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Unveiling the Potential: Valuing Onshore and Offshore Wind Energies through Real Options Perspective

Ana Carolina Neves Teles Evangelista Serrão

Master in Finance

Supervisor:

PhD José Carlos Dias, Full Professor,

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BUSINESS SCHOOL

Department of Finance

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Resumo

Esta tese utiliza a teoria das opções reais para avaliar a viabilidade financeira e o timing estratégico dos investimentos em energia eólica em Portugal, com ênfase em projetos onshore e offshore flutuantes. O principal objetivo é analisar a forma como incertezas (variações nos preços da eletricidade, avanços tecnológicos e oscilações nos custos dos projetos) afetam as decisões de investimento no setor das energias renováveis. Através de um modelo dinâmico, que incorpora simulações de Monte Carlo e a análise de opções reais, o estudo examina a flexibilidade em adiar investimentos em resposta a essas incertezas.

Os resultados mostram que os projetos de energia eólica offshore flutuante beneficiam significativamente do adiamento do investimento, devido às expectáveis melhorias tecnológicas e reduções de custos. Em contrapartida, os projetos onshore demonstram maior potencial para investimento antecipado, com o adiamento oferecendo menos vantagens comparativas. Embora o ano ótimo de investimento para ambos os tipos de projetos seja 2038, as condições de mercado e os incentivos políticos podem tornar a ação imediata mais atrativa para os projetos onshore.

As conclusões sublinham a importância do timing para maximizar os retornos financeiros de projetos deste tipo de energia renovável. O uso da teoria das opções reais revela-se uma abordagem eficaz para otimizar decisões de investimento no setor da energia eólica. Futuras investigações poderão expandir esta análise, integrando outras tecnologias renováveis e considerando variáveis de mercado mais complexas.

Palavras-chave: Energia Eólica; Opções Reais; Energia Eólica Onshore; Energia Eólica Ofshore; Timing de investimento; Fontes de Energia Alternativa; Técnicas de Optimização, Modelos de Programação, Análise Dinâmica

Abstract

This thesis applies real options theory to evaluate the financial viability and strategic timing of wind energy investments in Portugal, with a focus on onshore and floating offshore projects. The main goal is to analyze how uncertainties (fluctuations in electricity prices, technological advancements, and variations in project costs) impact investment decisions in the renewable energy sector. Using a dynamic model that incorporates Monte Carlo simulations and real options analysis, the study examines the flexibility to delay investments in response to these uncertainties.

The results show that floating offshore wind projects benefit significantly from delaying investments due to anticipated technological improvements and cost reductions. In contrast, onshore wind projects exhibit greater potential for earlier investment, with less comparative advantage in waiting. Although the optimal investment year for both types of projects is identified as 2038, market conditions and political incentives may make immediate action more attractive for onshore projects.

The findings emphasize the importance of timing to maximize financial returns in this type of renewable energy. The strategic use of real options theory proves to be an effective approach to optimize investment decisions in the wind energy sector. Future research could expand this analysis by integrating other renewable technologies and considering more complex market variables.

Keywords: Wind Energy; Real Options; Offshore Wind Energy; Onshore Wind Energy; Investment Timing; Alternative Energy Sources; Optimization Techniques, Programming Models, Dynamic Analysis.

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Glossary

AEP - Annual Energy Production

CAPEX - Capital Expenditure

DCF - Discounted Cash Flow

GW - Gigawatt

GWh - Gigawatt hours

IRR - Internal Rate of Return

LCOE - Levelized Cost of Electricity

MW - Megawatt

MWh - Megawatt hours

NPV - Net Present Value

OPEX - Operational Expenditure

PDE - Partial Differential Equations

RO - Real Options

ROA - Real Options Approach

R&D - Research and Development

TW - Terawatt

TWh - Terawatt hours

LSM - Least Squares Method

1. Introduction

The transition to renewable energy is one of the most pressing global challenges in the fight against climate change. Fossil fuels, which have historically dominated the global energy mix, are finite and have severe environmental impacts. Their extensive use has contributed significantly to greenhouse gas emissions, leading to global warming and climate instability. In response, governments and industries worldwide are increasingly turning to renewable energy sources, which offer sustainable and cleaner alternatives to fossil fuels. Among the various renewable options, wind energy stands out as one of the most promising and rapidly expanding sectors, particularly for countries with favorable geographic conditions like Portugal.

