has reinforced the industry's competitive advantage to fulfil the demand for electricity in the coming years. The trend of expansion of wind power generation in Brazil shows that in 2029 this source of energy will correspond to about 17% of the installed capacity of the national electric matrix (EPE, 2019).

4 Material and methods

Figure 20 summarizes the methodological procedure followed in this study.

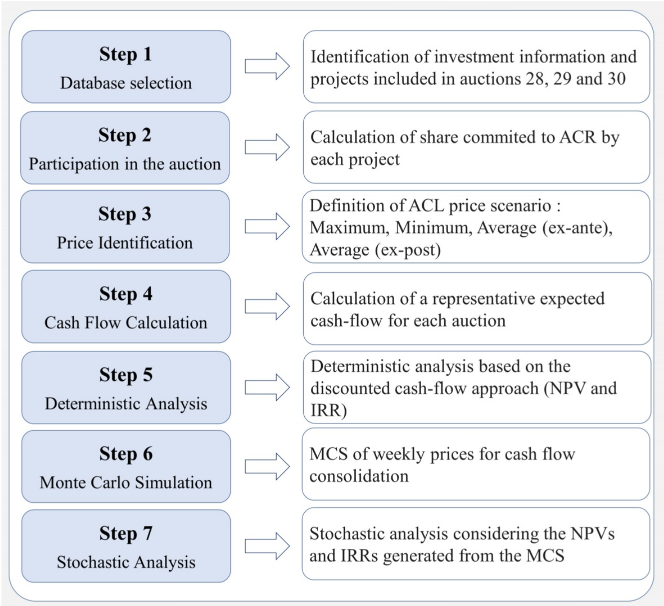

Figure 20 – Methodological procedures

In the first step, we investigated the number of participating companies in the Brazilian energy auctions during the second half of 2018 and the entire year of 2019. The first auction of 2018 was not considered as it was based on availability and tariff fixed remuneration and not on effective energy supplied.

Table 19 describes the data that was used to perform the analysis of the financial viability of wind energy projects in Brazil.

Table 19 – Dataset description

Year	Auction number	Number of companies
2018	28	48
2019	29	3
2019	30	44
	Total	95

In the second step, we calculated the percentage of energy committed to the regulated market by each project in the auctions, according to Equation (4.1).

$$p_r = \frac{\frac{TES}{tsh}}{Wr} \tag{4.1}$$

Where:

p_r = Percentage committed to the regulated market
TES = Total energy supply in the regulated market (KWh)
tsh = Total supply hours, considering 20 years (175,320 hours); and
Wr = Physical warranty (maximum available power of the plant (MWh/h).

The variable Wr corresponds to the maximum amount of energy that can be traded through contracts, measured in (MWh/h). Wr was established by MME Ordinance N. 258, of July 28, 2008, and replaced by MME Ordinance N. 101 of March 22, 2016 (MME, 2016).

Table 20 shows that the companies' commitment to the supply of energy in regulated contracts underwent a considerable reduction in 2019 as compared to 2018. Moreover, the frequency distribution presents a rather dispersed pattern for the first auction in 2018, with almost half of the companies committing less than 50% to the ACR and the remaining ones committing more than 50% to this market. In this auction, 10 out of the 48 companies committed more than 90% to the ACR. As for 2019, close to 70% of the companies committed 42% or less to the ACR and only 3 out of the 44 participants committed more than 90% of their production to the ACR. Thus, the companies seem to be using a strategy of offering a low share of energy produced to the ACR market and relying mainly on the ACL market for their operations.

Table 20 – Share committed to the ACR

Year	Number of Companies	Auction	%	Standard Deviation (%)
2018	48	28	54.69	27.03
2019	3	29	30.24	0.17
2019	44	30	36.27	17.13
Total	95	Average	40.04%	-

In the third step, four price scenarios for the ACL were defined. These scenarios differ in the price used as a proxy for the ACL Market. In the first scenario (Scenario A), the price used was the minimum limit of the PLD allowed by ANEEL. While for the second scenario (Scenario B) the price used as a proxy was the maximum limit allowed for the PLD. In the third scenario, (Scenario C) the price used as a proxy was an average between these limits. Finally, in Scenario D, the price used as proxy was an average of the real PLD market prices. In this sense, the average price of Scenario C was called ex-ante, while the average value used in Scenario D was called ex-post. We assumed that the electricity price follows a Geometric Brownian Motion (GBM), as shown in equation 4.2, with the initial price ($t = 0$) given by the price from each scenario.

Although there are different methods to simulate electricity prices, the GBM process is widespread in the literature (Lai and Locatelli, 2021). One of the advantages for this acceptance is that it is easy to be modeled. For commodity prices Pindyck (2001) point out that the use of GBM is unlikely to lead to substantial errors.

$$P_{t+1} = P_t + \sigma P_t W_t \tag{4.2}$$

Where, P_t is the electricity price at time t, σ is the standard deviation and W_t is the standard Wiener process.

The PLD price was used as a reference to analyze the viability of projects in the ACL market since accessing information about the real value of these prices is not public as they are freely determined between the parties that negotiate energy. PLD prices were used as a proxy for two main reasons. For logical reasons, it would not make sense for a power plant to migrate to the free market if its revenue obtained were not higher than that in the regulated market. This suggests that the price of energy in the free market should be higher than the minimum PLD price stipulated making selling electricity in the free market more lucrative than selling in the STM. In contrast, the price values in the ACL cannot significantly exceed the PLD price limits because, if that were the case, the buyers would remain in the regulated market, even if it meant buying energy in the short-term market. This suggests that the prices exercised in the ACL may be related to the expectation of prices in the electricity STM.

Table 21 shows the prices used as a proxy for each scenario.

Table 21 – Prices Short Term Market (US$/MWh)

Price\Year	2018	2019
Min. (A)	10.37	10.23
Max. (B)	130.53	124.12
Average (C)	70.45	67.17
Average (D)	70.78	40.39

Source: (ANEEL, 2018a, 2019b; CCEE, 2020c)

In the fourth step, based on individual data from each of the 95 projects, we calculated what we called a representative cash-flow per auction. We considered two sources of revenues in the cash flow calculation, namely, the energy sold on the free market (ACL), assuming the free prices scenarios, and the energy sold on the regulated market (ACR), accounting for the results of the auction including the committed share of each project and auction price. In the fifth step, a deterministic analysis for each of the representative projects was carried out using a discounted cash flow approach and fixed scenario prices for the 20 periods.

In the sixth step we used the weekly prices obtained in the 10,000-iteration simulated to obtain an average of annual prices for each 52-week period. After that, we programmed the existence of a gradual elasticity every five years so that the price evolution could reflect in the amount of energy sold. This way, Uhr et al. (2019) studying the price elasticity of demand among individuals in Brazil identified that the price elasticity of demand varies between -0.45 and -0.56 in the country. We will use this reference to trace an evolution of the correlation between price and quantity in the free market in four periods of 5 years (-0.15; -0.30; -0.45 and -0.6). With this, it is expected that this readjustment may represent, even partially, the dynamics of the migration of the energy supply to the ACL market and its impact on the reduction of prices. The NPV simulation process can be represented as follows:

```
for i in range (number of simulations):
        First Price = Normal Distribution (price scenarios)
        for i in range(1040):
            Add Next Price = Brownian Motion
            Actual Price = Next Price
        for i in range (20):
            Calculate the average for annual Prices
        for i in range (20):
        First Quantity = Normal Distribution (Given by database)
            Calculates price elasticity vs quantity
       for i in range (20):
            Calculate Cashflow
       Calculate NPV and IRR
```

Finally, we used the NPVs and IRRs obtained through the MCS to perform a stochastic analysis.

4.1 Model application

This section presents the economic model used to calculate the annual cash flow of the 95 wind energy projects that participated in energy auctions in the ACR market in 2018 and the entire year of 2019. In the following paragraphs, the parameters used, and the assumptions made related to the cost of investment, revenues, operation and maintenance costs (O& M), transmission fees, leasing, sectoral fees, taxes, depreciation costs, the project's lifespan, and the discount rate, are explained in detail.

We emphasize that the assumptions used to compute the cash flows of wind energy projects were based on information from 95 projects that won the last three auctions of the ACR (Auctions 28, 29, and 30). Tables 22 and 23 describe some of the main characteristics of the projects presented in these auctions, including the installed power and investment values.

Table 22 – Dispersion of project investments (US$)

Auction	Min	Max	Average	Std. Dev.
28	9,767,441	89,534,883	31,410,153	16,851,000
29	20,803,442	53,875,657	42,851,585	15,590,391
30	8,115,942	73,043,478	24,642,585	14,161,714

Table 23 – Installed Power (MW)

Auction	Min	Max	Average	Std. Dev.
28	8.4	69.3	26.05	15.09
29	21	37.1	31.73	7.59
30	8.4	75.6	23.64	13.83

Tables 22 and 23 reinforce that the auctions attract projects of different dimensions. However, when the investments are weighted by the MW, the values are less dispersed than when the values of the investments are analyzed separately. This is because the dispersion of investment values per MW is not severely affected by the different dimensions of the projects. Almost all investments per MW vary between US$ 845,410.63 and US$ 1,470,419.15 per MW. Only for Auction 28, four projects presented higher investment values that ranged between US$ 1,909,963.42 and US$ 2,239,350.31 per MW. This could occur due to external factors such as equipment shortage when constructing the plant at the time of the investment, which directly influences its acquisition price.

The plant's construction period was assumed to be equal to three years from the auction, that is, including the year in which the auction took place plus two more years. The investment amount for the construction was assumed to be released in two tranches of 50% each, with the first tranche disbursed in the year in which the auction takes place and the second tranche in the subsequent year. Although Aquila et al. (2017) and EPE (2018b) considered a period of two years to be apt for the construction of a wind plant, in this study, we considered three years to account for potential delays.

The sectoral fees followed the assumptions adopted by Custódio (2013). The reference of 1% of revenue is the parameter for estimating the fees according to CCEE and the National Electric System Operator (ONS in Portuguese).

The tax costs for the projects account for 1.65% of revenue with regards to the PIS/PASEP rate (taxes paid by companies to finance their employees'social integration programs), and 7.60% of revenue with regards to the Cofins rate (a federal tax created to finance Social Security). In addition, the values of 9% and 15% on the taxable profit regarding Social Contribution and Income Tax, respectively, were also considered. O & M costs were assumed to be equal to 12.5% of project revenues.

Leasing was also considered in the expense group, and according to COPEL (2007), the lease of land for wind farms depends on negotiations with the owners of the leased areas, which may vary between 1% and 2% of gross revenue. Therefore, following Aquila et al. (2017) and COPEL (2007), this work adopted the premise of 1% of the value of the revenue as a reference for this expense.

The depreciation rate of the equipment considered in the study was 5% of the cash-flow per year, allowing for the total depreciation of the investment over the useful life of the projects, which was assumed to be 20 years, this parameter is also found in other studies containing analyzes on the depreciation of wind farms Aquila et al. (2020).

All cost and revenues values were proportionally assigned to the ACR and ACL shares. The only exception was for costs related to transmission fees assigned only to the ACR market. This cost was set at US$1.60/KW in accordance with Technical Note n. 146/2018-SGT/ANEEL (ANEEL, 2018b), which establishes the tariffs for the use of the transmission system (TUST) for the 2018/2019 period. As specified in ANEEL, it is important to mention that wind farms with power up to 30MW are entitled to a reduction of at least 50% of these tariffs ANEEL (2004). For wind plants larger than 30 MW, the full tariff is due.

Finally, the discount rate of 7.66% in 2018 and 7.39% in 2019 was used based on the reference WACC rate for the sector released by ANEEL (ANEEL, 2020a). The fee charged for the inspection of electricity services (TFSEE) established by ANEEL according to law n. 9427/1996 was not considered in the calculation because the tax applies exclusively to the consumer; in this case, the generator agent only acts as the tax transfer operator (Brazil, 2013).

Table 24 summarizes the data used in this study, including the range of values for the set of projects used in the analysis. Here, the column titled ACRCF presents the values that make up the cash flow of the ACR portion of the project and the column titled ACLCF presents the same for the ACL portion.

To express price volatility over the years, we adopted the percentage of 34.75, a value obtained by observing the weekly data provided by CCEE (2020c). The period consulted was from April 2018 to May 2020.

Table 24 – Composition of Cash Flow by market

Cash Flow Assumptions	ACRCF	ACLCF
Initial Investment	Auction 28: 31,410,153 Auction 29: 42,851,585 Auction 30: 24,642,585	
Duration (Years)	20	
Estimated Production (MWh/year)	Auction 28: 76,668 Auction 29: 44,384 Auction 30: 36,055	Auction 28: 43,556 Auction 29: 102,270 Auction 30: 59,549
(X) Price (US$/MWh)	Auction 28: 23.31 Auction 29: 19.32 Auction 30: 23.85	Table 21
Weekly Volatility (%)	-	34.75
(=) Revenue (US$)	Price X Quantity	Price X Quantity
(−) PIS / PASEP (% Revenue)	1.65	1.65
(−) COFINS (% Revenue)	7.6	7.6
(−) Operational Costs (% Revenue)	12.5	12.5
(−) ONS / CCEE tariff (% Revenue)	1	1
(−) Leasing (% Revenue)	1	1

Table 24 – Composition of Cash Flow by market

Cash Flow Assumptions	ACRCF	ACLCF
(−) Transmission cost (US$/KWh)	Auction 28: 30.12 Auction 29: 43.71 Auction 30: 28.49	-
(=) Cash Flow	(US$)	(US$)
(−) Depreciation	(% Cash Flow)	(% Cash Flow)
(=) Taxable Cash Flow	(US$)	(US$)
(−) Social Contribution	(% Taxable Cash Flow)	(% Taxable Cash Flow)
(−) Income Tax	(% Taxable Cash Flow)	(% Taxable Cash Flow)
(+) Depreciation	(US$)	(US$)
(=) Free Cash Flow	(US$)	(US$)

Given the information provided in Table 24, ACLCF is obtained through Equations (4.3), (4.4), (4.5), (4.6) and (4.7). Thus, Equation (4.3) describes the annual cash-flow including all revenues (R) minus taxes, leasing, and OPEX costs, which account for 23.75% of these revenues. This value is obtained by adding the percentages of expenses related to 1.65% (PIS/PASEP), 7.6% (Cofins), 12.5% (OPEX), 1% (CCEE/ONS Fee), and 1% (Leasing).

$$ACLCF = R - 0,2375 \times R = R \times 0.7625 \tag{4.3}$$

Where: ACLCF = Cash Flow of the ACL portion; and
R = Revenue

Equation (4.4) describes the ACLCF after the depreciation of 5% to the cash flow amount, deriving the taxable cash flow.

$$ACLCF_T = ACLCF \times 0.95 = 0.724375 \times R \tag{4.4}$$

Where: $ACLCF_T$= Taxable Cash Flow of the ACL portion.

Equation (4.5) describes the amount of depreciation, which is obtained by subtracting the $ACLCF_T$ from the ACLCF.

$$d = ACLCF - ACLCF_T = 0.7625 \times R - 0.724375 \times R = 0.038125 \times R \tag{4.5}$$

Where: d = amount of depreciation.

The Free Cash Flow of the ACL portion before depreciation reincorporation, $ACLFCF_d$, is obtained by subtracting the percentage of taxes regarding Social Contribution (9%) and Income Tax (15%), accounting for a total of 24%, as presented in Equation (4.6).

$$ACLFCF_d = ACLCF_T \times (1 - 0.24) = 0.550525 \times R \tag{4.6}$$

Finally, the Free Cash Flow of the ACL portion (ACLFCF) is obtained by adding the depreciation amount discounted previously.

$$ACLFCF = 0.550525 \times R + 0.038125 \times R = 0.58865 \times R \tag{4.7}$$

In this way, the project's NPV can be represented by the combination of the two NPV parts, one part of the ACR Market and the other part of the ACL Market. The equation for the ACR portion will be obtained from the assumptions described in Table 24. Since the ACR cash flow includes the transmission cost as the only monetary value, the general expression for the ACRCF is not presented as a function of revenues because it cannot be represented using a constant multiplied by R as was done with the ACL portion.

Thus, the construction of the complete NPV of the project is expressed in Equation (4.8):

$$\begin{gathered} NPV = \left[\sum_{i=0}^{1} 0.5 \times \frac{(-I_o \times p_r)}{(1+k)^i} + \sum_{i=3}^{N} \left(\frac{(ACRCF_i)}{(1+k)^i}\right)\right] + \\ \left[\sum_{i=0}^{1} 0.5 \times \frac{(-I_0 \times (1-p_r))}{(1+k)^i} + \Sigma_{i=3}^{N} \left(\frac{(R_l \times 0.58865)}{(1+k)^i}\right)\right] \end{gathered} \tag{4.8}$$

Where:

$ACRCF_i$ = ACR Cash-flow portion
I_0 = Initial investment
p_r = Percentage committed in the Regulated market
CF_i = Cash Flow in the regulated market in the year i
k = Discount rate
N = Project's lifespan; and
R_l = Estimated free market revenue based on average of the Difference Settlement Price.

Figure 21 illustrates the cash flows. This figure summarizes the main assumptions and schedule of the project. Periods 0 and 1 correspond to the financial disbursement for the investment in equal tranches. Period 2 is reserved for the third year of construction of the plant. Finally, from Period 3 the project starts to be remunerated by the project's cash flow, which extends to the last year of the project's useful life.

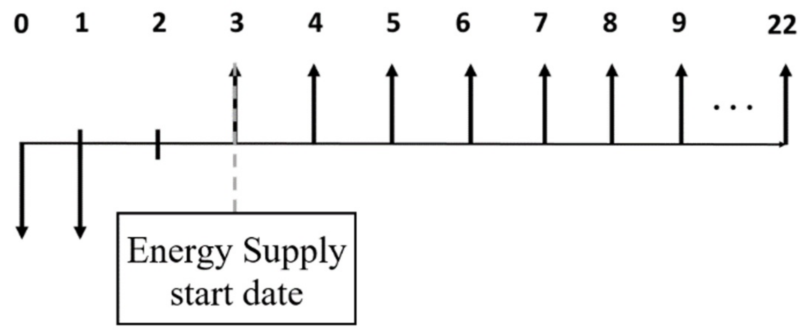

Figure 21 – Cash-flow illustration

5 Results and discussion

This section presents the results obtained with the deterministic approach, and then by adopting the stochastic approach. Both these results are discussed throughout this section.

5.1 Deterministic Analysis

Before the deterministic analysis of the scenarios, it is worth recalling that the rule for the term of supply of energy for the companies in Auction 29 was 4 years. The other two auctions had, as a rule, a period of 6 years for the supply of energy from the date the contracts were signed. Moreover, the small number of projects participating in Auction 29 (only three) and their massive option for allocating as much energy as possible to the free market is noteworthy. The NPV and IRR were computed for each representative project and the average values are reported for each scenario.

5.1.1 Scenario A

The results for all auctions under Scenario A presented a negative return, as shown by both the NPV and IRR values.

Table 25 – NPV and IRR (Scenario A)

Auction	NPV (US$)	IRR (%)	IRR–WACC (%)
28th	-18,993,520	-1.53	-9.19
29th	-31,649,641	-5.11	-12.5
30th	-16,331,533	-3.04	-10.43

The companies that participated in Auction 29 had the most negative NPV values. This is because, among the three auctions, the fewer companies that participated in Auction 29 allocated a higher share of the energy output to the ACL market. Scenario A assumes the minimum PLD prices as a proxy for the ACL market prices and this assumption severely affects the return obtained for this project. Other factors that affected this result are the changes in the WACC and exchange rate of the national currency from 2018 to 2019. Over this period, the WACC decreased by 3.65% and this contributed to improving the values of the projects that started in 2019.

These results suggest that when minimum PLD prices are considered for the ACL market, the projects tend to show a negative economic performance. Thus, minimum PLD prices can be considered as a pessimistic scenario for the investors.

5.1.2 Scenario B

In contrast to Scenario A, the results of Scenario B suggest that the auctions with a higher share of electricity allocated to the ACL market showed the best economic performance, both for NPV and IRR indicators. This is the case for Auctions 29 and 30.

Table 26 – NPV and IRR (Scenario B)

Auction	NPV (US$)	IRR (%)	IRR–WACC (%)
28th	7,761,046	10.33	2.67
29th	29,364,263	14.07	6.68
30th	19,310,951	14.9	7.51

The results in Table 26 also indicate that the use of maximum PLD values as a proxy for the analysis of the viability of these projects results in IRRs that are much higher than that suggested by the WACC for these types of projects.

Although Auction 29 generated a higher NPV than Auction 30 because of its higher installed power and investment, Auction 30 showed a slightly higher rate of return. Auctions 29 and 30 had a larger portion of its revenues concentrated in the ACL market as compared with Auction 28, which benefited these 2019 auctions given the optimistic scenario of PLD prices. .

5.1.3 Scenario C (average ex-ante)

The price used in Scenario C (average ex-ante) scales down the impact of the extremes of values found in Scenarios A and B because it is computed as the average of these values for each auction.

Table 27 – NPV and IRR (Scenario C)

Auction	NPV (US$)	IRR (%)	IRR–WACC (%)
28th	-5,619,755	5.46	-2.2
29th	-1,129,753	7.09	-0.3
30th	1,538,147	8.09	0.70

As shown in Table 27, the results of Auction 30 suggest that the assumed project is viable, and the values of Auction 29 are slightly below the reference WACC used to assess the viability of projects. The IRR of Auction 28 is also close to the minimum acceptable.

The results close to the suggested WACC reinforce the possibility that the projects may have other sources of revenue that are not being considered in this analysis. Accordingly, the electricity that sells under these conditions could bring nearly satisfactory results for most auctions and additional revenues could increase the economic performance of the projects. These additional revenues can come from the reduction of the construction period of the plant and anticipation of the first cash-flows as sales for the free market could be initiated as soon as the project is concluded. This would be possible for all auctions, but it is particularly relevant for Auctions 28 and 30 as the compulsory supply period starts only 6 years from the date the contracts were signed.