Wind energy offers a number of advantages, including the ability to generate electricity without emitting carbon dioxide, the use of inexhaustible natural resources, and the potential to reduce dependency on imported fossil fuels. However, harnessing wind energy comes with its own set of challenges. These challenges include the high initial capital costs, especially for offshore projects, fluctuations in wind availability, and the complex regulatory and permitting processes that can delay project implementation. In this context, understanding the economic feasibility and optimal timing for wind energy investments becomes essential to maximize returns and minimize risks for both onshore and offshore projects.

This thesis explores the application of real options (RO) theory to wind energy investments in Portugal. Real options theory provides a framework for evaluating investment decisions in environments of uncertainty, offering flexibility in decision-making by allowing investors to delay, expand, or abandon projects as conditions change. This flexibility is particularly relevant to the renewable energy sector, where technological advancements and policy developments can significantly affect project costs and returns over time. The primary aim of this research is to assess how real options analysis can improve the financial viability of wind energy projects in Portugal by taking into account uncertainties related to electricity prices, technological advancements, and project costs.

The focus of this study is on both onshore and floating offshore wind projects. Onshore wind farms have historically been more established, with lower capital costs and faster deployment times. Floating offshore wind is an emerging technology with higher upfront costs but greater long-term potential due to stronger and more consistent wind resources available at sea. The strategic question this thesis addresses is whether, and when, to invest in these projects to maximize their financial returns. By using real options analysis, this study identifies optimal investment periods and evaluates the value of waiting for more favorable conditions compared to immediate investment.

The motivation for this project stems from the urgent need for sustainable energy solutions and the growing role of wind energy in the global energy transition. In Portugal, wind energy has become a cornerstone of the country's renewable energy portfolio, contributing significantly to its national electricity supply. With ambitious targets to achieve carbon neutrality by 2050, Portugal is set to further expand its renewable energy capacity, with wind power playing a pivotal role. However, the question of when to invest in new wind projects, especially in the context of emerging offshore technologies, remains complex and requires careful consideration of future uncertainties.

In terms of methodology, this research employs a combination of financial modeling techniques, including Monte Carlo simulations and dynamic programming, to capture the stochastic nature of key variables such as electricity prices, capital and operational costs, and technological progress. The model simulates multiple investment scenarios over a long-term horizon, allowing for the comparison of different strategies in terms of their financial outcomes. By incorporating real options analysis into the decision-making process, the model evaluates the potential value of deferring investment in wind energy projects until more favorable conditions arise, such as lower costs due to technological advancements or higher electricity prices driven by market demand or policy shifts.

The data used in this study include historical electricity prices, cost data for wind energy projects, and technological trends in both onshore and offshore wind power. The electricity price data, which serves as a critical factor in determining project revenues, is modeled using stochastic processes to reflect the inherent volatility in energy markets. Similarly, capital and operational costs for wind energy projects are modeled as uncertain variables that may decrease over time as technologies improve and economies of scale are achieved. These data are integrated into the real options framework to assess the financial viability of wind energy projects under different market conditions.

By incorporating the value of flexibility into investment decisions, this research offers a more dynamic approach to project valuation than traditional methods, such as the net present value analysis, which assume static conditions and fixed investment timings. The RO approach recognizes that investment decisions are not made in isolation but evolve as new information becomes available, allowing investors to adapt their strategies to changing market conditions and technological innovations.

This thesis is structured in seven chapters. In Chapter 2, the contextualization focuses on the global wind energy sector, with a particular emphasis on Portugal’s wind energy industry, including both onshore and offshore projects. Chapter 3 presents a literature review, discussing key financial models such as the Black-Scholes-Merton model, the binomial model, Monte Carlo simulation, and the application of real options in the renewable energy sector. Chapter 4 describes the methodology employed in the study, followed by

Chapter 5, which details the data collection process. In Chapter 6, the results are presented, examining the evolution of the uncertain variables, net present value (NPV) and real options valuation, investment timing, and sensitivity analysis. Finally, Chapter 7 offers the conclusion, summarizing the main findings and discussing their broader implications.

2. Contextualization

2.1 Wind Energy Sector

It is widely recognized that decreasing our dependence on fossil fuels is essential for the future, and the transition to alternative energies is inevitable. Wind energy plays a critical role in reducing greenhouse gas emissions and promoting sustainability. It offers a clean and renewable source of power that helps mitigate the effects of climate change. The transition to wind energy is aligned with global efforts to achieve net-zero emissions and sustainable development goals (IEA, 2024).

In 2023, the wind energy sector witnessed unprecedented growth with over 100 gigawatts (GW) of new onshore installations and 11 GW of offshore installations, setting a new record for the industry and surpassing the milestone of 1 terawatt (TW) of installed capacity globally. This momentum, driven by significant policy interventions and legislative accomplishments such as the United States Inflation Reduction Act, the European Union's Wind Power Package, and China's Five-Year Plan, aims to accelerate installations to at least 320 GW annually by 2030 to meet global renewable energy targets (Global Wind Energy Council, 2024).

However, achieving these ambitious targets will require overcoming substantial challenges. Policy uncertainties, delayed responses, insufficient investment in grid infrastructures, and lengthy permitting processes—ranging from 2 to 9 years for onshore projects and averaging 9 years for offshore projects—pose significant obstacles. To align with the Net Zero Scenario, it is essential to facilitate permitting, gain public support, identify suitable sites, decrease costs, and reduce project development timelines (IEA, 2024).

Technological innovation plays a crucial role in addressing these challenges. For onshore wind, the focus is on increasing turbine productivity through longer blades and higher towers, although these are often restricted by environmental and public acceptance concerns. Offshore wind, on the other hand, benefits from fewer size restrictions, allowing for the development of larger turbines that reduce power generation costs. The advancement of cost-competitive and safe floating offshore wind turbines is particularly promising, unlocking the potential of deep ocean areas that are unsuitable for fixed turbines. Regions such as France, Japan, Korea, Norway, Portugal, the United Kingdom, and the west coast of the United States are expected to be early adopters of large-scale floating wind farms (IEA, 2024).

These advancements are critical as renewable electricity capacity continues to grow. By 2028, renewable electricity generation is projected to reach 14,430 Terawatt hours (TWh), a 70% increase from 2022. Milestones expected in the coming years include variable renewable generation surpassing hydropower in 2024, renewables overtaking coal-fired electricity in 2025, wind surpassing nuclear electricity in 2025, and solar photovoltaics surpassing nuclear and wind electricity generation by 2026 and 2028, respectively (IEA, 2024).

2.2 Wind Energy Sector in Portugal

Portugal has made significant strides in the renewable energy sector, becoming an international leader in wind energy integration. The country’s National Energy and Climate Plan aims to achieve carbon neutrality by 2050, with ambitious targets for emissions reductions, energy efficiency, and renewable energy deployment by 2030 (IEA, n.d.). Situated along the western coast of the Iberian Peninsula, this country holds a unique geographical advantage, harnessing the power of the Atlantic Ocean winds for sustainable energy production. Its extensive coastline, spanning over 1,200 kilometers, offers fertile ground for both onshore and offshore wind power installations (IEA, 2024).

In 2022, Portugal's total renewable energy capacity reached 16 329 megawatts (MW), with wind energy accounting for 5 455 MW. Onshore wind farms contributed 5 430 MW, while offshore installations, such as the WindFloat Atlantic project, added 25 MW (Irena, 2023). The WindFloat Atlantic, located off the coast of Viana do Castelo, is a pioneering floating offshore wind farm that became fully operational in 2020. It consists of three 8.4 MW turbines on semi-submersible platforms, providing electricity to 25 000 Portuguese households annually and demonstrating the potential for floating offshore wind technology (Windfloat Atlantic, 2022).

From January to May 2024, wind energy generated 6 561 Gigawatt hours (GWh) of electricity, with 84.2% of Portugal's energy during this period coming from renewable sources (APREN, 2024). The growth in renewable energy capacity has been steady since 2005, with a significant increase in installed capacity by 52% compared to that year. This growth was particularly marked by the decommissioning of fossil fuel plants, such as the Sines and Pego coal plants in 2021, leading to a reduction in fossil fuel capacity (APREN, 2024).

The reform of the electricity market, as highlighted by Jorge (2024), aims to create a more stable and sustainable model. New rules, applicable across all European Union member states, seek to reduce price volatility and attract private investment in renewable energy projects. This policy framework is designed to ensure that electricity prices are less influenced by fluctuations in fossil fuel markets, thereby benefiting both consumers and producers.