5.1.4 Scenario D (average ex-post)

According to the results for Scenario D, all projects presented a negative NPV.

Table 28 – NPV and IRR (Scenario D)

Auction	NPV (US$)	IRR (%)	IRR–WACC (%)
28th	-5,543,244	5.49	-2.17
29th	-15,557,752	2.64	-4.75
30th	-6,880,476	3.86	-3.53

In this scenario, Auction 28 demonstrated a slightly better result as compared to Auction 30, even though it had a smaller portion of its revenue from the ACL market. This is because the PLD prices in 2018 were higher than those in 2019. In addition, when compared to the prices in Scenario C, both scenarios' prices for 2018 are similar (the PLD prices are 0.45% higher than the prices used in Scenario C). However, when we compare two scenarios' prices in 2019, this is not the case. The PLD prices in 2019 are 31% lower than the those of Scenario C, which resulted in the underperformance of projects in Auctions 29 and 30.

5.2 Stochastic Analysis

The stochastic analysis assumed two main sources of uncertainty for the ACL market, namely, the market prices and quantity of energy supplied to the free market.

For the choice of the first weekly values of price and quantity, we assumed a lognormal distribution for price with mean in the price itself and standard deviation of 1% of this value, and a normal distribution for quantity with mean in the quantity itself and standard deviation of 10% of this value. The generation of random values for the analysis was obtained by the MCS method, using Python software version 3.8.3, with 10,000 simulations for each scenario, for the average values of the projects of the three auctions. When the companies'average data are simulated with the minimum PLD price (Scenario A), the chance that the IRR will be higher than the WACC was out of the 90% probability margin. The result of the simulations for the PLD maximum price (Scenario B) demonstrated a high return value for all scenarios, resulting in a highly unlikely scenario, given the characteristics of the investment. For this reason, the scenarios selected for the stochastic analysis were Scenarios C and D. Once simulated, prices evolve randomly based on the GBM (Locatelli et al., 2020). The annual average of weekly prices used for work does not fail to capture short-term price fluctuations, at the same time, the average of these weekly prices minimizes the impact of these fluctuations.

Tables 29 and 30 present the conditions assumed for the simulation.

Table 29 – Price conditions for the simulation in the ACL market (US$/MWh)

Auction (Scenario)	Average	Volatility.	Source
28th (C)	70.45	34.75*	(ANEEL, 2018a)
29th (C)	71.86	34.75*	(ANEEL, 2019a)
30th (C)	71.86	34.75*	(ANEEL, 2019a)
28th (D)	70.78	34.75*	(CCEE, 2020b)
29th (D)	40.39	34.75*	(CCEE, 2020b)
30th (D)	40.39	34.75*	(CCEE, 2020b)

* = The volatility for ACL was obtained from the PLD time series

Table 30 – Quantity conditions for the simulation in the ACL market (MWh/year)

Auction (Scenario)	Average	Std. Dev.	Source
28th (C/D)	43,556	30,374.30	(CCEE, 2019)
29th (C/D)	102,270	24,610.80	(CCEE, 2019)
30th (C/D)	59,549.03	43,003.54	(CCEE, 2019)

5.2.1 Ex-Ante average Prices

The results shown in Table 31 suggest that the IRR has a 90% chance of being between 3.45% and 7.15% for the projects representing Auction 28, 3.92% and 9.92% for the projects representing Auction 29, and 5.19% and 10.96% for the projects representing Auction 30.

Table 31 – MCS Ex-Ante Average Prices (Scenario C)

Auction	IRR (%)	Min (%)	Max (%)
28th	5.49	3.45	7.15
29th	7.14	3.92	9.92
30th	8.09	5.19	10.96

When Scenario C's prices were used, the results of the three projects suggested that there are different probabilities for the rate of return to be higher than WACC. In the projects for Auctions 29 and 30, this probability is the highest. For projects of

Auction 29 the probability of the rate of return being higher than WACC is 39.8%, while for those of Auction 30 it is 59.7%. For the projects of Auction 28, the probability of the rate of return being higher than the WACC is 4.6%. Figures 22 to 24 present the simulation performed for the projects representing Auctions 28, 29, and 30, respectively.

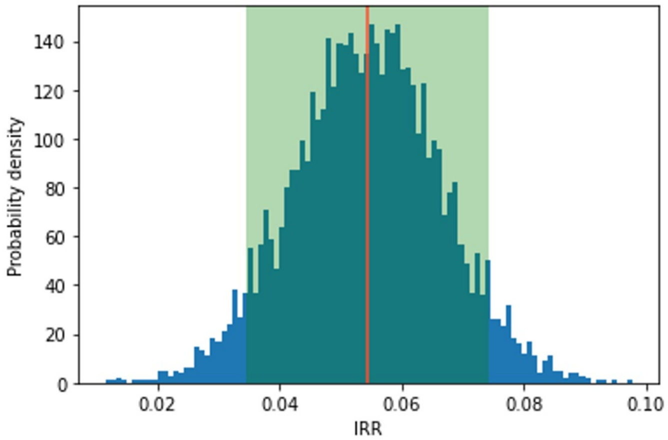

Figure 22 – MCS Ex-Ante - IRR 28th Auction

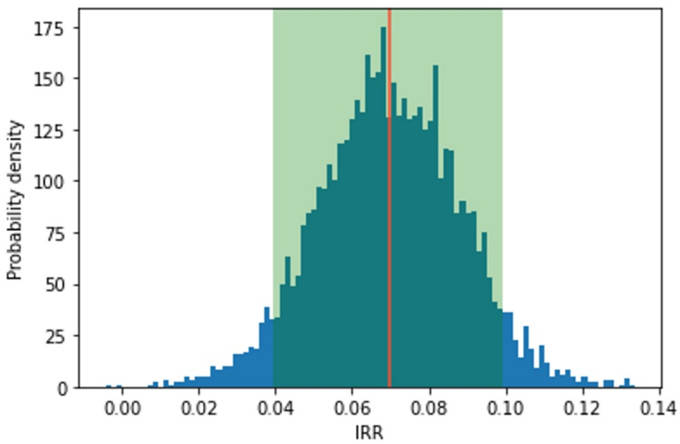

Figure 23 – MCS Ex-Ante - IRR 29th Auction

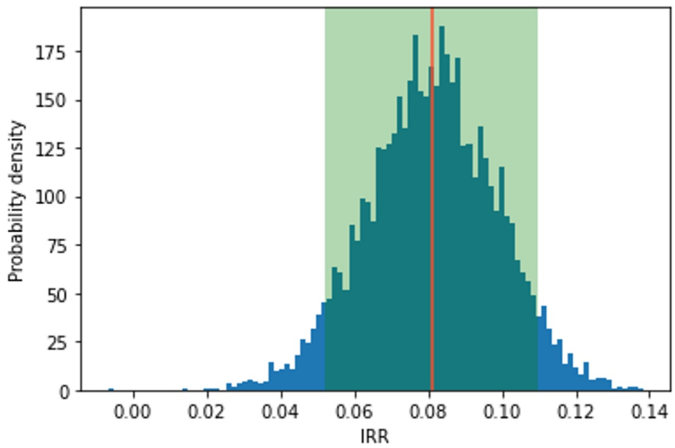

Figure 24 – MCS Ex-Ante - IRR 30th Auction

From the results of the simulations, it is possible to suggest that projects with greater participation in the ACL market are more likely to have their rates of return higher than the WACC rate. This is because ACL market prices are higher than prices published in auctions. Therefore, it would also be possible to suggest that in order to seek a greater probability of having a rate of return higher than the WACC rate, contracts negotiated in the ACL may need to establish prices above the average of the minimum and maximum prices authorized by ANEEL. These prices could be lower if the operators were able to obtain sources of revenue other than those estimated.

5.2.2 Ex-Post average Prices

The results of the stochastic analysis using ex-post price averages demonstrate lower economic performance of the projects analyzed as compared to the simulations using ex-ante prices. A peculiarity of this simulation is the low prices registered in 2019, in the results for Auctions 29 and 30. This underscores the fact that the high volatility found in the behavior of PLD prices can compromise their use as price estimators in contracts in the free market.

Table 32 – MCS Ex-Post Average Prices (Scenario D)

Auction	IRR (%)	Min (%)	Max (%)
28th	5.49	3.41	7.43
29th	2.69	0.16	4.93
30th	3.86	-1.53	6.03

Figures 25 to 27 present the simulation performed for the projects representing Auctions 28, 29, and 30, respectively.

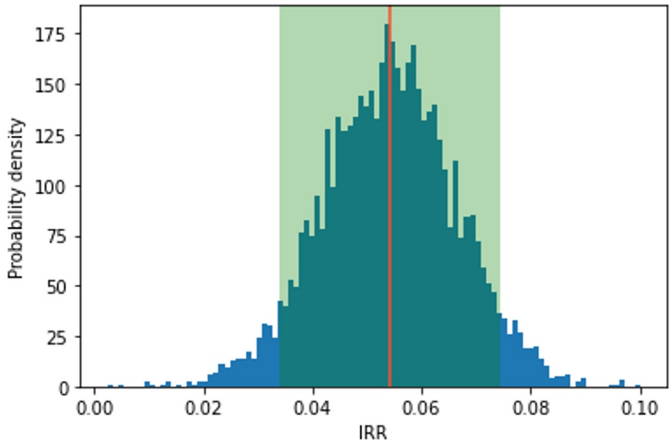

Figure 25 – MCS Ex-Post - IRR 28 th Auction

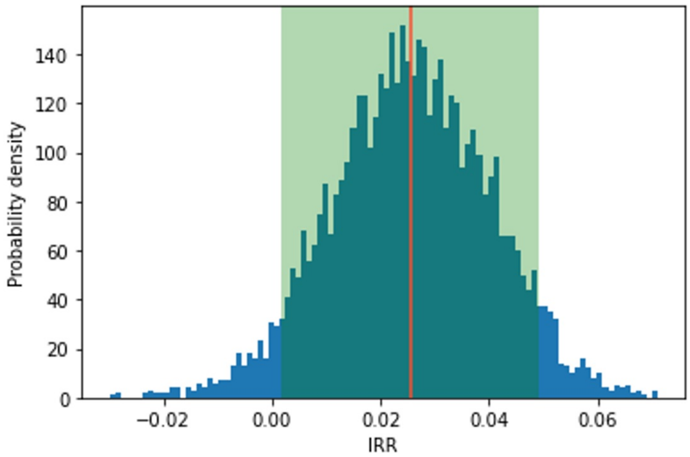

Figure 26 – MCS Ex-Post - IRR 29 th Auction

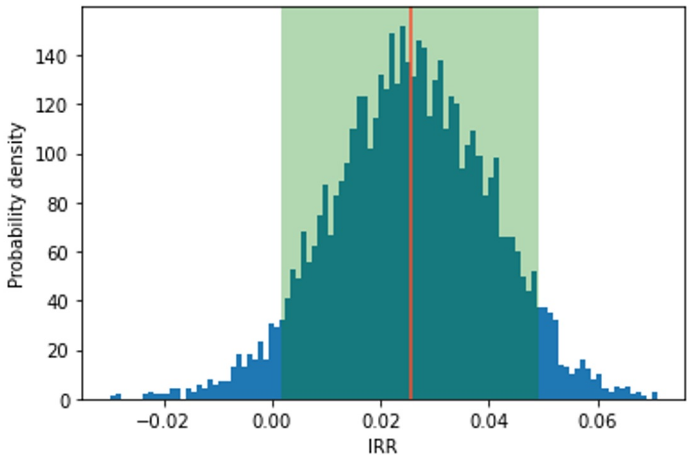

Figure 27 – MCS Ex-Post - IRR 30 th Auction

The results of these simulations, when PLD prices are used as a proxy, show that the probability of projects having a higher rate of return than WACC is considerably low. The prices used in 2019 were lower in this scenario than in the previous scenario. This drop reflects the high volatility found in the spot market. So, this would justify the investors' preference of investing in environments with less volatility, such as the ACL market, which has a greater predictability of revenue through bilateral contracts. This could also help explain the growing preference for the ACL market since 2018.

In addition, these results justify the argument that estimating the viability of wind energy projects in Brazil using PLD prices as a reference may not be the most suitable practice for assessing the financial health of the projects. Although the forecast of future energy prices is generally supported by historical prices, in the case of wind energy projects in Brazil, using the PLD historical prices can compromise the analysis of their financial viability.

6 Conclusion

The analysis of the economic viability of wind energy projects in Brazil in 2018 and 2019 demonstrated that under the assumed conditions the selected projects presented low IRR values, which were frequently below the WACC. This signifies that, under the assumed conditions, the use of PLD prices as a proxy may not the best alternative to estimate the viability of wind power projects that participate in the ACL and ACR markets together. In addition, the existence of complementary sources of revenue is an important component for the viability of these projects.

The absence of disclosure of electricity prices established in bilateral contracts in the ACL makes it difficult to identify the assumptions adopted by companies in the financial evaluations of the projects. However, the reduction in the percentage of energy committed to the regulated market in 2019 auctions (as close to the minimum as possible) suggests that the companies had a strong expectation of revenue from the ALC market. To identify the values that could help to justify this viability, we outlined 4 reference price scenarios for the ACL Market: a) minimum PLD values allowed by ANEEL; b) maximum PLD values allowed by ANEEL; c) average values of these limits; and d) PLD values that actually occurred during the project period.

With the development of the ACL market in Brazil, if the analysis of the viability of projects accounts for the fact that revenues are related to both ACR and ACL, it can improve the decision making regarding the shares allocated to each market. Thus, this paper proposes a method of analyzing the viability for these projects by considering the percentages invested in the two markets: ACL and ACR. This proposal can help banks and financiers to have a more comprehensive view of the economic interest and risks involved in the projects they finance, since it allows an analysis of the projects weighted by the percentage invested in each market. MCS was then used to account for the uncertainties in the prices of the ACL market and the amount of energy produced by the project. The results indicated that Scenario C produced a higher probability of the return rates being greater than the WACC.

The model's ability to evaluate the market reaction in four periods considering different price elasticity indices contributes to the viability estimates of these projects once it considers the potential of the project associated with the changes in the structure of the Brazilian electricity market, which is currently preparing to expand the ACL market model. In a moment when the expansion of the ACL market is a reality for the near future in Brazil, the use of a tool that can contribute to the analysis of the viability of projects while identifying this supply and demand dynamics in the market can improve tools decision-making.

As a way of making the analysis closer to reality, we simulated the prices in weekly periods, only afterwards that we used the annual averages. As a result, the short-term characteristics of price behavior have not been disregarded.

Furthermore, the identification of reference values for prices that are capable of making projects viable in the ACL are an important indicator for agents working in the regulation of these markets. In this sense, the study showed that using the average of the maximum and minimum prices announced by ANEEL (Scenario C) results in a higher probability of project viability than real PLD prices (Scenario D). Thus, it is possible to suggest that future announcements could influence the dynamics of the choice regarding which market a company would be willing to invest in, that is, the ACR market or ACL market. The results indicate that, in the absence of information on contract prices in the ACL market, a disclosure of minimum limits and maximum limits for the short-term market by ANEEL may signal some information about the behavior of prices in the ACL market. Although this information is limited, it can provide some guidelines regarding the expected economic viability of the projects.

Finally, the minimum percentages allowed for the ACR market by the companies suggests that it is attractive to offer most of the production to the ACL market. The simulations demonstrated that other sources of revenue may justify the economic interest of these wind power projects. Thus, we believe it is important for future studies to analyze these complementary sources of revenue and identify the best time for the company to start building its wind farms from the moment it wins the auction. When the companies win the auctions, a deadline is established to start offering energy in the ACR market. Generally, this interval is longer than the plant construction period. Given this, we suggest that significant additional revenues of the projects may come from the sale of energy by anticipating the construction of the power plants.

Therefore, some tools like real option analysis could be used to improve the valuation process, such that the sources of uncertainty existing in the prices exercised in the ACL market are mapped and examined in a more robust viability analysis. In particular, given the possibility of participating in the ACL market before the delivery deadline for each auction, the options to anticipate or defer the investment should be considered .

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Part III

The Application of Real Options to Wind Power projects in a mix of free and regulated market environments in Brazil

The Application of Real Options to Wind Power projects in a mix of free and regulated market environments in Brazil

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June 2021

Abstract

Brazil changed the remuneration format of supplementary energy auction contracts in 2018. As a result, companies that win these auctions are now remunerated for the amount of energy supplied in the contract, whereas before, the risk of power generation was assumed by the purchasing companies. With this change, companies began to prioritize the free energy market (ACL), where prices paid per KWh are more attractive. However, many companies still participate in energy auctions in the regulated market (ACR) to obtain other advantages, such as the priority in the concession of transmission lines. With greater participation in the ACL market, projects are subject to more price volatility. Consequently, this volatility tends to affect the ideal period for these companies to initiate the plant construction, since postponing an investment decision may enable better market conditions in the future. This article used real options analysis (ROA) to investigate the viability of wind projects installed by companies that participated in Brazil's energy auctions for the regulated market in 2018 and 2019, where the same project also supplied electricity for the ACL market. We assumed the price of electricity in the ACL and the amount of energy generated as the two variables of uncertainty in the projects. We also inserted a correlation between price and quantity in order to mirror the market dynamics present in the purchase and sale of electricity in Brazil. The results show that despite greater exposure to a volatile market, the option to defer is not always advantageous for projects. In addition, the study verified that an analysis of the volatility of project returns cannot disregard projects' proportional participation in each market (ACR and ACL), since a greater participation in the ACR market will lead to less volatility in the returns of the overall project.

1 Introduction

Wind power generation in Brazil has grown exponentially since 2007 and has become an important alternative source of energy for the country. Its reduced environmental impact, low production costs, in addition to increased wind speed during periods of drought, makes it possible to use this energy source as a complementary alternative to hydroelectric power (EPE, 2018). In 2019, wind power became the third most important renewable energy source in Brazil, representing 8.3% of the total energy matrix. When compared to 2018, total wind energy generated in 2019 grew by 15.5%, reaching a total of 56 TWh (EPE, 2020). In 2020, installed infrastructure exceeded 630 wind farms and 7,700 generators, representing a total installed wind energy capacity of 16.45 GW (ONS, 2020a).

Brazil is considered a country with high potential for the production of wind energy because it has areas that experience high volume of winds throughout the year and with little variation in its incidence(de Jong et al., 2017), especially in the northeastern and southern regions of the country. The northeastern region of Brazil alone accounted for more than 92% of the country's total wind energy production in August 2020 (ONS, 2020b). Most of the wind farms are located in six states in the region: Rio Grande do Norte (RN), Bahia (BA), Ceará (CE), Maranhão (MA), Pernambuco (PE), and Piauí (PI).

Like any investment project, remuneration for the generation of wind energy also seeks to pay all existing costs in the construction and operation of the plant, plus a rate of return capable of remunerating investors and paying creditors for the energy generated over the useful lifespan of the project. Generally, these projects have a useful lifespan of 20 years and have an average construction time of two years (Tolmasquim, 2016). As a parameter for this remuneration, the Brazilian National Electric Energy Agency (ANEEL) annually discloses a regulatory capital remuneration rate, which from the point of view of the electricity generation company, corresponds to the weight average cost of capital (WACC) used to review the tariff or revenue of distributors, transmitters, and electric power generators. For the years 2018, 2019, and 2020, the approved rates were 7.66%, 7.39% and 6.98%, respectively, for transmitters and generators, whereas for distributors, the approved rate was 7.32% for 2020 (ANEEL, 2020).

In Brazil, the electricity market is based on two trading environments: the regulated trading environment (ACR) and the free energy market (ACL) (CCEE, 2019). In the ACR, the government holds auctions through ANEEL and energy is traded between generators and buyers through an official government intermediary, the Electric Energy Trading Chamber (CCEE). In the ACL market, energy is freely negotiated between agents through bilateral contracts.

In the ACR, there are at least two types of contracts executed between the generating companies and the buyers of electricity through public auctions. Backup energy contracts (CER) seek to regulate the commercialization of energy in order to guarantee the security of electricity supplied to the national interconnected system (SIN). This energy is generated by contracted plants for this specific purpose. Another type of contract in the ACR is the additional energy contract (CCEAR), concluded between sellers and buyers supplying additional electricity to the SIN. In addition, participation in the electricity notices in the ACR allows the successful companies bidding in the auctions the benefit of requesting access to the basic grid through a transmission system use contract (CUST). This benefit of access to the transmission system can be considered one of the main incentives for participation in ACR auctions in recent years (Dalbem et al., 2014).

As a procedure to ensure security in the supply of electricity, the contracts established in the ACR stipulate that a failure to supply the contracted amount of electricity requires the generating companies to purchase additional energy in the so-called short-term market (STM), where the settlement price of differences (PLD) is established based on mathematical models that estimate the capacity of water reservoirs and the electric energy production for the subsequent periods. This price is limited by a minimum and a maximum price in force for each calculation period and set by ANEEL Normative Resolution No. 633/2014 (CCEE, 2020b).

Until mid-2018, the remuneration of contracts in the ACR was based on a fixed revenue for the availability of energy. Thus, if any risk were to compromise the supply of energy, this loss would be paid by the buyer (CCEE, 2020d). However, these conditions were changed in 2018, so that the bidding companies are now remunerated for the amount of energy supplied, as established in the contract. Consequently, the auction in the second half of 2018, called Auction 28, the auction in the first half of 2019, called Auction 29, and the auction in the second half of 2019, called Auction 30, all took place based on this new remuneration format. It is worth mentioning that each auction has a sign that indicates the deadline for the delivery of energy to the ACR market from the signing of the contract. That is, Auction 28 has the sign A-6 (A minus 6), meaning that the deadline for delivery of the contracted amount of energy is six years after the contract's signature date; the sign of Auction 29 is A-4 (A minus 4) and indicates that the deadline for the delivery of the contracted electricity is four years after the contract signature; and Auction 30 has the sign A-6, just like Auction 28.

More than that, companies that decide to participate in the auctions are authorized to have a minimum commitment of 30% of their energy generated for the ACR, if they choose to participate in the auction. Previous auctions required a minimum commitment of 70% of the plant's physical warranty. Despite this minimum commitment, companies that win the auction can direct all their energy produced to the ACL during the period that precedes the commitment term established in the contract (six or four years after the auction). This possibility is seen as a great opportunity to increase the internal rate of return of the project, since the anticipation of its construction can bring an additional revenue to the amount expected during the life of the project.

Departing from this change in the Brazilian energy regulatory framework, this study seeks to answer the following question: What is the impact of market uncertainty on the possible decision to defer the investment on wind power projects in Brazil?

To answer this question, real options reasoning was applied, since it is recognized that a deferring option might be embedded in the energy investment project. In particular, this paper will attempt to identify a real option for postponing the construction of the projects up to the deadline of three years before the moment of energy supply in the ACR, as determined by the signed contract. After this period, an option to abandon the project will be included. To accomplish this purpose, the paper will focus on the average values of the results of the last three auctions that took place in Brazil, in the years 2018 and 2019.

The approach proposed in this study contributes to the literature by presenting a structure for evaluating wind energy projects that have two sources of revenue: the ACR and the ACL markets. The work accepts that negotiations between agents in the ACL market occur based on the relationship between supply and demand and introduces a negative correlation in the portion traded in that market. The study also contributes to the improvement of mechanisms that assist in the decision-making of financing agents, since it uses the percentage of commitment of the projects in each market as a measure for the calculation of net present value (NPV) and internal rate of return (IRR), and uses the real options method to suggest more favorable timings for the start of the construction of the plants. It could help the development of credit products and services that are in line with the optimization of the viability of these projects.

The remainder of the study is organized as follows. The next section presents an overview of the literature regarding the wind energy contracts. The use of real options to incorporate future uncertainties in project evaluation is briefly addressed in section 3. Section 4 explains the methodology and the database used in the work. Section 5 presents the results obtained and a critical discussion of those results. Finally, Section 6 draws the main conclusions of the study and presents avenues for further research.

2 Wind energy contracts

The wind energy market in Brazil has several types of contracts used in different auctions. Among these auctions, the additional energy auctions are the only ones that negotiate electricity from new generation projects and that can supply energy to the ACR and ACL jointly. The main objective of these auctions is to meet the demand for electricity by distributors, which in turn supply the national demand for electricity from consumers in the ACR market (CCEE, 2020c).

Until 2018, the contracts for the ACR market had two distinct types of remuneration modalities: the “by quantity” modality, where the risks of generating the contracted amount of energy are assumed by the generators; and the “by availability,” where the distributors assume the possible risks of power generation due to uncontrollable factors (CCEE, 2020a). Additional energy contracts were characterized by the “by availability” modality. However, as of the 2018, additional they started to assume the “by quantity” modality.

Previously, the contracts allowed for the remuneration of the project weighted by the fixed revenue linked to the generating units committed to the contract and that had not entered into operation until the date foreseen in the grant act (see Equation 2.1).

$$\begin{aligned} RV_{i,m} = \Bigg[\left(\frac{Pot_{desc_{i,m}}}{Pot_{total_i}} \times RFU_{i,m} + \left(\frac{Pot_{delay_{i,m}}}{Pot_{Total_i}} \right) \times \right. \\ \left. P_{delay_{i,m}} + \left(\frac{Pot_{oc_{i,m}}}{Pot_{Total_i}} \right) \times RFU_{i,m} \right] \times EC_{i,m} \end{aligned} \tag{2.1}$$

where,

$RV_{i,m}$ = Sales revenue from the sale of electricity from plant “i”, in Brazilian currency Real (R\$), calculated in month “m”;
$EC_{i,m}$ = Contracted Energy of the plant “i”, in MWh, in the month “m”;
$Pot_{desc_{(i,m}}$ = Installed power of the generating units committed to the contract and not in commercial operation before the respective dates foreseen in the act of granting the power plant “i” calculated in the month “m”;
$Pot_{delay_{i,m}}$ = Installed power of the generating units committed to the contract and not in commercial operation after the respective dates foreseen in the act of granting the power plant “i” calculated in the month “m”
$Pot_{oc_{i,m}}$ = Installed power of the generating units committed to the CONTRACT and

in commercial operation of the plant "i" calculated in the month "m";
Pot_{total_i} = Installed power referring to the complete motorization of the plant "i", in the portion committed to the contract.
$P_{delay_{i,m}}$ = Transfer price in R$, defined according to Normative Resolution No. 165/2005, or a rule that will replace it, in the month "m"; and
$RFU_{i,m}$ = Fixed revenue per unit in R$/MWh of the plant "i" in the month "m" as defined by the auction.

In the additional energy contract in the "by quantity" modality, fixed remuneration was eliminated and the sale price established at the auction started to be used as a reference for the installed power that was up to date with the dates foreseen in the contract. In addition, a lower remuneration started to be applied to the generating units that had not entered into operation after the dates established in the contract (see Equation 2.2).

$$RV_{i,m} = \left[\left(\frac{Pot_{delay_{i,m}}}{Pot_{total_i}}\right) \times P_{delay_{i,m}} + \left(1 - \frac{Pot_{delay_{i,m}}}{Pot_{Total_i}}\right) \times PV_{i,m}\right] \times EC_{i,m} \tag{2.2}$$

where,

$RV_{i,m}$ = Sales revenue from the sale of electricity from plant "i", in Brazilian currency Real (R$), calculated in month "m";
$EC_{i,m}$ = Contracted Energy of the plant "i", in MWh, in the month "m";
$Pot_{delay_{i,m}}$ = Installed power of the generating units committed to the contract and not in commercial operation after the respective dates foreseen in the act of granting the power plant "i" calculated in month "m"
$P_{delay_{i,m}}$ = Transfer price in R$/MWh defined according to Normative Resolution No. 595 of 2013, or a rule that will replace it, in the month "m";
Pot_{total_i} = Installed power referring to the complete motorization of the plant "i" in the portion committed to the contract; and
$PV_{i,m}$ = Sale price, in R$/MWh of the plant "i" in month "m" as defined at the auction.

Despite the existence of more than one type of contract to sell electricity from renewable sources in Brazil's electricity system, contracts for additional energy have the capacity to decide the amount of energy they will allocate for sale at the auction and the quantity that will be allocated to the ACL market. For this reason, these contracts will be those used as the object of this study.

3 Real Options Overview

The real options theory incorporates the related future uncertainties reflected in projects to allow for managerial flexibility to adjust to uncertainties. As a result, it becomes possible to manage actions capable of adjusting the projects to adapt it to possible changes. In this sense, Kozlova (2017) points out that traditional literature classifies real options into at least seven types: 1) option to defer an investment, 2) option to divide an investment into several stages, 3) option to abandon an investment, 4) option to change the scale of the project, 5) option to stop and restart operations, 6) option to grow, and 7) option to change inputs/outputs.

In the energy sector, the growing deregulation associated with the high level of competitiveness in the sector has contributed to the appearance of additional costs related to market uncertainties that are often not properly measured by conventional viability analysis techniques (Fernandes et al., 2011; Santos et al., 2014). With this, real options analysis (ROA) has been applied with increasing frequency to the evaluation of renewable energy projects, such as hydroelectric, wind, and solar, among others (Martín-Barrera et al., 2016; Mancini et al., 2016) .

When the energy source of interest is wind, many studies justify the use of ROA to capture uncertainties related to energy prices and its production costs (Wesseh and Lin, 2016). In this regard, Kozlova (2017) highlights that 40% of studies related to real options applied to wind power generation are concentrated in a single source of uncertainty, namely, the price of electricity. Aquila et al. (2020) used real options to investigate the viability of a wind farm enterprise with the option to abandon it at any point throughout the life cycle of the project. The authors analyzed the aspect of the uncertainties inserted in the revenues from sales of electricity in the spot market. Zhang et al. (2020) used real options to identify equilibrium prices for wind energy in China in a scenario where the government plans to reduce or eliminate subsidies; the authors advocated the gradual reduction of subsidies in much of the country.

With another focus, Maeda and Watts (2019) incorporated the volatility of the costs associated with the technological evolution of renewable energy projects in their analysis and highlighted the importance of incorporating correlations between the different sources of uncertainty in the application of these studies, such as the price of electricity and the cost of energy generation, for example.

In addition, Gazheli and van den Bergh (2018) used ROA to investigate three investment possibilities between wind and photovoltaic energy. The authors concluded that the uncertainties regarding future prices, energy supply costs, initial costs and learning rates of each technology are factors that favor investment in only one energy source. This conclusion suggests that diversifying energy could be a wrong strategy.

However, there are also many other types of uncertainties such as uncertainties related to the consistency of wind sources and climate change (Kim et al., 2018; Martinez-Cesena and Mutale, 2012), regulated subsidy payments (Barroso and Iniesta, 2014; Eryilmaz and Homans, 2016), and technology (Barroso and Iniesta, 2014; Ritzenhofen and Spinler, 2016) that have been addressed by the use of ROA.

ROA is also used for the economic evaluation of projects integrated with the storage of wind energy. Liu et al. (2019), for example, for example, included the dynamic of energy storage costs and analyze some market scenarios. With that, considering a learning rate of 10% in storage costs, the authors proposed an ideal time window for investment in a wind power project.

The use of ROA is justified by the existence of uncertainties capable of changing the expected result of a project. As a result, the managerial flexibility found in these uncertainties makes it possible to make decisions focused on taking advantage of these opportunities. Several uncertainties can be analyzed in an investment

Blyth et al. (2007) addressed the uncertainties related to the effect of political decisions on changing expectations regarding the future price of carbon. Eryilmaz and Homans (2016) analyzed the impact of uncertainties present in government subsidies that impact the competitiveness of projects, Monjas-Barroso and Balibrea-Iniesta (2013) identified the uncertainties that affected projects in three countries, such as the cost and production of electricity, investment costs, and the consumer price index. Wickart and Madlener (2007) analyzed the risk of uncertainties related to the volatility of energy prices.

Kim et al. (2017) highlights the constant technological innovations in renewable energy area and the growing process of deregulation of the electricity market in several countries to point out that the volatility of the project's cash flow is much more important in RE projects than in traditional energy projects.

3.1 Source of uncertainty

The use of real options as a tool for analyzing the viability of projects is based on the uncertainties associated with these projects, which in turn is identified based on their volatility. To obtain a project's volatility we need to investigate the volatility of the uncertainties associated with the cash flow (Copeland and Antikarov, 2001). In this case, the price of energy on ACL market would be the main indicator associated with a project's uncertainty. This makes the price forecasting process, as well as its identification of volatility, important steps in the process of identifying these uncertainties.

Weron (2014) classifies the models used to forecast electricity prices in five groups: i) multi-agent models, ii) available models, iii) reduced form models, iv) econometric/statistical models, and v) computational intelligence models. According to the author, the reduced models are characterized by having statistical properties of electricity prices over time, with high-risk management and evaluation of derivatives. On the other hand, Nowotarski and Weron (2018) presented four approaches to the construction of electricity price probabilities: i) historical simulation, considering empirical forecast intervals for a given sample, ii) adjusted distribution-based probabilities, iii) bootstrapped prediction intervals, and iv) a quantile regression average (QRA).

For Benth and Paraschiv (2018), there are basically two ways to model future prices in commodity and energy markets: the use of stochastic models for the analysis of forward price trends based on the spot price, and alternatively, the direct identification of forward prices, known as the forward curve.

Regarding the price forecast terms, Weron (2014) points out that there is no consensus around this definition. However, short-, medium-, and long-term references can be considered important indicators. In this sense, the short-term forecast of these prices would generally involve a horizon of a few minutes to a few days ahead, while the medium-term reference would consider a horizon of a few days or months, and the long-term reference would be forecasts for months or even years ahead. According to the author, medium-term calculations are preferred for calculating risk management and pricing derivatives, where the valuation would be based on price distributions in a given future period.

According to Nowotarski and Weron (2018), the 'best guess' for defining a probabilistic forecast of electricity prices is to have the spot price as a starting point.

In addition, Nowotarski and Weron (2015) argue that the lack of systematic evidence of the performance of a specific model in relation to other electricity price forecasting models would motivate the use of spot prices as a good proxy for this type of forecast.

3.2 Stochastic process

The most popular stochastic process used in real options is the geometric Brownian motion (GBM) (Kitzing et al., 2017). It assumes that the variations in uncertainties in a project are normally distributed. This model was initially used by Black and Scholes (1973) to represent the evolution of the stock market. Today, the GBM is also used as a reference in many studies on real options, both for the simulation of values related to the value of projects in renewable energy (Liu and Ronn, 2020) and to electricity prices (Locatelli et al., 2020).

Several papers that study uncertainty variables associated with real option decisions use GBM as a stochastic process. Locatelli et al. (2020) used GBM to simulate electricity prices. According to the authors, the advantages are related to the ease of modeling this process in a spreadsheet, in addition to the few parameters necessary for its modeling. Boomsma et al. (2012) and Ritzenhofen and Spinler (2016) found that GBM does not bring significant losses because since investments in power generation are considered long-term investments, the effect of reversing the average in the short term would have less influence on the values. Ritzenhofen and Spinler (2016) used the real options model to evaluate investments in non-renewable energy. To this end, the authors considered the GBM as stochastic process to analyze investment uncertainties, in particular CO_2 prices and the cost of non-renewable energy.

Wesseh Jr and Lin (2016) argued that the GBM could be considered a realistic process and emphasized that energy prices in China do not necessarily reflect production costs accurately. Zhang et al. (2016b) assumed GBM as a stochastic process for CO_2 prices in both China and Europe and concluded that the high volatility of electricity and CO_2 prices generated high investment costs, discouraging immediate investments. Zhang et al. (2016a) also assumed the use of GBM as a stochastic process for modeling uncertainties related to CO_2 prices and investment costs. Following another path, Penizzotto et al. (2019) highlighted that uncertainties in the future dynamics of electricity tariffs and investment costs can be adequately described by a mixed stochastic process that combines GBM with jumps considering a Poisson distribution.

Madlener et al. (2019) also used GBM to investigate the expansion and technological development of wind turbines. The authors concluded that the reuse of wind turbines by repowering them could be economically viable considering the price dynamics of the spot market for electricity. In the same line, Kim et al. (2020) simulated uncertainties in fossil energy prices and carbon emission rights prices in Korea using GBM assumptions. According to the authors, the uncertainties in the price of carbon emission rights on investment in R&D generate positive effects in attractive option values for investment. Sendstad and Chronopoulos (2020) analyzed the impact of technological, political, and electricity price uncertainties in decisions to invest in renewable energy. The authors assumed that the price of electricity follows a GBM and that the uncertainties related to political and technological interventions are associated with an independent Poisson process.

Yao et al. (2020) used the real options theory to optimize the level of subsidy for the development of CO_2 removal technologies. The authors also used GBM to model uncertainties in operating and investment costs and point out the possibility of using other stochastic processes to capture the dynamics of the variables' uncertainty. However, the authors cited Boomsma et al. (2012) to highlight that GBM may be sufficient for spot energy prices. Fan et al. (2020) also evaluated investments in renewable energy considering subsidies for the development of technologies for carbon capture and used GBM as a stochastic process for modeling uncertainties related to CO_2 prices and generation costs.

The use of GBM by the vast majority of works that use real options is confirmed by Pringles et al. (2020) who developed a methodology to evaluate investments in electricity generation from photovoltaic sources and evaluated the option to defer investment in the expectation of better conditions or a better location for a project's installation. For this study, the authors used the GBM associated with Poisson jumps.

Despite the popularization of the use of models based on GBM, the mean reversion process can be considered more appropriate for commodity prices (Mac Cawley et al., 2020). The justification for this is supported by the microeconomic relationship between agents that, on the one hand, pressures demand when prices are below a long-term equilibrium level and on the other hand, induces demand reduction when prices assume values above this equilibrium level (de Lamare Bastian-Pinto, 2015). Hörnlein (2019) argued that commodity prices have a mean reversion behavior and modeled electricity and gas prices using mean-reverting Ornstein-Uhlenbeck process. In this sense, de Oliveira et al. (2019) identified that this stochastic process is the one that best explains electricity prices in Brazil.

In this way, Scarcioffolo et al. (2018) highlighted that the models of electricity prices must include characteristics related to the occurrence of peaks followed by a downward movement. According to the authors, the fact that electricity is not a storable asset implies a price behavior based on the occurrence of these jumps. The authors therefore used the mean reversion with Poisson jumps as a stochastic process for electricity prices.

Table 33 explores a recent view of the use of stochastic processes in papers related to renewable energy.

Table 33 – Stochastic process in renewable energy studies

Study	Source	Country	Process	Uncertainties
(Zhang et al., 2016c)	Solar	China	GBM	CO2 Price, Energy cost, Investment cost

Table 33 – Stochastic process in renewable energy studies

Study	Source	Country	Process	Uncertainties
(Wesseh and Lin, 2016)	Wind	China	GBM	Costs
(Ritzenhofen and Spinler, 2016)	Wind	Germany	GBM	Price
(Zhang et al., 2016a)	Solar	China	GBM	Investment costs CO2 Price
Scarcioffolo et al. (2018)	Wind	USA	MR PJ	Price
(Finjord et al., 2018)	Wind	Norway Sweden	GBM	Price Green cert. Price
(Hörnlein, 2019)	Gas-fired	Germany	MR PJ	Prices
(Madlener et al., 2019)	Wind	Germany	GBM	Revenue
(Penizzotto et al., 2019)	Solar	Argentina	GBM PJ	Tariffs Investment Costs
(de Oliveira et al., 2019)	-	Brazil	MR	-
(Aquila et al., 2020)	Wind	Brazil	MR PJ	Price
(Locatelli et al., 2020)	-	-	GBM	Price Capital costs Fuel Price Greenhouse costs
(Kim et al., 2020)	-	Korea	GBM	Fossil energy price
(Sendstad and Chronopoulos, 2020)	Wind	-	GBM PJ	Price Political Technological
(Yao et al., 2020)	-	China	GBM	Operational costs Investiment Costs
(Pringles et al., 2020)	Solar	Argentina	GBM PJ	investment costs
(Fan et al., 2020)	Coal-fired Wind	China	GBM	Carbon Price Capital Costs Operational Costs
(Liu and Ronn, 2020)	Solar	China	GBM	Price CO2 Price Investment Cost

To model commodity prices, mean reversion can be considered the more suitable process (Adkins and Paxson, 2016; Boomsma and Linnerud, 2015; Mac Cawley et al., 2020; Ritzenhofen and Spinler, 2016). The justification for this is supported by the microeconomic relationship between agents, which on the one hand pressures demand when prices are below a long-term equilibrium level and which on the other hand induces demand reduction when prices assume values above this equilibrium level (de Lamare Bastian-Pinto, 2015). Andersson (2007) studied about 300 different commodities over three years to confirm the clear evidence that commodity prices, in general, follow mean reversion process patterns.

4 Methodology

4.1 Methodological procedures

The calculations performed in this study followed a sequence of six steps: the first step was to identify the assumptions used in project cash flow forecasts. For this, actual data from 95 wind energy projects that won Auctions 28, 29, and 30 for additional energy in the ACR Brazilian market were selected. Then, a representative cash flow was built for each auction with the data from each project. In the third step, a representative Net Present Value (NPV) and Internal Rate of Return (IRR) for each auction were calculated. In the fourth step, a stochastic analysis of ACL energy prices and the amount of energy supplied by the projects was carried out. The stochastic process used for the analysis of energy prices in the ACL market was the mean reversion process with Poisson jumps as the database used as reference showed these characteristics. In the fifth step, a Monte Carlo simulation to identify the volatility of the projects based on their return was performed. Finally, in the sixth step, we calculated the expanded NPV and built the decision tree for the projects.

Figure 28 illustrates the construction of the adopted procedures.

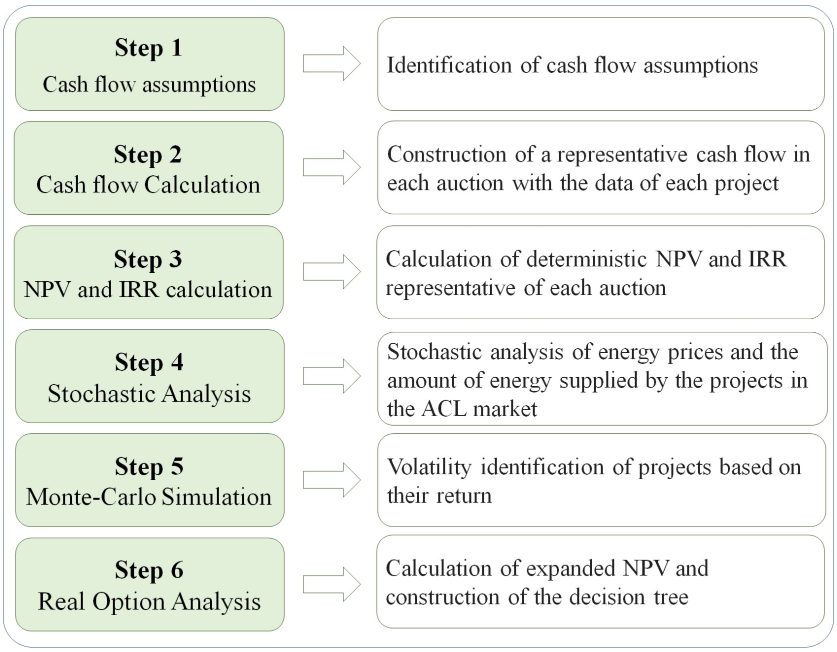

Figure 28 – Methodological Procedures

4.2 Cash flow assumptions

Considering that it takes an average of two years to build a wind farm, it was assumed that the project starts generating revenues in period $t = 3$,Moreover, since both contracts from auctions 28 and 30 have the mandatory power supply in ACR at $t = 6$ and the contract from auction 29 has the mandatory power supply at $t = 4$, the net present value, NPV, for each project is given by Equations (4.1) and (4.2), respectively.