Portugal faces challenges in its renewable energy sector, including policy uncertainties, insufficient investment in grid infrastructure, and lengthy permitting processes. However, opportunities abound, particularly in the advancement of offshore wind technology.

The environmental benefits of wind energy in Portugal are significant, with wind accounting for 27% of the country's electricity generation in 2022. Wind energy is also the largest source of non-combustible renewable electricity in the country, contributing 52% of renewable electricity production in the same year (IEA, n.d.). Economically, the sector supports job creation and attracts investment, bolstered by government policies that promote renewable energy projects and aim to stabilize the market

2.3 Onshore and Offshore Wind Energy

There are two main methodologies of wind energy utilization: onshore and offshore wind farms. Both provide a renewable and inexhaustible source of energy that does not emit greenhouse gases or other pollutants during operation, thus contributing to environmental sustainability (Repsol, 2023).

Onshore wind energy, the most common form of wind power generation, involves the installation of wind turbines on land, typically situated at least 3 kilometers from the coast to harness terrestrial air currents effectively (Repsol, 2023). These turbines convert the kinetic energy of the wind into mechanical power, which is then transformed into electricity by a generator. This process involves capturing wind energy using the blades, which rotate and drive a low-speed shaft connected to a gearbox. The gearbox increases the rotational speed, allowing the high-speed shaft to produce electricity through the generator (WindEurope, 2024).

One of the major advantages is its reduced environmental impact. The construction and operation of onshore wind farms create significantly fewer emissions than other energy sources, and the land where wind farms are located can still be used for farming (NationalGrid, 2022). It is also cost-effective, being one of the least expensive forms of renewable energy, significantly less expensive than offshore wind power. This affordability helps lower electricity bills due to cheaper infrastructure and maintenance costs. Onshore wind farms can be constructed relatively quickly and are easier to maintain compared with offshore farms. Furthermore, they contribute to job creation, with significant employment opportunities in the energy sector as part of efforts to achieve net zero emissions by 2050 (NationalGrid, 2022). On the other hand, consistency of electricity generation from wind farms can be challenged by varying wind speeds and changes in wind direction. When wind levels are intermittent or non-existent, electricity generation ceases, necessitating a mix of energy solutions to meet demand. Additionally, some people find the appearance and noise of wind farms objectionable, and there are concerns about the impact on local wildlife, particularly birds. Onshore wind farms also produce less energy than their offshore counterparts due to planning restrictions that limit the height of turbines (NationalGrid, 2022).

Offshore wind farms are positioned in bodies of water, commonly along coastlines or in offshore locations. Offshore sites tend to harness stronger and more consistent winds, resulting in higher energy outputs compared to onshore locations. They have reduced visual impact as they are away from densely populated areas, and the vast expanses available in coastal regions and oceans allow for larger installations, accommodating larger turbines and contributing to increased energy production (McCloy, 2022). On the other hand, deploying an offshore wind farm is a complex challenge that involves several professionals and various tasks, such as dredging the seafloor, transporting, assembling, and setting the foundations, and installing submarine cables (EDP, n.d.).

One of the benefits of offshore wind farms is their increased capacity, and therefore offshore wind turbines are more efficient because they harness high-speed, consistent winds. While onshore turbines typically range between 2 and 5 MW in capacity, offshore turbines offer greater potential, averaging 7.8 MW in 2019 (Tang, 2020). Besides that, they are located far from human activities and do not interfere with land use. Like onshore wind farms, they provide renewable energy without using water and create job opportunities (McCloy, 2022). However, offshore wind energy also faces significant challenges. The process of transporting electricity from offshore turbines to land is expensive due to the necessary technology. Offshore turbines endure more wear and tear due to strong winds and waves, resulting in higher maintenance costs. They are harder to access, which can delay repairs and maintenance. The impact on marine life and birds is not fully understood, adding uncertainty to their environmental benefit (McCloy,2022). Comparing both methods, initial investments for offshore wind farms are higher, but they often yield greater energy outputs and lower long-term maintenance costs, since their location provides stronger and more consistent winds (McCloy,2022).

Advancements in technology have facilitated the creation of floating wind farms, which use floating structures instead of traditional fixed ones. This innovation enables the deployment of wind turbines in expansive and deeper offshore areas with higher wind potential. Floating wind farms offer distinct advantages, such as reducing environmental impact and optimizing manufacturing and installation procedures. By constructing floating turbines and platforms on land before towing them to the offshore installation site, these systems facilitate ease in production and installation, potentially reducing environmental disruptions. Furthermore, their placement in deeper offshore regions allows them to utilize strong winds, enhancing energy efficiency (Iberdrola, 2021).