The calculation model of the full NPV for the projects considered two parts: the first part containing the cash flow exclusively from the ACL market (up to t = 5 in figure 29 and at t = 3 in Figure 30) plus a second part containing the cash flow from the ACL and ACR jointly, considering the proportion for each market at the time of the auction. In the calculations, it was also assumed that the investment is made in two equal parts: the first disbursement in the year of the auction and the second in the subsequent year.

$$NPV_{28,30} = \sum_{i=0}^{1} 0.5 \times \left(\frac{-I}{(1+k)^i}\right) + \sum_{t=3}^{5} \times \left(\frac{CF_{ACL_i}}{(1+k)^t}\right) + \sum_{t=6}^{25} \times \left(\frac{CF_{prop_i}}{(1+k)^t}\right) \tag{4.1}$$

$$NPV_{29} = \sum_{i=0}^{1} 0.5 \times \left(\frac{-I}{(1+k)^i}\right) + \left(\frac{CF_{ACL_i}}{(1+k)^3}\right) + \sum_{t=4}^{23} \times \left(\frac{CF_{prop_i}}{(1+k)^t}\right) \tag{4.2}$$

Where,

NPV = Net present value of the project (considering the auctions 28 and 30, on the one hand, and auction 29, on the other hand;
I = Investment projected by the company;
CF_{ACL_i} = Cash flow obtained from the sale of energy on the ACL market before the deadline for delivery at the auction.
CF_{prop_i} = Cash flow obtained from the estimated sale of energy proportionally in the ACR and ACL markets from the beginning of the energy supply period, according to the contract.
k = discount rate.

The investment announced for the projects was also divided into two equal parts between t_0 and t_1, assuming the disbursement will not occur in one go. Unlike Auctions 28 and 30, the period considered for the winning companies in Auction 29 is four years from the date of the auction, that is, they must deliver the energy contracted at the auction to the regulated market from January 1, 2023, leaving them only a period of one year for additional revenue if they choose to anticipate.

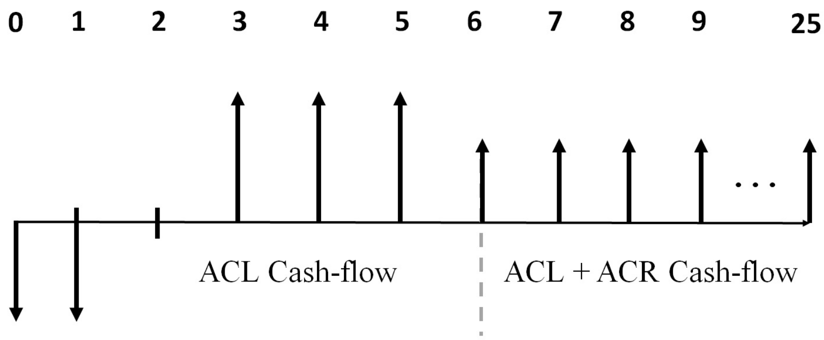

Figure 29 – The Cash flow diagram of successful companies at the auctions 28 and 30

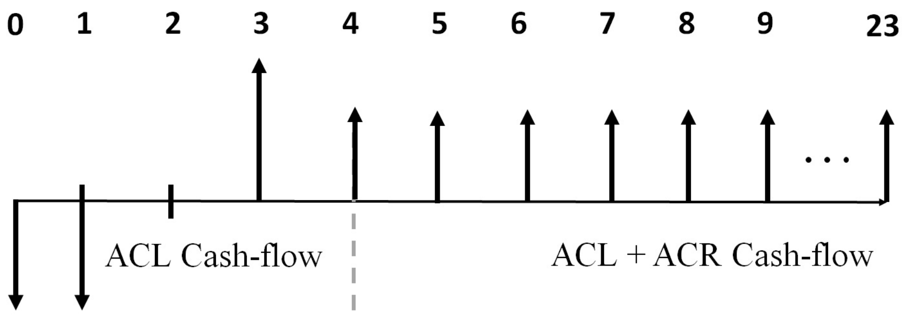

Figure 30 – The Cash flow diagram of successful companies at the auctions 29

4.3 Stochastic analysis of energy prices and quantities

In Brazil, the formation of the electricity price in the spot market is linked to the Brazilian electric matrix's capacity for energy generation which is driven mainly by hydro sources. Thus, rainfall unpredictability becomes an important component of this uncertainty.

This dynamic can be represented by the high volatility of the spot price in recent years in Brazil, as shown in Figure 31. Thus, the volatility of the spot price in Brazil would not be an appropriate reference for the forecast of future energy prices. As evidenced, this high volatility has been one of the incentives for the migration of generating companies to the ACL market, where contracts tend to have less volatile prices defined by bilateral contracts. The annual average for the volatility of the spot price in the country ranged from 20.97% to 51.29%. Overall, the average for the period was 31.25% (CCEE, 2020d).

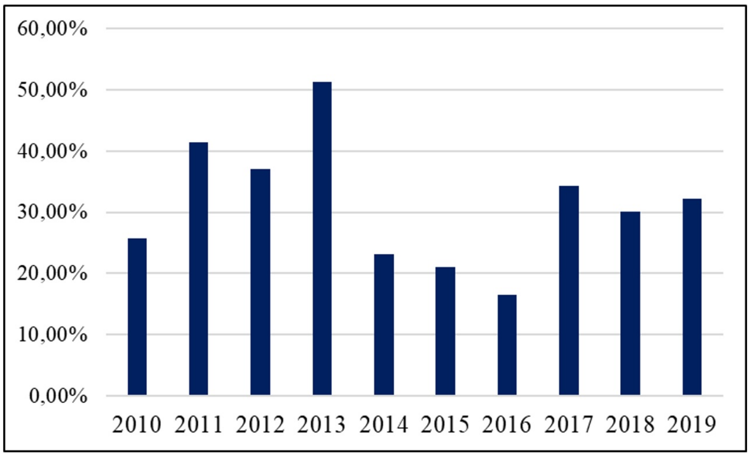

Figure 31 – Spot Price average annual volatility

Contracts traded in the ACR market have significant differences when compared to contracts traded in the ACL market because these two environments have different risk matrices (Pilipovic, 2007). These differences make it difficult to forecast prices accurately for the Brazilian electric market. In addition, the lack of a standardized trading environment for contracts in the ACL market induces agents to negotiate energy based on the spot price, adding a premium or a discount depending on the behavior of this price. With this, it is possible to verify that the price of energy in the ACL market tends to vary more than the price of energy in the regulated market (established at the auction), but less than the spot price (Dalbem et al., 2014).

Dalbem et al. (2014) also assumed that the volatility parameters of energy prices in the free market are subjectively defined, based on the views of market professionals, in which case the volatility considered by the authors in Brazil was 30%.

Considering the high variability, the main problem in using models based on the spot price is that the forward prices would be obtained endogenously from the dynamics of the spot price, not portraying consistently the prices observed in the forward market (Koekebakker and Ollmar, 2005). The alternative of modulating prices via the forward curve would be the most reliable if the information were public. However, in view of this limitation, one of the alternatives would be the construction of the forward curve based on information captured from customers by specialized companies for this type of modeling.

The modeling of the forward energy price curve is made from two dimensions, temporal, which expresses the time in which the price is measured, and spatial, which expresses the distance or maturity until the supply of energy $F_{(t,h)}$. Thus, it represents the price of energy quoted at time t for maturity h. It was used a historical basis provided by the company Dcide LTDA.

To perform the stochastic analysis of energy prices and quantities, weekly prices for the ACL market were simulated. Then it was possible to identify the average annual values of these prices that served as a basis for the construction of the annual cash flows. Equations (4.3) to (4.5) are used to assess whether the mean reversion stochastic process is relevant in the study, considering the price series for the ACL market analyzed (we used data provided by a company that research prices in the ACL market in Brazil). Equation (4.6) expresses the data generating process, while equations (4.7) and (4.8) demonstrate the calculation of the series trend line and the mean reversion speed, respectively.

Following Aquila et al. (2020) as well as Scarcioffolo et al. (2018) we simulated electricity prices using a mean reversion stochastic process with Poisson jumps. The simplest representation of the mean reversion process is the Ornstein–Uhlenbeck process represented by the Equation (4.3).

$$dx = \eta(\overline{x} - x)dt + \sigma dz \tag{4.3}$$

Where, η is the reversal speed and $\overline{x}$ is the long-term equilibrium of variable x.

Although electricity prices in Brazil are commonly modeled on the PLD price, it is important to highlight that the expansion of the ACL market through bilateral contracts tends to distance it more and more from the high volatility identified in the price dynamics of the short-term market.

Alternatively, using data provided by a company that conducted price research in the ACL market, it was possible to identify more congruent behavior of prices in that market. In this sense, we estimated the parameters of the data generating process that follows an autoregressive process with one lag, which in its discrete version can be represented by Equation (4.4).

$$ln(x_t) - ln(x_{t-1}) = a + b\ ln(x_{t-1}) + \epsilon_t \tag{4.4}$$

Where,

x_t = is the value of the variable in t
x_{t-1} = is the value of the variable in $t-1$
a and b = are the estimated coefficients of the regression equation
ϵ_t = is a white noise i.i.d. $\sim$ N(0, σ^2)

One way to identify if prices are better modeled by the GBM or MR precess is to estimate the coefficient b of the Equation 4.4 and check if it is significantly different from zero (Dixit and Pindyck, 1994).The result of this estimation is presented in Equation (4.5).

$$ln(x_t) - ln(x_{t-1}) = 0 + 0.15\ ln(x_{t-1}) + \epsilon_t \tag{4.5}$$

An alternative method is to perform a unit root test, where the rejection of the null hypothesis will indicate a mean reversion process (Dixit and Pindyck, 1994). The results are shown in Table 34.

Table 34 – ADF Test Results

ADF Statistic:	-6.454897
p-value:	0
Critical Values:	
1%	-3.446
5%	-2.868
10%	-2.57

Unit root tests of the returns of the series analyzed as a price reference have the characteristics of being stationary, therefore attending to the principle of reversion to the mean. However, Dixit and Pindyck (1994) warn about possible problems related to the series analysis and to the need for many years to state the condition of its reversion safely. For this reason, the authors suggest that the analyses should be based on the theoretical framework of how the equilibrium mechanism tends to work instead of focusing exclusively on statistical tests to decide whether or not to model a variable like a mean reversion process.

Once the stationarity of the data series was identified, we assumed that the series would follow a mean reversion process with tendency and jumps. Following Monjas-Barroso and Balibrea-Iniesta (2013), the process was represented by Equation (4.6).

$$Y_t = Y_{t-1} - b^*[Y_{t-1} - (aX + c)] + \varepsilon^* \sqrt{\Delta t} * \sigma + \eta\varphi \tag{4.6}$$

where

Y_t = Simulated value of the variable in year t.
Y_{t-1} = Simulated value of the variable in year $t-1$.
b = Mean reverting speed (assumed as the average of the percentage difference between the Y_t represented as the value in the regression line at time t and the value in Y_{t-1}. Thus, the farther from the average the value of Y_{t-1} is, the greater the reversal speed.
$aX + c$ = Straight regression line of the variable capable of capturing the trend of the

simulated values over time
ε = Random value N (0,1)
Δ t = Time interval, as the data was sent in weekly periods, Δ t was considered 1.
σ = Weekly standard deviation of the observed variable.
η = Represents a bernoulli distribution to identify the probability of the jumps occurence at time t with intensity φ , where:

$\varphi = 1$ with probability $(\lambda\ \Delta t)$;
$\varphi = 0$, with probability $(1 - \lambda\ \Delta t)$.

Then, there will be a probability of $\lambda\Delta t$ of occurence of a jump of magnitude φ, in the interval Δt.

We used the weekly price in the ACL market provided by a company in the sector during the period from January 2012 to May 2020 and then performed a linear regression of the straight line to capture the trend of the simulated values over time (Equation 4.7).

$$aX + c = -0.14007X + 306.22 \tag{4.7}$$

The mean reversion speed calculation was obtained from an average value that could express the magnitude of this variable throughout the series. To do this, we subtract the expected value of Y_{t-1} eliminated at each period from the value of Y_{t-1} and divided this value for the value Y_{t-1} (Equation 4.8). The percentage racio of this operation resulted in an average speed of 0.013.

$$b = \frac{Y_{t-1} - [Y_{t-1} - (aX + c)]}{Y_{t-1}} \tag{4.8}$$

Figure 32 shows the relationship between the series price evolution and the calculated mean reversion speed (ilustrated in the red line and in the right axis). It is possible to see that the speed identified by the red line follows a contrary path comparing with the price (blue line), pressing the values to the average line (Equation 4.7) expressed in green.

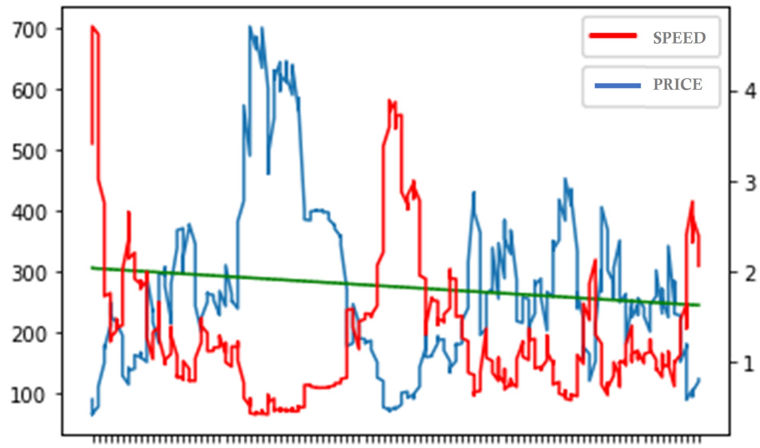

Figure 32 – Price ACL in Brazil (BRZ Real/MWh) x Mean Reversion Speed

After that, we used the weekly price series to run the Monte Carlo Simulation (MCS) in order to simulate 10,000 iterations of weekly prices for 1040 periods (52 weeks in 20 years). Then, we extracted the annual sample mean from the results to calculate the annual cash flow. Once the stochastic process of the ACL prices were estimated, it was possible to calculate the quantities for each of the 10,000 scenarios generated and from there the cash flows (Table 35).

Table 35 – Parameters used in the data generating process

Parameters	Values (Auctions)		
Auctions	28	29	30
Initial Prices (BRZ Real)	272.68	278.12	67.18
Initial quantities (KWh)	43,556.06	102,270	59,549.03
b (MR speed)		0.013	
σ (%)		6.9	
λ (%)		0.2	
φ (BRZ Real)		(275; 140)	
$aX + c$		-0.1414X + 306.22	

Variable φ represents the mean and the variance magnitude of the Poisson jumps and λ represents the probability of occurrence of these jumps. Both variables were calculated based on the historical series.

The existence of a correlation between the price and the amount of energy demanded in the ACL market was also considered in this study. To do this we should analyze the price elasticity of demand for this commodity in order to assess its magnitude. However, the use of PLD to identify the existence of elasticity between price and demand does not reflect reality since PLD is a value used to settle differences between the supply and demand of energy in the short-term market. Moreover, the verification that buyers choose the ACL market mainly because of price advantages reinforces the argument that there is some correlation between price and demand for these cases

Uhr et al. (2019) studied the elasticity of electricity price in Brazil and found that it varies between -0.45 and -0.56. We considered these values to stablish the correlation between price and quantity in the ACL market in four periods of five years (-0.15; -0.30; -0.45 and -0.6). With this, we hope that a microeconomic relationship between demand and supply will be present, even partially, in the ACL market.

4.4 Monte Carlo Simulation

The Monte Carlo simulation was used to identify the dispersion of project results based on their volatility. Then, it is important to note that price volatility cannot be confused with the project´s volatility itself. The volatility of the project is different from the volatility of the uncertain variable. Therefore, when one wants to analyze the managerial decision around the viability of projects based on their uncertainties, the best proxy is the rate of return of the project itself (Copeland and Antikarov, 2001).

In this sense, Copeland and Antikarov (2001) presented the concept of marketed asset disclaimed (MAD) arguing that the least biased way of estimating the market value of an investment project is to start from the present value of the project's own cash flow without flexibility. In this way, the authors suggested the use of the Monte Carlo simulation in the project's NPV rate of return to identify the probability of a return distribution in a future period, discounted to present value, then the logarithmic ratio can be calculated. The authors also point out that the standard deviation of interest is based on the percentage change, Z, in the value of the project from one period to the next (Equation 4.9).

$$z = ln\left(\frac{PV_1 + FC_1}{PV_0}\right) \tag{4.9}$$

Where the present value at time 0, (PV_0), is used as the denominator, and the present value at time 1, PV_1, is given by Equation (4.10) (FCF stands for free cash flow):

$$PV_1 = \sum_{2}^{N} \frac{FCF_t}{(1 + WACC)^{t-1}} \tag{4.10}$$

The volatility of the project is a fundamental step in the binomial tree construction and represents the speed of price movements of an asset over time. To calculate the volatility of project value returns, we followed the steps proposed by Barroso and Iniesta (2014) and proceeded as follows:

1. Calculation of the project's present values without flexibility;
2. Modelling of the uncertainties associated with the projects;
3. Identification of the price elasticity of the electricity for the ACL Market portion;
4. Use of MCS to generate the distribution of present values at t and $t + 1$;
5. Calculation of the return on the project using Equation (4.11):

$$vol = ln\left(\frac{PV_1}{PV_0}\right) \tag{4.11}$$

The volatility (vol) was calculated keeping the present value at time $t = 0$ (PV_0) constant and iterating the uncertainties inserted in the project's cash flows causing the present value at time $t = 1$ (PV_1) to change with each iteration. The Cash Flow FCF_1 of Equation 4.10 was not considered because the first three periods of a project's cash flow do not contain revenues given the grace period for the construction of the project as shown in Figures 29 and 30. With this, we combined the uncertainties and the correlation between electricity supply and demand considered in the projects in a single source of uncertainty, which is the project's volatility.

4.5 Real Option analysis

4.5.1 Binominal Tree Construction

Options to defer can be characterized as an american call option, where the decision to invest at a given time must occur if the project's NPV is greater than the calculated option. The calculation of these options can be performed using the binomial tree method proposed by Cox et al. (1979). This binomial tree method has been well received as tool for the evaluation of real options, as it has a certain ease of implementation at the same time that it approaches the Black and Scholes model (1973) (Zou and Gong, 2017).

From the calculation of the project's volatility, we can calculate the movement nodes of each period in the decision tree. That is, $u = e^{(\sigma\sqrt{T})}$, and $d = e^{(-\sigma\sqrt{T})}$. A binomial tree (Figure 33) can be seen as a network of probabilities with binary branches, where at each point (node) the up and down movements (u and d) occur based on a specific probability for each direction. We used the risk neutral probability method to calculate the option value in the context of binomial tree.

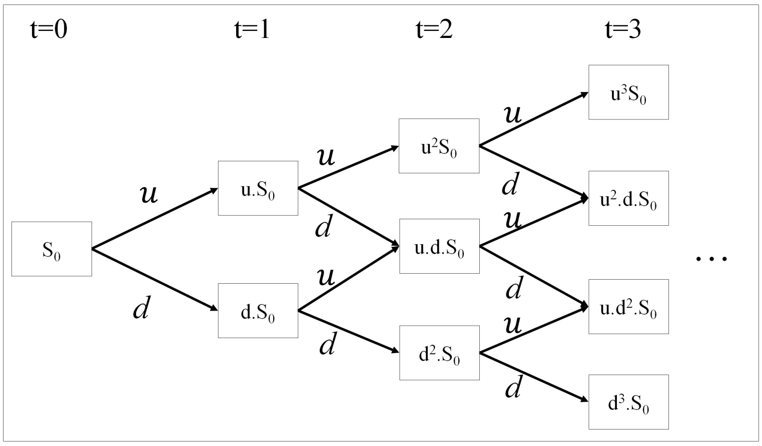

Figure 33 – Binomial tree diagram

The distance between the nodes is one period each, consequently the variable ΔT will be equal to 1. The stock price rise or fall probability simulates a GBM and has as parameters: the risk-free interest rate (rf), σ (within the parameters u and d), and the probability (π) of each moviment. It can be expressed by Equation (4.12) and (4.13).

$$\pi = \frac{(exp^{rf*\Delta T} - d)}{(u - d)} \tag{4.12}$$

$$q = 1 - \pi \tag{4.13}$$

At the moment when the option expires, that is, at the end of the tree, the values will be max$[(S - X), 0]$ for call options, and $MAX[(X - S), 0]$, for put options. Table 41, in the next section, shows the parameters used for its construction.

4.5.2 Projects Database

This study is based on the analysis of the viability of projects that participated in additional energy auctions (Auctions 28, 29 and 30) in 2018 and 2019. The calculations to identify the viability of the projects were made using the local currency (BRZ Real). This analysis focuses on the projects that were successful in these three selected auctions, corresponding to 95 contracts, as described in Table 36.

Table 36 – Project information by region

Region	Number of projects	Power (MW)*	Energy supply (MWh)*	Investment (BRZ Real) *
BA	45	24.7	1,069,062	107,655,121
PB	6	35.8	867,834	146,375,133
PI	4	33.4	845,919	180,914,242
RN	40	23.1	1,284,219	110,236,801
Total	95	25.12	1,137,549	114,272,213

(CCEE, 2020c) *Average Values

The values highlighted in the last row of Table 3 refer to the average value of all the projects.

Table 37 shows a regional overview of the winning companies analyzed in this study, where it is possible to verify that two states—RN and BA—are the main places for the installation of wind farms and account for about 90% of all the winning companies analyzed.

Table 37 – Number of companies by region and Auction

Region\Auction	28	29	30
BA	21		24
RN	27	1	12
PI		2	2
PB			6

BA = Bahia; PB = Paraíba; PI = Piauí; and RN = Rio Grande do Norte

The characteristics of the auctions are summarized in Table 38 and show that despite the small number of existing projects in Auction 29, the average projects' investment was greater than the average of the winning projects in the other auctions. Table 38 also shows that the average values of energy supply in MWh in Auction 28 was the highest when compared with other auctions, namely, 72.7% higher than the average value of projects in Auction 29 and 112.6% higher than the average value of projects in Auction 30. Despite this higher amount, the average value of investment in auction 28 (in BRZ Real) only exceeded the value of the investment in projects of Auction 30 by 19.1%.

Table 38 – Project information by Auction

Auction	Number of projects	Enabled power (MW)*	Energy supply (MWh)*	Investment (BRZ Real) *
28	48	26.1	1,534,415	121,557,295
29	3	31.7	888,288	177,405,563
30	44	23.6	721,601	102,020,305
Total	95	25.1	1,137,549	114,272,213

(CCEE, 2020c) *Average Values

Regarding the dispersion of the investment value of the projects, Table 39 presents a regional overview, while Table 40 presents an auction overview. In Table 39 it is possible to conclude that investments in RN had the largest standard deviation, among the four states. RN and BA were the only states that had winning companies at Auction 28, so the investment dispersion at this auction was greater than at other auctions, as shown in Table 40.

Table 39 – Investment information by Region (BRZ Real)

Region	Min	Max	Standard Deviation
BA	33,600,000	302,400,000	52,640,527
PB	70,868,000	197,427,000	47,068,330
PI	137,381,610	223,045,220	42,142,634
RN	33,600,000	346,500,000	73,709,725

(CCEE, 2020c)

Table 40 – Investment information by Auction (BRZ Real)

Auction	Min	Max	Standard Deviation
28	37,800,000	346,500,000	65,213,371
29	86,126,250	223,045,220	64,544,221
30	33,600,000	302,400,000	58,629,496

(CCEE, 2020c)

Table 41 presents the parameters used in the binomial tree. The stock price is the calculated present value of the project (underlying asset) and the exercise price is the investment value of the project.

The reference risk-free rate for these studies is generally represented by the US treasury American 10-year bond (ANEEL, 2016). However, ANEEL (Technical Note 212/2016) started to adopt the interest rates of Brazil's public securities that pay real interest (NTN-B, indexed to inflation) as a guide, which was also the reference used in this study.

Table 41 – Parameters used in the Binomial Tree

Parameters	Values (Auctions)		
	28	29	30
Stock Price (S) BRZ Real	123,700,718	180,539,734	123,264,431
Exercise Price (X) BRZ Real	121,557,295	177,405,563	102,020,305
Time to Expiration (years)	3	1	3
vol (%)	5.76	11.8	8.79
u	1.059	1.125	1.092
d	0.945	0.889	0.916
π	0.813	0.556	0.593
q	0.187	0.444	0.407
rf (%)	3.66	2	2
ΔT	1 year		

After determining the parameters, it is possible to construct the asset value of each node in the binomial tree. Assuming that the option's behavior has a risk-neutral measure, its expected value is equal to the expected value of its future values discounted by rf. In other words, the expected value of option can be calculated from the two values existing in the two scenarios of the future period (C_u^{t+1} and C_d^{t+1}), which can be determined by their probabilities, expressed by Equation (4.14).

$$C_t = [\pi C_u^{t+1} + (1 - \pi) C_d^{t+1}]/exp^{rf \Delta T} \tag{4.14}$$

Once the value of the underlying asset (S_0) is known at time $t = 0$, its value will follow an upward and downward trajectory until the time of maturity ($t = 3$ for projects 28 and 30 and $t = 1$ for project 29). Thus, it is possible to identify the option value in the maturity period by subtracting the values of the underlying asset to the exercise price and calculating the values of the previous nodes weighted according to Equation (4.14). The value of C_t represents the expected discounted value of not exercising the option in period t and waiting until the next period to decide. It is also possible to assign the name of $NPV_{expanded}$ to this value.

Finally, the values calculated in the binomial tree are used as a reference for the decision for investing or postponing the investment, since the decision that would make the most sense would be to postpone when the net value of the option to defer ($NPV_{expanded} - NPV_t$) exceeds the NPV of the investment at the period t ($S_0 u^i d^j - X_t$). The decision tree could be built considering equation (4.15).

$$NPV_{Expanded} = NPV_t + NV_{Optionvalue} \tag{4.15}$$

Where $NV_{Optionvalue}$ expresses the net value of the option. Given the opportunity cost in the decision to postpone the investment, the investment should be made when its NPV exceeds the net value of the option to defer ($NV_{Optionvalue}$). This happens because when choosing to invest at time t, the investor loses the opportunity to invest later, this corresponds the value of the option do defer (Santos et al., 2014).

5 Results and Discussion

This section presents the results obtained in the deterministic analysis of the representative cash flows in each auction, the calculation of the volatility of a project's return (vol) considering the sources of uncertainty, and the construction of the project's decision tree.

Figure 34 shows the weekly price simulations considering the mean reversion process with Poisson jumps. Two images are presented for each project, a first image containing 10 simulations for a better visualization and then a second image containing the 10,000 simulations. In the figure, it is possible to identify the characteristic behavior of prices, which after the jumps occur, revert to the average.

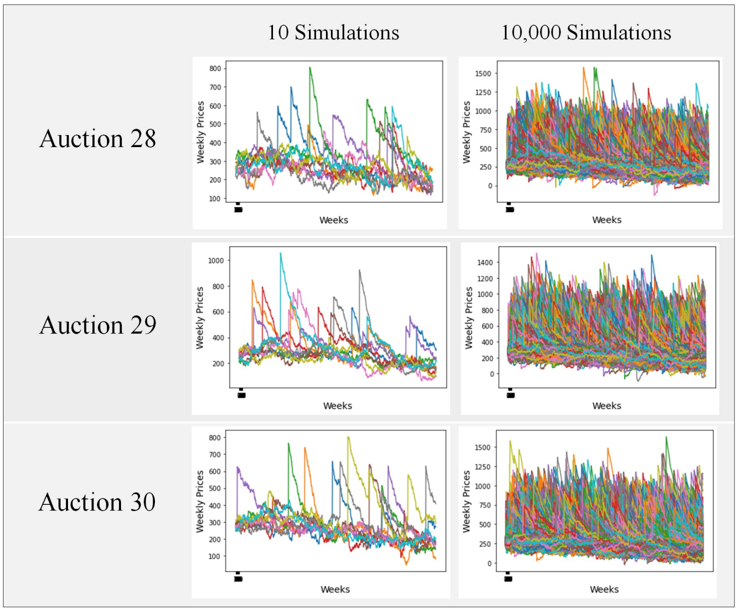

Figure 34 – Weekly Prices simulation

For the calculation of the NPV and IRR displayed in Table 42, it was assumed that the construction would start immediately after the auction and energy supply to the ACL market could start on the beginning of year 3.

Table 42 – NPV and IRR

Auction	NPV (BRZ Real)	IRR (%)	IRR–WACC (%)
28	2,143,423	7.87	0.21
29	3,134,170	7.59	0.2
30	21,244,126	9.59	2.2

The WACC rate used as a reference was 7.66% for the 2018 projects and 7.39% for the 2019 projects.

The anticipation of the construction of the plants with the objective of supplying the surplus energy from this period to the ACL market contributes to the increase in the viability of the projects.

5.1 Binomial Tree Analysis

The binomial trees represented in Figures 35, 36 and 37 show the values of the underlying assets in the yellow cells and the values of the NPV of the projects at time t with the options to defer embedded in them, represented by the brown cells. The values of the underlying asset can rise or fall according to the magnitude presented by the variables u and d, and the last column of the binomial tree expresses the option's maturity date as well as the possible values of the asset on that date.

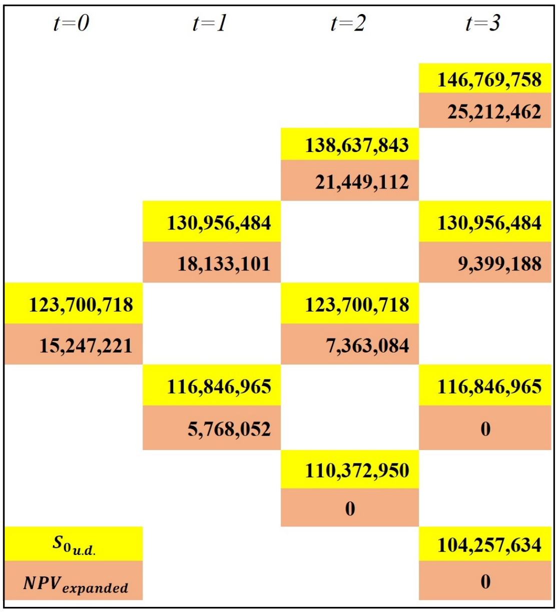

Figure 35 – Binomial Tree Auction 28

In the binomial tree of the project from Auction 28 (Figure 35), it is possible to verify that the value of the option at time $t = 0$ is BRZ Real 13,103,798 and it exceeds the value of the deterministic NPV of the project (BRZ Real 2,143,423). This condition suggests that in the year in which the auction takes place ($t = 0$), the volatility associated with the project would justify the postponement of the investment decision for the next period ($t = 1$). However, from the first year after the auction, opportunities are restricted by low volatility caused by the project's high commitment to the ACR market, a market that does not involve uncertainty related to prices once they are established in the auction. So, the results suggest that the decision to invest in the project at $t = 0$ could be postponed to the following year ($t = 1$), when it will be possible to carry out a new analysis.

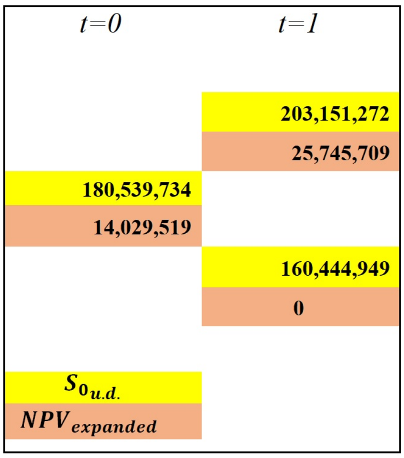

Figure 36 – Binomial Tree Auction 29

The results of the representative project for Auction 29 (Figure 36) differ from the other two projects because of the shorter deadline for supplying energy to the ACR market. Therefore, investors have only one chance to decide whether they want to invest or postpone the investment. In a deterministic context (table 42), it was possible to verify that Project 29 has the lowest rate of return among the three projects, which makes sense since the possibility of obtaining revenue by anticipating the construction of the plant is restricted to just one year. Considering the uncertainty, it was possible to verify that the project from Auction 29 has the highest volatility. This is explained by the fact that the Auction 29 project is the one with the highest revenue commitment to the ACL market (close to the maximum), this makes the volatility of its cash flow more exposed to the uncertain variable (price in the ACL market) than the others.

The results also suggest that the decision to invest in the project at $t = 0$ could be postponed to the following year ($t = 1$). However, one cannot fail to consider that the short period of time for the construction of the plant brings a greater risk of completion than the other projects. In this sense, it would be important to analyze this type of project from the perspective of other risks besides the risks related to price fluctuation, such as the risk of completion.

t=0	*t=1*	*t=2*	*t=3*
			160,457,947
			58,437,642
		146,955,805	
		46,955,637	
	134,589,835		**134,589,835**
	36,569,803		**32,569,530**
123,264,431		**123,264,431**	
27,651,286		**23,264,263**	
	112,892,032		**112,892,032**
	16,039,426		**10,871,727**
		103,392,445	
		6,317,169	
$S_{0_{u.d.}}$			**94,692,225**
$NPV_{expanded}$			**0**

Figure 37 – Binomial Tree Auction 30

The binomial tree of the project referring to Auction 30 (Figure 37) is similar to the binomial tree for the project from Auction 28. However, the greater commitment of the project of Auction 30 to supply energy to the ACL market when compared to the project from Auction 28 makes its volatility slightly higher than the volatility of the underlying asset of the project from Auction 28.

The project from Auction 30 had an average commitment in the ACR market of 36.3% for the generated energy, while the project from Auction 28 had an average commitment of 54.7%. The volatility identified in the two projects reflects this difference. While the calculated volatility of the project from Auction 28 was around 5.7%, the volatility of the project from Auction 30 project was 8.8%. However, this difference in volatility between projects is not able to ensure that the strategy of postponing the decision to build the plant in search of better opportunities is viable for project from Auction 30.

5.2 Decision Tree Analysis

The value of the project with the deferral option embedded in it is represented by $NPV_{expanded}$ cells, and the value of the options is given by the difference between the $NPV_{expanded}$ and the calculated NPV at time t. The net value of an option higher than the NPV should induce a postponement of the project, as the value of the option to defer exceeds the value of investing at that moment. However, when the project's NPV value exceeds the option's value, the investment must be made. This occurs because the decision to invest implies the loss of future opportunities and must occur when the value generated by the project exceeds this opportunity cost. Based on these premises, we could build the decision trees for each auction project (28, 29, and 30) represented in Figures 38, 39 and 40, respectively.

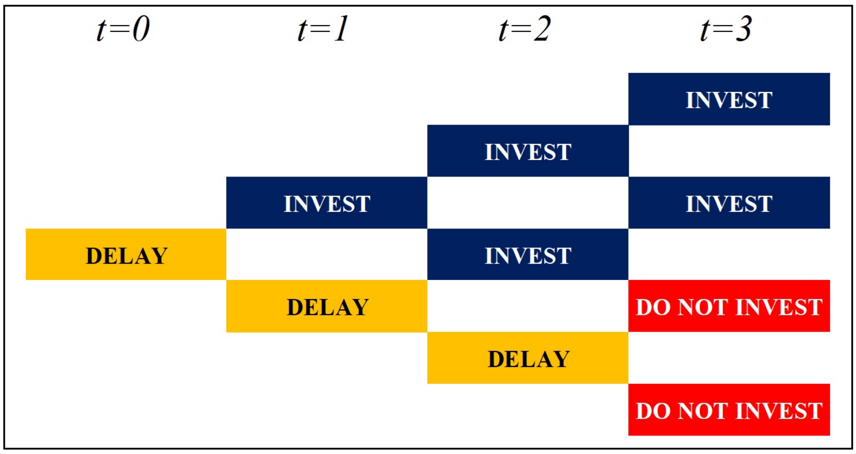

Figure 38 – Decision Tree Auction 28

In the project from Auction 28 (Figure 38), the decision to invest or not should take place in the years following the auction. As the value of the option to defer is greater than the value of the project's NPV in the period ($t = 0$), the first node of the decision tree is marked with the decision to postpone the investment.

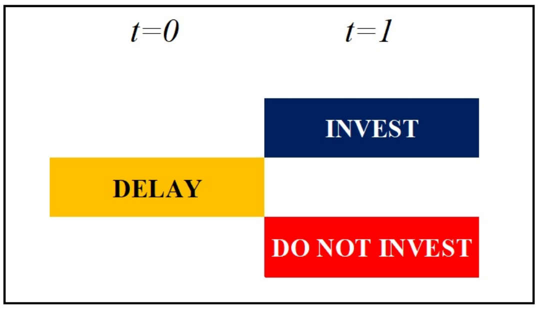

Figure 39 – Decision Tree Auction 29

In the Auction 29 project (Figure 39), the value of the option to defer greater than the project's NPV in the period ($t = 0$) also suggests a postponement of the investment to the year following the year of the auction. However, as mentioned before, this decision cannot fail to consider the characteristics of the short time for the construction of the plant.

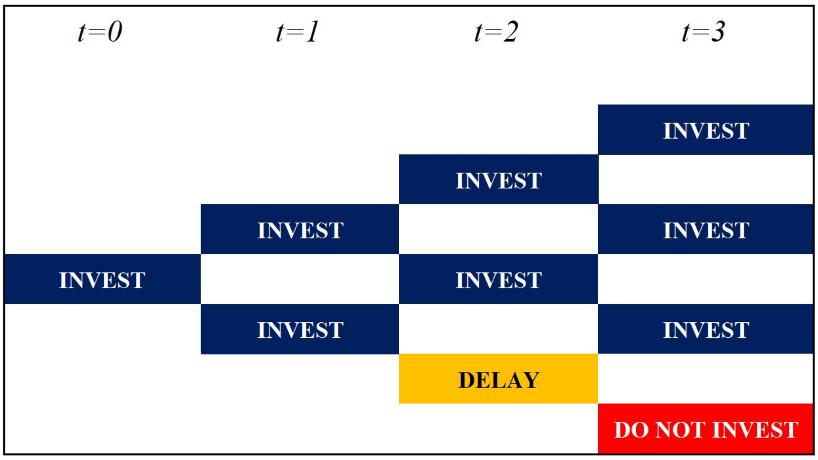

Figure 40 – Decision Tree Auction 30

The decision tree of the project from the Auction 30 (Figure 40) results on expanded NPV values that are closer to the deterministic NPV. This makes the decision to invest earlier even more viable when the values are compared to those of the Auction 28 project. Although the project is more exposed to the ACL market, where the price is configured as an uncertain variable, the revenue opportunities arising from the anticipation of the investment and the sale of additional energy in the ACL market in the period from $t = 3$ to $t = 5$ outweigh the possible opportunities included in the option to defer.

A comparison between the evolution of the ratios between the net value of option to defer and the NPV_t in the most optimistic path of the binomial tree of projects 28 and 30 is illustrated in Figure 41. A decision to defer the investment due to better future opportunities would make sense if the value of the option exceeded the proportional value of 1. In the first period ($t = 0$), it is already possible to verify that this decision is not favored by the value of the option in project 30.

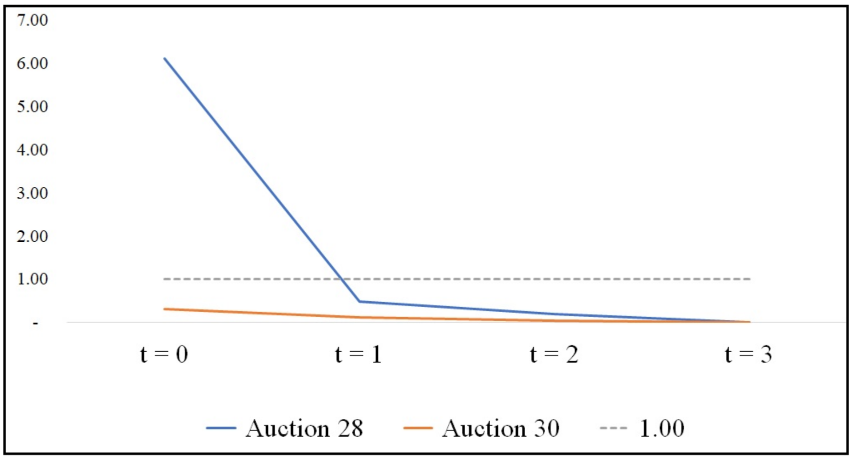

Figure 41 – Ratio between Option Values and $NPV_{expanded}$

The results suggest that the decision to defer or not the invest in a project in the case of wind energy in Brazil is based much more on the value of the project's return than on uncertainties related to the price in the ACL market. The results of the project from Auction 30 show that the early start of the construction of the plants can be an important strategy so that the additional revenue from the sale of energy in the first years can increase the viability of wind energy projects. This finding can contribute to the development of financing alternatives for these construction projects since projects with lower credit risk can generate cheaper interest rates.

6 Conclusion

This study analyzed the financial data of 95 projects that participated in the last three additional energy auctions in Brazil in 2018 and 2019. These auctions inaugurated a remuneration format based on the quantity of energy supplied to the ACR market. We constructed three representative cash flows with the average project data for each auction in order to identify the average investment profile of these projects. It was possible to verify that the projects had different profiles, both in relation to the amount invested and in relation to its returns.

The results from projects 28 and 29 suggest the postponement of the decision to invest for at least one year ($t = 1$), when it will be possible to analyze again from that period what the new decision should be. When projects with the same characteristics are compared (projects 28 and 30), it is possible to verify that the price volatility in the ACL market is not enough to create opportunities capable of inducing the postponement of the construction of the plants. This is evident when the project with the largest portion of its revenue in the ACL market (project 30) does not have favorable options to defer the investment, while the project with the smallest portion in the ACL market resulted on a favorable option to defer in the first period.

Some studies use the volatility of electricity spot prices as a proxy to identify options included in electricity generation projects. This approach does not reflect the real volatility of the project that must be obtained by the volatility of its returns. In addition, many studies that analyze volatility in project returns in Brazil do not consider these projects' joint participation in different markets. Projects' participation in both the ACR and ACL markets tends to change the dynamics of the projects' volatility considerably, since the more a project is committed to the ACR market, the lower its volatility. This is explained by the fact that in the ACR market future prices cannot be considered as an uncertainty, since they are defined by the auction. At the same time, price volatility in the ACL market also cannot be faithfully represented by the volatility of prices practiced in the short-term market. Although there is a certain correlation between the prices practiced in the ACL and in the short-term markets, we found that the volatility present in the contracts carried out in the ACL market was lower than the volatility in spot prices practiced in the short-term market. This difference cannot be disregarded when identifying project volatility. The study demonstrated that a project's participation in different markets influences the calculation of the return volatility of wind power generation projects in Brazil. This mixed participation leads to greater volatility in projects that have greater exposure to the ACL market. Even so, joint participation in the two markets does not produce opportunities related to the volatility of energy prices in the ACL market that justifies the postponement for more than one period of the construction of the wind farms.

The study also proposes an analysis focused on capturing the weekly behavior of electricity prices in Brazil and is based on data directly linked to the ACL market instead of using spot prices from the short-term market as a benchmark. In this way, the short-term characteristics of these prices are not lost in the viability analysis of the projects. In addition, the study also considers the evolution of the dynamics between electricity supply and demand in Brazil by inserting four measures of price elasticity over the 20 years of the projects. With this, it is expected that the market dynamics between supply and demand will be captured to represent the evolution of a developing market.

We believe that the results of this study are important because they contribute to the development of financing products and services better fitted to the construction of these plants. The realization that its anticipation may bring higher viability to the project opens a space for the creation of credit solutions for the construction of these plants. More than that, it is possible to identify better risk levels for projects, thus contributing to the reduction of interest rates linked to these solutions. The use of real options as a complementary tool for valuing wind energy projects that can help banks and financiers to protect themselves from any surprises presented in the scenario of an expanding ACL market. The viability analysis of projects that have two sources of revenue must consider the amount of energy supplied by the company to each market. In this sense, a complementary model for viability analysis based on real options for these projects can contribute to decision-making related to the most opportune moment to start the construction of a project. From the regulators' point of view, these results can contribute to the formulation of tax incentives to induce projects that build their plants in advance, as this increases their viability and reinforces the energy supply to the system as a whole.

Finally, the paper also recognized that the use of spot price volatility may not be the most realistic estimate for viability analysis in the ACL market. This postulation can be used to develop mechanisms capable of measuring the behavior of prices in the ACL market, and to propose more improved estimates in the future.

Within the limitations of the study, we can highlight the possibility of including shocks related to political uncertainties capable of impacting the stochastic process of the ACL market price. Future studies may also explore the inclusion of new options, such as completion options that can improve decision making as to the most convenient time for projects with a short term for investment in energy supply.

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Conclusion

With the recent changes in the Brazilian electric sector, power generation companies are more likely to negotiate electric energy in the ACL market. Contracts signed in the ACL market tend to generate higher revenues than those signed in the ACR market. The prices for the regulated market are established in auctions and therefore are known in advance. However, when companies are unable to supply the amount committed to the ACR market, they must negotiate energy in the short-term market using the PLD price as reference, which has greater volatility and less predictability. With the possibility of participating in both markets (ACR and ACL), the viability analysis of electricity generation projects cannot fail to reflect the characteristics of both markets in their respective proportions.

This work proposed to study the viability of wind power generation projects considering their joint participation in the ACL and ACR markets. To do so, we used data from projects that won energy auctions in the ACR market in the years 2018 and 2019 in Brazil. The thesis integrates three studies that complement each other and should contribute not only to improve the decision-making process for managers who participate in this market in Brazil but will also provide relevant information for policy makers and researchers.

In the first study, we mapped and analyzed different methods for the evaluation of renewable energy projects over the past 10 years. The reviewed papers were grouped into four main methods: i) Traditional methods (NPV, IRR, and Payback); ii) Levelized Cost of Energy; iii) Return on Investment (ROI), and iv) Real Options Analysis (ROA). The results showed that the traditional methods are widespread and used for different renewable energy technologies. More complex methods such as ROA are still not extensively used but show a promising growth trend, in particular for the wind energy sector.

In the second study, we analyzed 95 wind energy projects in Brazil assuming their participation in the ACR and ACL markets together. The study relied on data released from projects that won energy auctions in Brazil in 2018 and 2019 to calculate the percentage of project participation in each market. Firstly, a deterministic analysis was used departing from the formulation of three representative projects (one for each auction) and their respective cash flows assuming an energy share allocated to each market. Secondly, the Brownian Geometric Movement stochastic process was assumed to simulate future weekly prices over 20 years. We also considered four different values for the elasticity of demand for the projects in four different periods during the project's life cycle. From that, a Monte Carlo simulation approach was used to estimate the probability of success of projects assuming four initial electricity price scenarios. The study showed that the use of the average value between the minimum values and the maximum values allowed for the PLD prices, published by ANEEL, could signal relevant information about the agents' price expectation in the ACL market and provide some guidelines for ex-ante project evaluation.

In the third study, we assumed a Mean Reversion process with Poisson jumps to estimate the viability of wind energy projects in Brazil assuming flexibility on the investment timing. The real options theory was used to analyze the economic interest in postponing the investment given the assumed volatility conditions of the ACL market price. The study used a series of electricity prices surveyed by a company in the sector as a reference to identify price volatility in the ALC market. The yearly cash flows estimation was based on average electricity prices obtained from weekly simulations.

The results show that despite the exposure to the volatility of the ACL market, the option to defer is not always advantageous for projects. Under the assumed conditions, the joint participation in the free and regulated markets seems to limit the market uncertainty and reduce the value of the option to defer. The results indicate that the price volatility in the ACL market does not produce future opportunities that stimulate the postponement of the investment for more than one period. Among the three projects analyzed, in two of them the results suggested that the investment could be made in the year following the auction, while in one of them, the best period to invest would be the year in which the auction takes place.

In a growing market such as the case of the ACL market in Brazil, the use of tools capable of estimating the financial performance of projects with this market dynamics and with the joint participation in regulated and free markets can contribute to the analysis of credit risk to these projects. The use of tools that indicate the viability of wind generation projects from the moment when the auction takes place can allow the simulation of the granting of credit for the civil construction of these plants. In addition, the identification of the partial volatility of the ACL market and the analysis of its influence on the total volatility of the project may allow studies related to the emergence of energy derivatives to be traded in the Brazilian market.

The presented studies also contribute to an improvement in the governmental management of the sector, since the policies of disclosure of prices and market rates can influence the decision for the greater participation of companies in the ACL market. In this way, an analysis that can better express the performance of these companies taking into account the percentage of their participation in each market can contribute to the incentive policies for the energy sector more effective.

Finally, the studies showed the need to improve the tools for analyzing the viability of renewable energy projects considering specific characteristics of each market where the companies operate. With that, it was possible to suggest that the opportunities generated by the expansion of the ACL market in Brazil could be better explored with methods better fitted to an environment where energy trading takes place freely between agents and tends to reflect the rules of supply and demand for this commodity. The proposed study can also be a starting point for the analysis of other sources of renewable energy since the premises used to commercialize energy in the two existing markets in Brazil are the same.

This thesis also opens up other important avenues for future research that can rely on the developed models and extend them to overcome the limitations of the work.

Within the limitations of this thesis, it is important to cite that the calculation of price volatility in the ACL market was carried out considering constant volatility over time. An important evolution of the study could be the inclusion of different volatility values over time, allowing a more detailed simulation of prices. We cannot help contemplating that the evaluation based on average values or representative cash flows is also a limitation of the studies. Therefore, an analysis of each one of the projects included in each auction could bring more detailed information about the characteristics of the projects and their option values taking into account aspects such as the project dimension or different locations.

Appendix

Database

Table 43 – Projects Database

Year	Auction	id	MW	Investment	ACR %	MWh	P. W*	Bid Price	Start	End	Amount	Tust
2018	28	BA.037083-5.01	18.8	65800000	1.00	1472688	8.4	88.46	2024	2043	130273980.5	60254
2018	28	BA.040609-0.01	23.5	82250000	1.00	1963584	11.2	88.97	2024	2043	174700068.5	75317.5
2018	28	BA.040611-2.01	25.85	90475000	1.00	2068776	11.8	88.46	2024	2043	183003925	82849.25
2018	28	BA.040612-0.01	16.45	57575000	1.00	1332432	7.6	88.46	2024	2043	117866934.7	52722.25
2018	28	RN.037075-4.01	69.3	346500000	0.98	5242068	30.6	93.33	2024	2043	489242206.4	444213
2018	28	RN.032518-0.01	69.3	238388000	0.97	7012800	41.2	87	2024	2043	610113600	444213
2018	28	RN.032519-8.01	65.835	227806000	0.97	6855012	40.3	87	2024	2043	596386044	422002.35
2018	28	RN.033881-8.01	58.905	206642000	0.97	5697900	33.5	87	2024	2043	495717300	377581.05
2018	28	RN.040584-1.01	24.255	87217000	0.97	2279160	13.4	87	2024	2043	198286920	77737.28
2018	28	BA.034889-9.01	25.3	139616790	0.90	1963584	12.4	94.33	2024	2043	185224878.7	81086.5
2018	28	BA.032644-5.01	29.4	132301000	0.85	2296692	15.5	92.11	2024	2043	211548300.1	94227
2018	28	BA.033529-0.01	29.4	132301000	0.77	1981116	14.6	92.11	2024	2043	182480594.8	94227
2018	28	BA.033530-4.01	29.4	132301000	0.76	1928520	14.5	92.11	2024	2043	177635977.2	94227
2018	28	BA.032535-0.01	34.5	190386530	0.75	2226564	16.9	94.33	2024	2043	210031782.1	221145
2018	28	BA.033523-1.01	29.4	132301000	0.71	1928520	15.5	92.11	2024	2043	177635977.2	94227
2018	28	BA.035234-9.01	32.2	177694090	0.65	1963584	17.3	94.33	2024	2043	185224878.7	206402

Table 43 – Projects Database

Year	Auction	id	MW	Investment	ACR %	MWh	P. W*	Bid Price	Start	End	Amount	Tust
2018	28	BA.033521-5.01	29.4	132301000	0.63	1700604	15.4	92.11	2024	2043	156642634.4	94227
2018	28	RN.036980-2.01	22	90227510	0.61	1437624	13.4	93	2024	2043	133699032	70510
2018	28	RN.037299-4.01	29.4	164023430	0.58	1735668	17.2	94	2024	2043	163152792	94227
2018	28	RN.038326-0.01	31.185	127897510	0.54	1455156	15.4	93	2024	2043	135329508	199895.85
2018	28	RN.038325-2.01	31.185	127897510	0.53	1455156	15.7	93	2024	2043	135329508	199895.85
2018	28	RN.037298-6.01	29.4	164569550	0.52	1490220	16.2	94	2024	2043	140080680	94227
2018	28	RN.037297-8.01	29.4	167301350	0.52	1560348	17	94	2024	2043	146672712	94227
2018	28	RN.037296-0.01	29.4	164569750	0.52	1542816	16.9	94	2024	2043	145024704	94227
2018	28	RN.038327-9.01	31.185	127897510	0.49	1437624	16.8	93	2024	2043	133699032	199895.85
2018	28	RN.038035-0.01	34.65	122818000	0.46	1595412	19.7	87	2024	2043	138800844	222106.5
2018	28	BA.032536-8.01	36.8	203078950	0.39	1034388	15.3	94.33	2024	2043	97573820.04	235888
2018	28	BA.033508-8.01	28.6	128700000	0.33	876600	15.3	91.33	2024	2043	80059878	91663
2018	28	BA.033532-0.01	28.6	128700000	0.31	753876	13.7	91.33	2024	2043	68851495.08	91663
2018	28	BA.033533-9.01	28.6	128700000	0.31	753876	13.7	91.33	2024	2043	68851495.08	91663
2018	28	RN.037999-9.01	21	159116000	0.31	631152	11.7	89.89	2024	2043	56734253.28	67305
2018	28	RN.038323-6.01	8.4	37800000	0.31	210384	3.9	89	2024	2043	18724176	26922

Table 43 – Projects Database

Year	Auction	id	MW	Investment	ACR %	MWh	P. W*	Bid Price	Start	End	Amount	Tust
2018	28	RN.038006-7.01	14.7	116754000	0.31	455832	8.5	89.89	2024	2043	40974738.48	47113.5
2018	28	RN.038002-4.01	10.5	90996000	0.31	315576	5.9	89.89	2024	2043	28367126.64	33652.5
2018	28	RN.038321-0.01	8.4	37800000	0.30	245448	4.6	89	2024	2043	21844872	26922
2018	28	RN.037295-1.01	29.4	167101350	0.30	788940	14.9	94	2024	2043	74160360	94227
2018	28	RN.037959-0.01	23.1	170745000	0.30	701280	13.3	89.88	2024	2043	63031046.4	74035.5
2018	28	RN.037294-3.01	29.4	167301350	0.30	806472	15.3	94	2024	2043	75808368	94227
2018	28	BA.037103-3.01	8.4	37800000	0.30	210384	4	79	2024	2043	16620336	26922
2018	28	BA.040625-2.01	8.4	37800000	0.30	210384	4	89	2024	2043	18724176	26922
2018	28	RN.038322-8.01	8.4	37800000	0.30	210384	4	89	2024	2043	18724176	26922
2018	28	RN.038310-4.01	8.4	37800000	0.30	245448	4.7	89	2024	2043	21844872	26922
2018	28	RN.038320-1.01	8.4	37800000	0.30	245448	4.7	89	2024	2043	21844872	26922
2018	28	BA.037102-5.01	8.4	37800000	0.29	210384	4.1	79	2024	2043	16620336	26922
2018	28	BA.037104-1.01	8.4	37800000	0.29	210384	4.1	79	2024	2043	16620336	26922
2018	28	RN.038318-0.01	8.4	37800000	0.29	245448	4.8	89	2024	2043	21844872	26922
2018	28	RN.038319-8.01	8.4	37800000	0.29	245448	4.8	89	2024	2043	21844872	26922
2018	28	BA.032641-0.01	28.6	128700000	0.16	420768	14.9	91.33	2024	2043	38428741.44	91663

Table 43 – Projects Database

Year	Auction	id	MW	Investment	ACR %	MWh	P. W*	Bid Price	Start	End	Amount	Tust
2019	29	PI.044367-0.01	37.1	223045220	0.30	1034388	19.4	80.01	2023	2042	82761383.88	237811
2019	29	PI.044555-0.01	37.1	223045220	0.30	1051920	19.8	80	2023	2042	84153600	237811
2019	29	RN.036984-5.01	21	86126250	0.30	578556	11	79.92	2023	2042	46238195.52	67305
2019	30	BA.044961-0.01	21.2	99064300	0.31	385704	7.1	99.75	2025	2044	38473974	67946
2019	30	BA.044962-8.01	15.9	74298220	0.31	333108	6.2	99.75	2025	2044	33227523	50959.5
2019	30	RN.035172-5.01	12.6	58877840	0.32	262980	4.7	98.2	2025	2044	25824636	40383
2019	30	BA.044959-8.01	29.4	137381610	0.31	596088	11.1	98.2	2025	2044	58535841.6	94227
2019	30	BA.044960-1.01	29.4	137381210	0.30	683748	12.9	98.2	2025	2044	67144053.6	94227
2019	30	BA.032804-9.01	29.4	137381610	0.30	596088	11.2	98.2	2025	2044	58535841.6	94227
2019	30	BA.032805-7.01	21.2	99064300	0.30	473364	9	98.2	2025	2044	46484344.8	67946
2019	30	PI.032863-4.01	30	140184920	0.30	596088	11.3	99.75	2025	2044	59459778	192300
2019	30	PI.040567-1.01	29.4	137381610	0.30	701280	13.2	99.75	2025	2044	69952680	94227
2019	30	RN.032870-7.01	11	64439000	0.30	280512	5.3	98	2025	2044	27490176	35255
2019	30	RN.035008-7.01	26.4	154654000	0.30	718812	13.5	98	2025	2044	70443576	84612
2019	30	RS.035270-5.01	28.6	167542000	0.30	771408	14.6	98	2025	2044	75597984	91663
2019	30	RS.035271-3.01	28.6	167542000	0.30	753876	14.2	98	2025	2044	73879848	91663

Table 43 – Projects Database

Year	Auction	id	MW	Investment	ACR %	MWh	P. W*	Bid Price	Start	End	Amount	Tust
2019	30	BA.038077-6.01	30	120000000	0.44	1016856	13.3	96.99	2025	2044	98624863.44	192300
2019	30	BA.038078-4.01	30	120000000	0.31	648684	12.1	96.98	2025	2044	62909374.32	192300
2019	30	BA.038079-2.01	30	120000000	0.39	981792	14.2	97	2025	2044	95233824	192300
2019	30	BA.038081-4.01	30	120000000	0.32	824004	14.8	96.97	2025	2044	79903667.88	192300
2019	30	BA.038082-2.01	30	120000000	0.95	2209032	13.2	99.88	2025	2044	220638116.2	192300
2019	30	BA.038083-0.01	30	120000000	0.30	736344	13.9	96.98	2025	2044	71410641.12	192300
2019	30	BA.038084-9.01	30	120000000	0.36	824004	13.2	96.97	2025	2044	79903667.88	192300
2019	30	BA.038085-7.01	30	120000000	1.00	2507076	14.3	99.88	2025	2044	250406750.9	192300
2019	30	BA.038088-1.01	30	120000000	0.41	981792	13.8	97	2025	2044	95233824	192300
2019	30	BA.038089-0.01	30	120000000	1.00	2472012	14.1	99.88	2025	2044	246904558.6	192300
2019	30	PB.035225-0.01	17.325	70868000	0.32	420768	7.6	99.68	2025	2044	41942154.24	55526.63
2019	30	PB.035226-8.01	45.045	183754400	0.31	1139580	20.9	99.68	2025	2044	113593334.4	288738.45
2019	30	PB.035227-6.01	34.65	142733000	0.30	859068	16.3	99.68	2025	2044	85631898.24	222106.5
2019	30	PB.038304-0.01	24.255	99714000	0.31	578556	10.7	99.68	2025	2044	57670462.08	77737.28
2019	30	PB.040613-9.01	45.045	183754400	0.30	1157112	21.7	99.68	2025	2044	115340924.2	288738.45
2019	30	PB.038305-8.01	48.51	197427000	0.30	1051920	19.7	99.68	2025	2044	104855385.6	310949.1

Table 43 – Projects Database

Year	Auction	id	MW	Investment	ACR %	MWh	P. W*	Bid Price	Start	End	Amount	Tust
2019	30	BA.037004-5.01	27.5	96250000	0.41	876600	12.1	98.88	2025	2044	86678208	88137.5
2019	30	BA.044878-8.01	75.6	302400000	0.30	2121372	40.2	99.88	2025	2044	211882635.4	484596
2019	30	BA.032642-9.01	8.4	33600000	0.30	210384	4	98.98	2025	2044	20823808.32	26922
2019	30	BA.033547-9.01	8.4	33600000	0.30	210384	4	98.98	2025	2044	20823808.32	26922
2019	30	BA.033548-7.01	8.4	33600000	0.32	227916	4.1	98.99	2025	2044	22561404.84	26922
2019	30	BA.033549-5.01	8.4	33600000	0.30	210384	4	99	2025	2044	20828016	26922
2019	30	BA.037101-7.01	8.4	33600000	0.30	210384	4	98.99	2025	2044	20825912.16	26922
2019	30	RN.032593-7.01	8.4	33600000	0.30	262980	5	98.99	2025	2044	26032390.2	26922
2019	30	RN.033681-5.01	8.4	33600000	0.31	262980	4.9	98.98	2025	2044	26029760.4	26922
2019	30	RN.034937-2.01	8.4	33600000	0.31	262980	4.9	98.97	2025	2044	26027130.6	26922
2019	30	RN.033690-4.01	8.4	33600000	0.31	280512	5.2	99	2025	2044	27770688	26922
2019	30	RN.033691-2.01	8.4	33600000	0.30	262980	5	98.98	2025	2044	26029760.4	26922
2019	30	RN.045010-3.01	8.4	33600000	0.31	262980	4.9	99	2025	2044	26035020	26922
2019	30	RN.045011-1.01	8.4	33600000	0.31	262980	4.8	98.98	2025	2044	26029760.4	26922
2019	30	RN.045012-0.01	8.4	33600000	0.31	262980	4.8	98.97	2025	2044	26027130.6	26922

* Physical warranty (maximum available power of the plant (MWh/h).

Calculation Code

```
# -*- coding: utf-8 -*-
'''
Created on Wed Mar  3 22:20:29 2021
@author: vande
'''

import matplotlib.pyplot, numpy, numpy_financial, random, math
import pylab as pl
import scipy.stats as stats
from scipy.stats import poisson

# lendo o arquivo csv
arquivo = open('valuation.csv')

# quebrando em linhas e ignorando o cabeçalho
lista_linhas = arquivo.readlines()[1 : ]
arquivo.close()

# criando a lista com todos os valores da coluna do total_mwh
lista_totais_mwh = []
for linha in lista_linhas:
    celulas = linha.split(';')
    lista_totais_mwh.append(float(celulas[8]))

# criando a lista com todos os valores da coluna do bid_price
lista_bid_prices = []
for linha in lista_linhas:
    celulas = linha.split(';')
    lista_bid_prices.append(float(celulas[10]))

# criando a lista com todos os valores da coluna Percentual
lista_percentuais = []
for linha in lista_linhas:
    celulas = linha.split(';')
    lista_percentuais.append(float(celulas[6]))
```

```
# criando a lista com todos os valores da coluna POWER
lista_potencia = []
for linha in lista_linhas:
    celulas = linha.split(';')
    lista_potencia.append(float(celulas[4]))

# grupos dos leilões  pelos valores
lista_auctions = []
for linha in lista_linhas:
    celulas = linha.split(';')
    lista_auctions.append(int(celulas[1]))

# dicionario dos auctions e qts vzes se repetem
dicionario_auctions_qtdds = dict()
for auction in lista_auctions:
    dicionario_auctions_qtdds[auction] =\
    lista_auctions.count(auction)

# dicionário com os valores dos auctions e associamos a 0.0
dicionario_medias_auctions = dict()
for auction in dicionario_auctions_qtdds:\
dicionario_medias_auctions[auction] = 0.0

# lista resultado total_mwh x bid_price
lista_receita_regulado = []
for i in range(len(lista_linhas)): \
lista_receita_regulado.append((lista_totais_mwh[i] \
/ 175320 * 8766) * lista_bid_prices[i])

# médias da soma resultados por num de auctions
for i in range(len(lista_linhas)):
    numero_auction = lista_auctions[i]
    qtdd_auction = dicionario_auctions_qtdds[numero_auction]
    # já somamos o resultado pela qtdd do auction
    dicionario_medias_auctions[numero_auction] += \

    lista_receita_regulado[i] / qtdd_auction
```

```
# Medias da soma dos bid_price pelo número de auctions
dicionario_medias_bids = dict()
for auction in dicionario_auctions_qtdds:\
dicionario_medias_bids[auction] = 0.0
for i in range(len(lista_linhas)):
    numero_auction = lista_auctions[i]
    qtdd_auction = dicionario_auctions_qtdds[numero_auction]
    # resultado dividido pela qtdd do auction correspondente
    dicionario_medias_bids[numero_auction] += \
    lista_bid_prices[i] / qtdd_auction

# Medias da soma dos receita_regulado pelo num auctions
dicionario_medias_rec_reg = dict()
for auction in dicionario_auctions_qtdds:\
dicionario_medias_rec_reg[auction] = 0.0
for i in range(len(lista_linhas)):
    numero_auction = lista_auctions[i]
    qtdd_auction = dicionario_auctions_qtdds[numero_auction]
    # Resultado dividido pela qtdd do auction correspondente
    dicionario_medias_rec_reg[numero_auction] += \
    lista_receita_regulado[i] / qtdd_auction

#################

# qtdd médias por Leilões REGULADO
dicionario_medias_qtdd = dict()
for auction in dicionario_auctions_qtdds: \
dicionario_medias_qtdd[auction] = 0.0
for i in range(len(lista_linhas)):
    numero_auction = lista_auctions[i]
    qtdd_auction = dicionario_auctions_qtdds[numero_auction]
    # Resultado dividido pela qtdd do auction correspondente
    dicionario_medias_qtdd[numero_auction] += \
    lista_totais_mwh[i] / qtdd_auction

# cria as variáveis de Qttd regulado
qtdd_reg_28 = ((dicionario_medias_qtdd[28]) / 175320) * 8760
qtdd_reg_29 = ((dicionario_medias_qtdd[29]) / 175320) * 8760
qtdd_reg_30 = ((dicionario_medias_qtdd[30]) / 175320) * 8760
```

```python
# define as médias de preços licitados por leilão
prec_reg_28 = (dicionario_medias_bids[28])
prec_reg_29 = (dicionario_medias_bids[29])
prec_reg_30 = (dicionario_medias_bids[30])

# define as médias da receita do ACR
rec_28_reg = (dicionario_medias_rec_reg[28])
rec_29_reg = (dicionario_medias_rec_reg[29])
rec_30_reg = (dicionario_medias_rec_reg[30])

# MÉDIA DE PREÇOS DO ACL - ESSE VALOR É DADO
prec_liv_28 = [40.16, 505.18, 272.670, 273.904166666667]
prec_liv_29 = [42.35, 513.88, 278.115, 166.731666666667]
prec_liv_30 = [42.35,513.88, 278.115, 166.731666666667]

# aqui escolhemos qual prec_liv vamos usar
prec_escolhido = input("28, 29, ou 30? ")
if prec_escolhido not in ["28", "29", "30"]:
    print("Valor inválido.")
    exit()

# Input dos índice pra saber qual prec_liv usar
indice = int()
escolha = input("MIN, MAX, MED_ANTES, MED_DEPOIS: ")
if escolha == "MIN": indice = 0
elif escolha == "MAX": indice = 1
elif escolha == "MED_ANTES": indice = 2
elif escolha == "MED_DEPOIS": indice = 3
else:
    print("Digitado Incorretamente")
    exit()

# Input da volatilidade calculada na série de preços semanais
volatilidade = input("Digite o desvio padrão dos preços: ")
if volatilidade == "": volatilidade = 6.9
else: volatilidade = float(volatilidade)
speed = float(input('Veloc Reversão à Média : '))
lista_tempos = list(range(1, 1041))
```

```
def calcular_proximo_elemento(elemento_atual, tempo):
    return elemento_atual - speed * (elemento_atual -\
    (tempo * -0.1414 + 306.22)) + numpy.random.normal(0, 1) * \
    volatilidade+sum(numpy.random.binomial(size=1, n=1,p= 0.002))*\
    numpy.random.normal(275, 140)

# Manter os preços calculados sobre o prec_liv_28 e
# armazenar semanais
lista_precos_liv_28, lista_precos_semanais_28 = [], []
# primeiro elemento de lista_precos_semanais_28, vai gerar
#todos os outros 1040 (20 ANOS DE 52 SEMANAS) valores
elemento_atual = prec_liv_28[indice]
for i in range(1040):
    lista_precos_semanais_28.append(elemento_atual)
    proximo_elemento = calcular_proximo_elemento(elemento_atual,\
    lista_tempos[i])
    elemento_atual = proximo_elemento
for i in range(20):
    lista_precos_liv_28.append(numpy.mean(lista_precos_semanais_28\
    [i * 52: i * 52 + 52]))

# repete acima, para o prec_liv_29
lista_precos_liv_29, lista_precos_semanais_29 = [], []
elemento_atual = prec_liv_29[indice]
for i in range(1040):
    lista_precos_semanais_29.append(elemento_atual)
    proximo_elemento = calcular_proximo_elemento(elemento_atual,\
    lista_tempos[i])
    elemento_atual = proximo_elemento
for i in range(20):
    lista_precos_liv_29.append(numpy.mean(lista_precos_semanais_29\
    [i * 52: i * 52 + 52]))

# repete acima, para o prec_liv_30
lista_precos_liv_30, lista_precos_semanais_30 = [], []
elemento_atual = prec_liv_30[indice]
for i in range(1040):
```

```
    lista_precos_semanais_30.append(elemento_atual)
    proximo_elemento = calcular_proximo_elemento(elemento_atual,\
    lista_tempos[i])
    elemento_atual = proximo_elemento
for i in range(20):
    lista_precos_liv_30.append(numpy.mean(lista_precos_semanais_30\
    [i * 52: i * 52 + 52]))

# Calcular a lista com as quantidades livres
lista_qtdd_livre = []
for linha in lista_linhas:
    celulas = linha.split(';')
    lista_qtdd_livre.append(((float(celulas[8]) / 175320 * 8766) \
    / float(celulas[6])) * (1 - float(celulas[6])))

# Criar o dicionario com as medias das quantidades livres
dicionario_medias_qtdd_livre = dict()
# ele começa todo igual a 0.0
for auction in dicionario_auctions_qtdds:\
dicionario_medias_qtdd_livre[auction] = 0.0
for i in range(len(lista_linhas)):
    numero_auction = lista_auctions[i]
    qtdd_auction = dicionario_auctions_qtdds[numero_auction]
    # Resultado dividido pela qtdd do auction correspondente
    dicionario_medias_qtdd_livre[numero_auction] +=\
    lista_qtdd_livre[i] / qtdd_auction

# Variáveis de Qtdd livre e suas listas, para cada
#qtdd livre nós teremos uma lista com os 20 valores, a
#qtdd_liv é apenas o primeiro valor
qtdd_liv_28 = dicionario_medias_qtdd_livre[28]
lista_quantidades_28 = [qtdd_liv_28]
for i in range(len(lista_precos_liv_28) - 1):
    if i < 5: lista_quantidades_28.append(lista_quantidades_28[i] + \
    lista_quantidades_28[i] * 0.15 * (lista_precos_liv_28[i] - \
    lista_precos_liv_28[i + 1]) / \
    lista_precos_liv_28[i])
    elif i < 10: lista_quantidades_28.append(lista_quantidades_28[i] \
    + lista_quantidades_28[i] * 0.30 *\
```

```
    (lista_precos_liv_28[i] - lista_precos_liv_28[i + 1]) / \
    lista_precos_liv_28[i])
    elif i < 15: lista_quantidades_28.append \
    (lista_quantidades_28[i] + \
    lista_quantidades_28[i] \
    * 0.45 * (lista_precos_liv_28[i] - lista_precos_liv_28[i + 1]) \
    / lista_precos_liv_28[i])
    elif i < 20: lista_quantidades_28.append\
    (lista_quantidades_28[i] + lista_quantidades_28[i] \
    * 0.60 * (lista_precos_liv_28[i] -\
    lista_precos_liv_28[i + 1]) \ \

    / lista_precos_liv_28[i])

qtdd_liv_29 = dicionario_medias_qtdd_livre[29]
lista_quantidades_29 = [qtdd_liv_29]
for i in range(len(lista_precos_liv_29) - 1):
    if i < 5: lista_quantidades_29.append(lista_quantidades_29[i] +\
    lista_quantidades_29[i] * 0.15 * (lista_precos_liv_29[i] - \
    lista_precos_liv_29[i + 1]) / lista_precos_liv_29[i])
    elif i < 10: lista_quantidades_29.append\
    (lista_quantidades_29[i] + lista_quantidades_29[i] \
    * 0.30 * (lista_precos_liv_29[i] - lista_precos_liv_29[i + 1]) \
    / lista_precos_liv_29[i])
    elif i < 15: lista_quantidades_29.append\
    (lista_quantidades_29[i] + lista_quantidades_29[i] * 0.45 \
    * (lista_precos_liv_29[i] - lista_precos_liv_29[i + 1]) \
    / lista_precos_liv_29[i])
    elif i < 20: lista_quantidades_29.append\
    (lista_quantidades_29[i] \
    + lista_quantidades_29[i] * 0.60 * (lista_precos_liv_29[i] \
    - lista_precos_liv_29[i + 1]) \
    / lista_precos_liv_29[i])

qtdd_liv_30 = dicionario_medias_qtdd_livre[30]
lista_quantidades_30 = [qtdd_liv_30]
for i in range(len(lista_precos_liv_30) - 1):
    if i < 5: lista_quantidades_30.append\
    (lista_quantidades_30[i] \
```

```
    + lista_quantidades_30[i] * 0.15\
    * (lista_precos_liv_30[i] \
    - lista_precos_liv_30[i + 1]) \
    / lista_precos_liv_30[i])
    elif i < 10: lista_quantidades_30.append\
    (lista_quantidades_30[i] \
    + lista_quantidades_30[i] * 0.30 \
    * (lista_precos_liv_30[i] \
    - lista_precos_liv_30[i + 1]) \
    / lista_precos_liv_30[i])
    elif i < 15: lista_quantidades_30.append\
    (lista_quantidades_30[i] \
    + lista_quantidades_30[i] * 0.45 \
    * (lista_precos_liv_30[i] \
    - lista_precos_liv_30[i + 1]) / lista_precos_liv_30[i])
    elif i < 20: lista_quantidades_30.append\
    (lista_quantidades_30[i] \
    + lista_quantidades_30[i] * 0.60 \
    * (lista_precos_liv_30[i] - \
    lista_precos_liv_30[i + 1]) \
    \
    / lista_precos_liv_30[i])

# Aqui cria as variáveis receitas
rec_28 = prec_reg_28 * qtdd_reg_28 + \
prec_liv_28[indice] * qtdd_liv_28
rec_29 = prec_reg_29 * qtdd_reg_29 + \
prec_liv_29[indice] * qtdd_liv_29
rec_30 = prec_reg_30 * qtdd_reg_30 + \
prec_liv_30[indice] * qtdd_liv_30

# Listas com as receitas ACL (livre)

lista_rec_liv_28 = []
for i in range(len(lista_precos_liv_28)):
    lista_rec_liv_28.append(lista_precos_liv_28[i] * \
    lista_quantidades_28[i])
lista_rec_liv_29 = []
for i in range(len(lista_precos_liv_29)):
```

```
    lista_rec_liv_29.append\
    (lista_precos_liv_29[i] * \ lista_quantidades_29[i])
lista_rec_liv_30 = []
for i in range(len(lista_precos_liv_30)):
    lista_rec_liv_30.append\
    (lista_precos_liv_30[i] * \
    lista_quantidades_30[i])

# Listas com as receitas ACR
lista_rec_reg_28 = [rec_28_reg] * \
len(lista_rec_liv_28)
lista_rec_reg_29 = [rec_29_reg] * \
len(lista_rec_liv_29)
lista_rec_reg_30 = [rec_30_reg] * \
len(lista_rec_liv_30)

# Listas com as receitas TOTAIS
lista_rec_total_28 = []
for i in range(len(lista_rec_liv_28)): lista_rec_total_28.append\
(lista_rec_liv_28[i] + \
lista_rec_reg_28[i])\
lista_rec_total_29 = []
for i in range(len(lista_rec_liv_29)):\
lista_rec_total_29.append(lista_rec_liv_29[i] \
+ lista_rec_reg_29[i])
lista_rec_total_30 = []
for i in range(len(lista_rec_liv_30)):\
lista_rec_total_30.append\
(lista_rec_liv_30[i] + lista_rec_reg_30[i])

# CRIA A DE PIS PASEP TOTAL
lista_pis_pasep_total_28 = []
for i in range(len(lista_rec_liv_28)): lista_pis_pasep_total_28.append\
(lista_rec_total_28[i]  * 0.0165)
lista_pis_pasep_total_29 = []
for i in range(len(lista_rec_liv_29)): lista_pis_pasep_total_29.append\
(lista_rec_total_29[i] * 0.0165)
lista_pis_pasep_total_30 = []
for i in range(len(lista_rec_liv_30)): lista_pis_pasep_total_30.append\
```

```
(lista_rec_total_30[i] * 0.0165)

# CRIA A DE COFINS TOTAL
lista_cofins_total_28 = []
for i in range(len(lista_rec_liv_28)): lista_cofins_total_28.append\
(lista_rec_total_28[i]  * 0.076)
lista_cofins_total_29 = []
for i in range(len(lista_rec_liv_29)): lista_cofins_total_29.append\
(lista_rec_total_29[i]  * 0.076)
lista_cofins_total_30 = []
for i in range(len(lista_rec_liv_30)): lista_cofins_total_30.append\
(lista_rec_total_30[i]  * 0.076)

# CRIA A LISTA OPEX TOTAL
lista_opex_total_28 = []
for i in range(len(lista_rec_liv_28)): lista_opex_total_28.append\
(lista_rec_total_28[i]  * 0.125)
lista_opex_total_29 = []
for i in range(len(lista_rec_liv_29)): lista_opex_total_29.append\
(lista_rec_total_29[i] * 0.125)
lista_opex_total_30 = []
for i in range(len(lista_rec_liv_30)):\
lista_opex_total_30.append\
(lista_rec_total_30[i] * 0.125)

# CRIA A LISTA ONS & CCEE
lista_ons_ccee_28_total = []
for i in range(len(lista_rec_liv_28)):\
lista_ons_ccee_28_total.append\
(lista_rec_total_28[i]  * 0.01)
lista_ons_ccee_29_total = []\

for i in range(len(lista_rec_liv_29)):\
lista_ons_ccee_29_total.append(lista_rec_total_29[i] * 0.01)
lista_ons_ccee_30_total = []\

for i in range(len(lista_rec_liv_30)):\
lista_ons_ccee_30_total.append\
(lista_rec_total_30[i] * 0.01)
```

```
# CRIA A LISTA LEASING TOTAL
lista_leasing_28_total = []
for i in range(len(lista_rec_liv_28)):\
lista_leasing_28_total.append\
(lista_rec_total_28[i]  * 0.01)
lista_leasing_29_total = []
for i in range(len(lista_rec_liv_29)):\
lista_leasing_29_total.append\
(lista_rec_total_29[i] * 0.01)
lista_leasing_30_total = []
for i in range(len(lista_rec_liv_30)):\
lista_leasing_30_total.append\
(lista_rec_total_30[i] * 0.01)

# CRIA A LISTA TUST SÓ REGULADO POIS no ACL é o consumidor que paga
lista_tust_reg = []
for linha in lista_linhas:
    celulas = linha.split(';')
    lista_tust_reg.append(float(celulas[14]))

# CRIA dicionário TUST
dicionario_medias_tust_regulado = dict()
for auction in dicionario_auctions_qtdds:\
dicionario_medias_tust_regulado[auction] = 0.0
for i in range(len(lista_linhas)):
    numero_auction = lista_auctions[i]
    qtdd_auction =
    dicionario_auctions_qtdds[numero_auction]\

    # somamos o resultado dividido pela qtdd auction correspondente
    dicionario_medias_tust_regulado[numero_auction] \
    += lista_tust_reg[i] / qtdd_auction

# cria as variáveis médias de TUST REGULADO TOTAL
tust_reg_28 = dicionario_medias_tust_regulado[28]
tust_reg_29 = dicionario_medias_tust_regulado[29]
tust_reg_30 = dicionario_medias_tust_regulado[30]
```

```
# CRIA TODAS AS DESPESAS TOTAL
lista_despesas_total_28 = []
for i in range(len(lista_rec_liv_28)):\
lista_despesas_total_28.append\
(lista_pis_pasep_total_28[i] + lista_cofins_total_28[i] \
+ lista_opex_total_28[i] + lista_ons_ccee_28_total[i] \
+ lista_leasing_28_total[i] + tust_reg_28)
lista_despesas_total_29 = []
for i in range(len(lista_rec_liv_29)):\
lista_despesas_total_29.append\
(lista_pis_pasep_total_29[i] + lista_cofins_total_29[i] \
+ lista_opex_total_29[i] + lista_ons_ccee_29_total[i] \
+ lista_leasing_29_total[i] + tust_reg_29)
lista_despesas_total_30 = []
for i in range(len(lista_rec_liv_30)):\
lista_despesas_total_30.append\
(lista_pis_pasep_total_30[i] + lista_cofins_total_30[i] \
+ lista_opex_total_30[i] + lista_ons_ccee_30_total[i] \
+ lista_leasing_30_total[i] + tust_reg_30)

# CRIA TODAS OS FLUXOS DE CAIXA TOTAL
lista_fc_total_28 = []
for i in range (len(lista_rec_liv_28)):\
lista_fc_total_28.append\
(lista_rec_total_28[i] - lista_despesas_total_28[i])
lista_fc_total_29 = []
for i in range (len(lista_rec_liv_29)):\
lista_fc_total_29.append(lista_rec_total_29[i] \
- lista_despesas_total_29[i])
lista_fc_total_30 = []
for i in range (len(lista_rec_liv_30)): lista_fc_total_30.append\
(lista_rec_total_30[i] - lista_despesas_total_30[i])

# CRIA TODAS AS DEPRECIAÇÕES FLUXOS DE CAIXA TOTAL
lista_depre_total_28 = []
for i in range (len(lista_rec_liv_28)): lista_depre_total_28.append\
(lista_fc_total_28[i] * 0.05)
lista_depre_total_29 = []
for i in range (len(lista_rec_liv_29)): lista_depre_total_29.append\
```

```
(lista_fc_total_29[i] * 0.05)
lista_depre_total_30 = []
for i in range (len(lista_rec_liv_30)): lista_depre_total_30.append\
(lista_fc_total_30[i] * 0.05)

# CRIA TODAS AS DEPRECIAÇÕES FLUXOS DE CAIXA TOTAL
lista_fc_trib_total_28 = []
for i in range (len(lista_rec_liv_28)): lista_fc_trib_total_28.append\
(lista_fc_total_28[i] - lista_depre_total_28[i])
lista_fc_trib_total_29 = []
for i in range (len(lista_rec_liv_29)): lista_fc_trib_total_29.append\
(lista_fc_total_29[i] - lista_depre_total_29[i])
lista_fc_trib_total_30 = []
for i in range (len(lista_rec_liv_30)): lista_fc_trib_total_30.append\
(lista_fc_total_30[i] - lista_depre_total_30[i])

# CRIA TODAS A VARIAVEL IMPOSTO TOTAL
lista_imposto_total_28 = []
for i in range (len(lista_rec_liv_28)): lista_imposto_total_28.append\
(lista_fc_trib_total_28[i] * 0.24)
lista_imposto_total_29 = []
for i in range (len(lista_rec_liv_29)): lista_imposto_total_29.append\
(lista_fc_trib_total_29[i] * 0.24)
lista_imposto_total_30 = []
for i in range (len(lista_rec_liv_30)): lista_imposto_total_30.append\
(lista_fc_trib_total_30[i] * 0.24)

# CRIA O FLUXO DE CAIXA LIVRE TOTAL
lista_fcl_total_28 = []
for i in range (len(lista_rec_liv_28)): lista_fcl_total_28.append\
((lista_fc_trib_total_28[i] - lista_imposto_total_28[i]) \
+ lista_depre_total_28[i])
lista_fcl_total_29 = []
for i in range (len(lista_rec_liv_29)): lista_fcl_total_29.append\
((lista_fc_trib_total_29[i] - lista_imposto_total_29[i]) \
+ lista_depre_total_29[i])
lista_fcl_total_30 = []
for i in range (len(lista_rec_liv_30)): lista_fcl_total_30.append\
((lista_fc_trib_total_30[i] - lista_imposto_total_30[i]) \
```

```
+ lista_depre_total_30[i])

# Investimentos dos Projetos TOTAL
invest_28 = 121557295.4166670000
invest_29 = 177405563.3333330000
invest_30 = 102020305.0000000000

# WACC DOS PROJETOS TOTAL
taxa_28 = 0.0766
taxa_29 = 0.0739
taxa_30 = 0.0739

#####   NPV TOTAL   ######
npv_28_total = numpy_financial.npv(taxa_28, \
[-invest_28*0.5, -invest_28*0.5, 0,\
lista_fcl_total_28[0], lista_fcl_total_28[1],\
lista_fcl_total_28[2], lista_fcl_total_28[3],\
lista_fcl_total_28[4], lista_fcl_total_28[5],\
lista_fcl_total_28[6], lista_fcl_total_28[7],\
lista_fcl_total_28[8], lista_fcl_total_28[9],\
lista_fcl_total_28[10], lista_fcl_total_28[11],\
lista_fcl_total_28[12], lista_fcl_total_28[13],\
lista_fcl_total_28[14], lista_fcl_total_28[15],\
lista_fcl_total_28[16], lista_fcl_total_28[17],\
lista_fcl_total_28[18], lista_fcl_total_28[19]])

npv_29_total = numpy_financial.npv(taxa_29,\
[-invest_29*0.5, -invest_29*0.5, 0,\
lista_fcl_total_29[0], lista_fcl_total_29[1],\
lista_fcl_total_29[2], lista_fcl_total_29[3],\
lista_fcl_total_29[4], lista_fcl_total_29[5],\
lista_fcl_total_29[6], lista_fcl_total_29[7],\
lista_fcl_total_29[8], lista_fcl_total_29[9],\
lista_fcl_total_29[10], lista_fcl_total_29[11],\
lista_fcl_total_29[12], lista_fcl_total_29[13],\
lista_fcl_total_29[14], lista_fcl_total_29[15],\
lista_fcl_total_29[16], lista_fcl_total_29[17],\
lista_fcl_total_29[18], lista_fcl_total_29[19]])\
```

```
npv_30_total = numpy_financial.npv(taxa_30,\
[-invest_30*0.5, -invest_30*0.5, 0,\
lista_fcl_total_30[0], lista_fcl_total_30[1],\
lista_fcl_total_30[2], lista_fcl_total_30[3],\
lista_fcl_total_30[4], lista_fcl_total_30[5],\
lista_fcl_total_30[6], lista_fcl_total_30[7],\
lista_fcl_total_30[8], lista_fcl_total_30[9],\
lista_fcl_total_30[10], lista_fcl_total_30[11],\
lista_fcl_total_30[12], lista_fcl_total_30[13],\
lista_fcl_total_30[14], lista_fcl_total_30[15],\
lista_fcl_total_30[16], lista_fcl_total_30[17],\
lista_fcl_total_30[18], lista_fcl_total_30[19]])\


####### IRR TOTAL #########
irr_28_total = numpy_financial.irr([-invest_28*0.5, \
-invest_28*0.5, 0, lista_fcl_total_28[0],\
lista_fcl_total_28[1], lista_fcl_total_28[2],\
lista_fcl_total_28[3], lista_fcl_total_28[4],\
lista_fcl_total_28[5], lista_fcl_total_28[6],\
lista_fcl_total_28[7], lista_fcl_total_28[8],\
lista_fcl_total_28[9], lista_fcl_total_28[10],\
lista_fcl_total_28[11], lista_fcl_total_28[12],\
lista_fcl_total_28[13], lista_fcl_total_28[14],\
lista_fcl_total_28[15], lista_fcl_total_28[16],\
lista_fcl_total_28[17], lista_fcl_total_28[18],\
lista_fcl_total_28[19]])
irr_29_total = numpy_financial.irr([-invest_29*0.5, \
-invest_29*0.5, 0, lista_fcl_total_29[0],\
lista_fcl_total_29[1], lista_fcl_total_29[2],\
lista_fcl_total_29[3], lista_fcl_total_29[4],\
lista_fcl_total_29[5], lista_fcl_total_29[6],\
lista_fcl_total_29[7], lista_fcl_total_29[8],\
lista_fcl_total_29[9], lista_fcl_total_29[10],\
lista_fcl_total_29[11], lista_fcl_total_29[12],\
lista_fcl_total_29[13], lista_fcl_total_29[14],\
lista_fcl_total_29[15], lista_fcl_total_29[16],\
lista_fcl_total_29[17], lista_fcl_total_29[18],\
lista_fcl_total_29[19]])
```

```
irr_30_total = numpy_financial.irr([-invest_30*0.5, \
-invest_30*0.5, 0, lista_fcl_total_30[0],\
lista_fcl_total_30[1], lista_fcl_total_30[2],\
lista_fcl_total_30[3], lista_fcl_total_30[4],\
lista_fcl_total_30[5], lista_fcl_total_30[6],\
lista_fcl_total_30[7], lista_fcl_total_30[8],\
lista_fcl_total_30[9], lista_fcl_total_30[10],\
lista_fcl_total_30[11], lista_fcl_total_30[12],\
lista_fcl_total_30[13], lista_fcl_total_30[14], \
lista_fcl_total_30[15], lista_fcl_total_30[16],\
lista_fcl_total_30[17], lista_fcl_total_30[18],\
lista_fcl_total_30[19]])

#####SMC#######

# calcula a lista com as dispersões de valores
def dispersao_valor(n, prec_liv, qtdd_liv, prec_reg, qtdd_reg, \
tust_reg, taxa, invest):
    lista_de_listas_com_precos_pra_mostrar_grafico,\
    lista_de_listas_com_quantidades_pra_mostrar_grafico, \
    lista_de_listas_com_precos_semanais = [], [], []
    lista_npv, lista_z = [], []
    lista_fcl_antec = []
    lista_npv_antec =[]
    pv0 = 0

    # calcular as listas p/ depois desenha-las
    for x in range(n):
        lista_precos_semanais, lista_precos_liv = [], []

        elemento_atual = numpy.random.normal\
        (prec_liv, prec_liv * 0)
        for i in range(1040):
            lista_precos_semanais.append\
            (elemento_atual)
            proximo_elemento = calcular_proximo_elemento\
            (elemento_atual, lista_tempos[i])
            elemento_atual = proximo_elemento
        lista_de_listas_com_precos_semanais.append\
```

```
(lista_precos_semanais)

for i in range(20):
    lista_precos_liv.append(numpy.mean\
    (lista_precos_semanais[i \
    * 52: i * 52 + 52]))

lista_quantidades = [numpy.random.normal\
(qtdd_liv, qtdd_liv * 0)]
for i in range(len(lista_precos_liv) - 1):
    if i < 5: lista_quantidades.append\
    (lista_quantidades[i] + lista_quantidades[i] \
    * 0.15 * (lista_precos_liv[i] \
    - lista_precos_liv[i + 1]) \
    / lista_precos_liv[i])
    elif i < 10: lista_quantidades.append\
    (lista_quantidades[i] + lista_quantidades[i] * 0.30 \
    * (lista_precos_liv[i] - lista_precos_liv[i + 1]) \
    / lista_precos_liv[i])
    elif i < 15: lista_quantidades.append\
    (lista_quantidades[i] + lista_quantidades[i] * 0.45 \
    * (lista_precos_liv[i] - lista_precos_liv[i + 1]) \
    / lista_precos_liv[i])
    elif i < 20: lista_quantidades.append\
    (lista_quantidades[i] + lista_quantidades[i] * 0.60 \
    * (lista_precos_liv[i] - lista_precos_liv[i + 1]) \
    / lista_precos_liv[i])

nova_lista_fcl_total = []
for i in range(len(lista_precos_liv)):
    rec_total = prec_reg \
    * qtdd_reg + lista_precos_liv[i] * lista_quantidades[i]
    despesa_total = rec_total \
    * 0.0165 + rec_total * 0.076 \
    + rec_total * 0.125 + rec_total \
    * 0.01 + rec_total * 0.01 + tust_reg
    fc_total = rec_total \
    - despesa_total
    depre_total = fc_total * 0.05
```

```
        fc_trib_total = fc_total - depre_total
        imposto_total = fc_trib_total \
        * 0.24
        fcl_total = (fc_trib_total - imposto_total + depre_total)
        nova_lista_fcl_total.append(fcl_total)

    npv = numpy_financial.npv(taxa, [-invest
    * 0.5, -invest * 0.5, 0,\
    nova_lista_fcl_total[0],\
    nova_lista_fcl_total[1],\
    nova_lista_fcl_total[2],\
    nova_lista_fcl_total[3],\
    nova_lista_fcl_total[4],\
    nova_lista_fcl_total[5],\
    nova_lista_fcl_total[6],\
    nova_lista_fcl_total[7],\
    nova_lista_fcl_total[8],\
    nova_lista_fcl_total[9],\
    nova_lista_fcl_total[10],\
    nova_lista_fcl_total[11],\
    nova_lista_fcl_total[12],\
    nova_lista_fcl_total[13],\
    nova_lista_fcl_total[14],\
    nova_lista_fcl_total[15],\
    nova_lista_fcl_total[16],\
    nova_lista_fcl_total[17],\
    nova_lista_fcl_total[18],\
    nova_lista_fcl_total[19]])\


    lista_npv.append(npv)

    for i in range(3):
        rec_antec = (qtdd_reg + lista_quantidades[i]) \
        * lista_precos_liv[i]
        despesa_antec = rec_antec * 0.0165 \
        + rec_antec * 0.076 + rec_antec * 0.125 + rec_antec \
        * 0.01 + rec_antec * 0.01 + tust_reg
        fc_antec = rec_antec - despesa_antec
```

```
        depre_antec = fc_antec * 0.05
        fc_trib_antec = fc_antec - depre_antec
        imposto_antec = fc_trib_antec * 0.24
        fcl_antec = (fc_trib_antec \
        - imposto_antec + depre_antec)
        lista_fcl_antec.append(fcl_antec)

    npv_antec = numpy_financial.npv(taxa, [-invest \
    * 0.5, -invest * 0.5, 0, lista_fcl_antec[0],\
    lista_fcl_antec[1], lista_fcl_antec[2],\
    nova_lista_fcl_total[0],\
    nova_lista_fcl_total[1],\
    nova_lista_fcl_total[2],\
    nova_lista_fcl_total[3],\
    nova_lista_fcl_total[4],\
    nova_lista_fcl_total[5],\
    nova_lista_fcl_total[6],\
    nova_lista_fcl_total[7],\
    nova_lista_fcl_total[8],\
    nova_lista_fcl_total[9],\
    nova_lista_fcl_total[10],\
    nova_lista_fcl_total[11],\
    nova_lista_fcl_total[12],\
    nova_lista_fcl_total[13],\
    nova_lista_fcl_total[14],\
    nova_lista_fcl_total[15],\
    nova_lista_fcl_total[16],\
    nova_lista_fcl_total[17],\
    nova_lista_fcl_total[18],\
    nova_lista_fcl_total[19]])\
    lista_npv_antec.append(npv_antec)

    pv0_antec = numpy_financial.npv(taxa, [0, 0,\
    0, lista_fcl_antec[0], lista_fcl_antec[1],\
    lista_fcl_antec[2], nova_lista_fcl_total[0],\
    nova_lista_fcl_total[1],\
    nova_lista_fcl_total[2],\
    nova_lista_fcl_total[3],\
    nova_lista_fcl_total[4],\
```

```
nova_lista_fcl_total[5],\
nova_lista_fcl_total[6],\
nova_lista_fcl_total[7],\
nova_lista_fcl_total[8],\
nova_lista_fcl_total[9],\
nova_lista_fcl_total[10],\
nova_lista_fcl_total[11],\
nova_lista_fcl_total[12],\
nova_lista_fcl_total[13],\
nova_lista_fcl_total[14],\
nova_lista_fcl_total[15],\
nova_lista_fcl_total[16],\
nova_lista_fcl_total[17],\
nova_lista_fcl_total[18],\
nova_lista_fcl_total[19]])\


if x == 0: pv0 = numpy_financial.npv(taxa, [0, 0, 0, \
lista_fcl_antec[0], lista_fcl_antec[1],\
lista_fcl_antec[2], nova_lista_fcl_total[0],\
nova_lista_fcl_total[1],\
nova_lista_fcl_total[2],\
nova_lista_fcl_total[3],\
nova_lista_fcl_total[4],\
nova_lista_fcl_total[5],\
nova_lista_fcl_total[6],\
nova_lista_fcl_total[7],\
nova_lista_fcl_total[8],\
nova_lista_fcl_total[9],\
nova_lista_fcl_total[10],\
nova_lista_fcl_total[11],\
nova_lista_fcl_total[12],\
nova_lista_fcl_total[13],\
nova_lista_fcl_total[14],\
nova_lista_fcl_total[15],\
nova_lista_fcl_total[16],\
nova_lista_fcl_total[17],\
nova_lista_fcl_total[18],\
nova_lista_fcl_total[19]])\
```

```
        for i in range (1):
            pv1 = numpy_financial.npv(taxa, [0, 0,\
            lista_fcl_antec[0], lista_fcl_antec[1],\
            lista_fcl_antec[2],\
            nova_lista_fcl_total[0],\
            nova_lista_fcl_total[1],\
            nova_lista_fcl_total[2],\
            nova_lista_fcl_total[3],\
            nova_lista_fcl_total[4],\
            nova_lista_fcl_total[5],\
            nova_lista_fcl_total[6],\
            nova_lista_fcl_total[7],\
            nova_lista_fcl_total[8],\
            nova_lista_fcl_total[9],\
            nova_lista_fcl_total[10],\
            nova_lista_fcl_total[11],\
            nova_lista_fcl_total[12],\
            nova_lista_fcl_total[13],\
            nova_lista_fcl_total[14],\ nova_lista_fcl_total[15],\
            nova_lista_fcl_total[16],\
            nova_lista_fcl_total[17],\
            nova_lista_fcl_total[18],\
            nova_lista_fcl_total[19]])\

        z = numpy.log((pv1 ) / pv0)
        lista_z.append(z)



        lista_de_listas_com_quantidades_pra_mostrar_grafico.append\
        (lista_quantidades)\

        lista_de_listas_com_precos_pra_mostrar_grafico.append\
        (lista_precos_liv)

    # gráficos das listas dos preços
    #e das listas das quantidades,
    matplotlib.pyplot.xticks(range(20))
```

```
    for lista in lista_de_listas_com_precos_semanais:\
    matplotlib.pyplot.plot(list(range(0, 1040)), lista, scalex=True)
    matplotlib.pyplot.xlabel('Years', fontsize=14)
    matplotlib.pyplot.ylabel('Weekly Prices', fontsize=14)
    matplotlib.pyplot.show()

    matplotlib.pyplot.xticks(range(20))
    for lista in lista_de_listas_com_precos_pra_mostrar_grafico:\
    matplotlib.pyplot.plot(list(range(0, 20)), lista, scalex=True)
    matplotlib.pyplot.xlabel('Years', fontsize=14)
    matplotlib.pyplot.ylabel('Prices', fontsize=14)
    matplotlib.pyplot.show()

    matplotlib.pyplot.xticks(range(20))
    for lista in lista_de_listas_com_quantidades_pra_mostrar_grafico:\
    matplotlib.pyplot.plot(list(range(0, 20)), lista, scalex=True)
    matplotlib.pyplot.xlabel('Years', fontsize=14)
    matplotlib.pyplot.ylabel('Quantity', fontsize=14)
    matplotlib.pyplot.show()

    # aqui vamos desenhar o gráfico da lista_z
    comeco = numpy.percentile(lista_z, 5)
    fim = numpy.percentile(lista_z, 95)
    matplotlib.pyplot.hist(lista_z, bins = 100)
    matplotlib.pyplot.ylabel('lista z')
    matplotlib.pyplot.xlabel('lista z')
    matplotlib.pyplot.axvline(numpy.mean(lista_z),\
    color = '#fc4f30', label = 'Median')\

    matplotlib.pyplot.axvspan\
    (comeco, fim, facecolor = 'g', alpha = 0.3)
    matplotlib.pyplot.show()

    print ('DESVIO PADRÃO LISTA Z', numpy.std(lista_z))

    return lista_npv

# Função que calcula a lista com as dispersões de taxas
def dispersao_taxa(n, prec_liv, qtdd_liv, \
```

```
prec_reg, qtdd_reg, tust_reg, invest):
    lista_irr = []

    # nesse loop calculamos a lista criada acima
    for i in range(n):
        lista_precos_semanais, lista_precos_liv = [], []

        elemento_atual = numpy.random.normal(prec_liv, prec_liv * 0)
        for i in range(1040):
            lista_precos_semanais.append\
            (elemento_atual)
            proximo_elemento = calcular_proximo_elemento\

            (elemento_atual, lista_tempos[i])
            elemento_atual \
            = proximo_elemento

        for i in range(20):
            lista_precos_liv.append\
            (numpy.mean(lista_precos_semanais\
            [i \
            * 52: i * 52 + 52]))

        lista_quantidades = [numpy.random.normal(qtdd_liv, \
        qtdd_liv * 0)]
        for i in range(len\
        (lista_precos_liv) - 1):
            if i < 5: lista_quantidades.append\
            (lista_quantidades[i] \
            + lista_quantidades[i] \
            * 0.15 * (lista_precos_liv[i] \
            - lista_precos_liv[i + 1]) / lista_precos_liv[i])
            elif i < 10: lista_quantidades.append\
            (lista_quantidades[i] \
            + lista_quantidades[i] * 0.30 \
            * (lista_precos_liv[i] - lista_precos_liv[i + 1]) \
            / lista_precos_liv[i])
            elif i < 15: lista_quantidades.append\
            (lista_quantidades[i] + lista_quantidades[i] * 0.45 \
```

```
    * (lista_precos_liv[i] \
    - lista_precos_liv[i + 1]) / lista_precos_liv[i])
    elif i < 20: lista_quantidades.append\
    (lista_quantidades[i] + lista_quantidades[i] \
    * 0.60 * (lista_precos_liv[i] \
    - lista_precos_liv[i + 1]) \
    / lista_precos_liv[i])

nova_lista_fcl_total = []
for i in range(len(lista_precos_liv)):\

    rec_total = prec_reg * qtdd_reg \
    + lista_precos_liv[i] * lista_quantidades[i]
    despesa_total = rec_total \
    * 0.0165 + rec_total * 0.076 \
    + rec_total * 0.125 + rec_total\
    * 0.01 + rec_total * 0.01 + tust_reg
    fc_total = rec_total - despesa_total
    depre_total = fc_total \
    * 0.05
    fc_trib_total = fc_total \
    - depre_total
    imposto_total = fc_trib_total \
    * 0.24
    nova_lista_fcl_total.append\
    (fc_trib_total - imposto_total \
    + depre_total)

resultado = numpy_financial.irr([-invest *\
0.5, -invest * 0.5, 0,\
nova_lista_fcl_total[0],\
nova_lista_fcl_total[1],\
nova_lista_fcl_total[2],\
nova_lista_fcl_total[3],\
nova_lista_fcl_total[4],\
nova_lista_fcl_total[5],\
nova_lista_fcl_total[6],\
nova_lista_fcl_total[7],\
nova_lista_fcl_total[8],\
```

```
        nova_lista_fcl_total[9],\
        nova_lista_fcl_total[10],\
        nova_lista_fcl_total[11],\
        nova_lista_fcl_total[12],\
        nova_lista_fcl_total[13],\
        nova_lista_fcl_total[14],\
        nova_lista_fcl_total[15],\
        nova_lista_fcl_total[16],\
        nova_lista_fcl_total[17],\
        nova_lista_fcl_total[18],\
        nova_lista_fcl_total[19]])
        lista_irr.append(resultado)
    return lista_irr
```

Desenhar gráficos

```
# Função que desenha o gráfico de dispersões de valores
def desenhar_grafico_valores(n, prec_liv, qtdd_liv,\
prec_reg, qtdd_reg, tust_reg, \
taxa, invest):
    lista = dispersao_valor(n, prec_liv, qtdd_liv, prec_reg, \
    qtdd_reg, tust_reg, taxa, invest)
    comeco = numpy.percentile(lista, 5)
    fim = numpy.percentile(lista, 95)
    matplotlib.pyplot.hist(lista, bins = 100)
    matplotlib.pyplot.ylabel('Probability density')
    matplotlib.pyplot.xlabel('NPV')
    matplotlib.pyplot.axvline(numpy.mean(lista), color = '#fc4f30',\
    label = 'Median')
    matplotlib.pyplot.axvspan(comeco, fim, \
    facecolor = 'g', alpha = 0.3)
    matplotlib.pyplot.show()

# Função que desenha o gráfico de dispersões de taxas
def desenhar_grafico_taxas(n, prec_liv, qtdd_liv, \
prec_reg, qtdd_reg, \
tust_reg, invest):
    lista = dispersao_taxa(n, prec_liv, qtdd_liv,\
    prec_reg, qtdd_reg, \
```

```
    tust_reg, invest)

    comeco = numpy.percentile(lista, 5)
    fim = numpy.percentile(lista, 95)
    matplotlib.pyplot.hist(lista, bins= 100)
    matplotlib.pyplot.ylabel('Probability density')
    matplotlib.pyplot.xlabel('IRR')
    matplotlib.pyplot.axvline(numpy.mean(lista), \
    color ='#fc4f30', label= 'Median')
    matplotlib.pyplot.axvspan(comeco, fim, \
    facecolor = 'g', alpha = 0.3)
    matplotlib.pyplot.show()

variaveis_valores = tuple()
variaveis_taxas = tuple()

if prec_escolhido == "28":
    variaveis_valores = (10000, prec_liv_28[indice],\
    qtdd_liv_28, prec_reg_28, qtdd_reg_28,\
    tust_reg_28, taxa_28, invest_28)\

    variaveis_taxas = (10000, prec_liv_28[indice],\
    qtdd_liv_28, prec_reg_28, qtdd_reg_28,\
    tust_reg_28, invest_28)


elif prec_escolhido == "29":
    variaveis_valores = (10000, prec_liv_29[indice],\
    qtdd_liv_29, prec_reg_29, qtdd_reg_29,\
    tust_reg_29, taxa_29, invest_29)\

    variaveis_taxas = (10000, prec_liv_29[indice],\
    qtdd_liv_29, prec_reg_29, qtdd_reg_29,\
    tust_reg_29, invest_29)


elif prec_escolhido == "30":
    variaveis_valores = (10000, prec_liv_30[indice],\
    qtdd_liv_30, prec_reg_30, qtdd_reg_30,\
```

```
    tust_reg_30, taxa_30, invest_30)\

    variaveis_taxas = (10000, prec_liv_30[indice],\
    qtdd_liv_30, prec_reg_30, qtdd_reg_30,\
    tust_reg_30, invest_30)


else:
    print("Número inválido")
    exit()

desenhar_grafico_valores(*variaveis_valores)
desenhar_grafico_taxas(*variaveis_taxas)
```