Floating wind farms offer a diverse range of designs, featuring four primary types: tension-leg platform, semi-submersible, barge, and spar buoy (*figure 1*). The tension-leg platform, lighter in construction compared to others, boasts a smaller mooring footprint and heightened stability post-installation but may face challenges during transport and installation due to its lighter design. Conversely, the semi-submersible platform, with its versatile nature, suits varied conditions and offers relatively straightforward installation, yet it may lack stability compared to other designs and possess complex construction requirements. Similarly, the barge type, resembling a ship hull, presents versatility and simplified installation but tends to compromise stability. Lastly, spar buoy platforms, simple in construction and stable, demand a deep harbor or specialized vessels for installation owing to its depth, delineating its need for unique installation conditions (Orsted, n.d.).

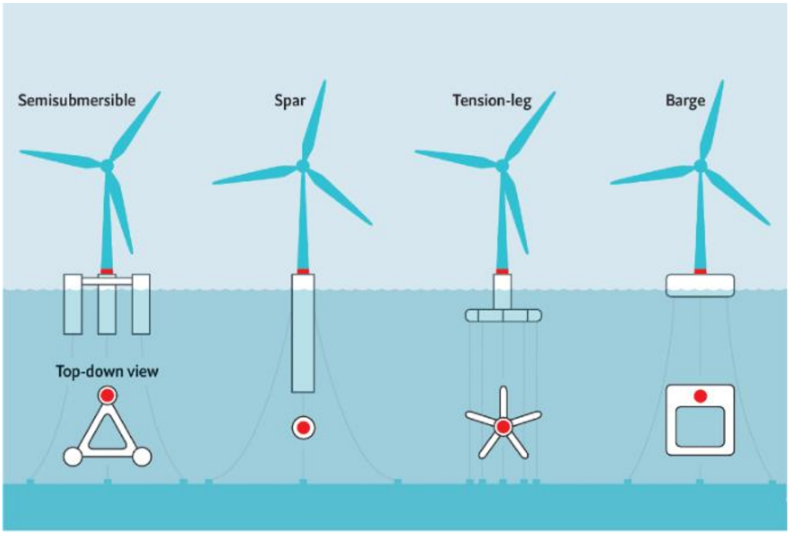

Figure 1: Four primary designs - floating offshore.

The efficiency and output of wind turbines depend on several key variables. Firstly, wind speed plays a crucial role as stronger winds enable higher electricity production. Turbines installed at greater heights are more likely to encounter stronger winds, generating power at speeds ranging from 4 to 25 meters per second. Secondly, the blade radius significantly influences power output; larger blades capture more wind energy, enhancing electricity generation. To conclude, air density, which is higher at lower altitudes, improves the efficiency of turbines by exerting greater lift on the rotor blades (WindEurope, 2024).

Technological advancements in wind energy continue to improve the efficiency and versatility of wind turbines. Innovations include longer blades, higher towers, and even bladeless wind turbines that oscillate to generate electricity (Repsol, 2023). These technologies help increase power output and reduce costs, making wind energy the cheapest form of new power generation in many parts of Europe today (WindEurope, 2024). Combining wind turbines with energy storage systems such as batteries, pumped hydro storage, or high-energy supercapacitors ensures a stable power supply, even when wind levels are low. This integration is crucial for the energy transition, enhancing the reliability and efficiency of wind power (WindEurope, 2024).

3 Literature Review

3.1 Financial Options

An option is a financial instrument that grants its holder the right, but not the obligation, to trade an underlying asset at a fixed price, known as the strike price, at any time before or on a specified date, referred to as the expiration date. The process of executing this transaction is called exercising the option (Cox et al., 1979).

There are two types of financial options: call options and put options. A call option grants the holder the right to purchase the underlying asset by a specified date at a predetermined price, while a put option gives the holder the right to sell the underlying asset by a specified date at a predetermined price. As the strike price increases, the price of a call option decreases, whereas the price of a put option increases. Each option contract involves two parties: the investor in the long position (the buyer of the option) and the investor in the short position (the seller or writer of the option) (Hull, 2012). *Figure 2* represents the payoff, at maturity, of each scenario for standard options, where K stands for the strike price.

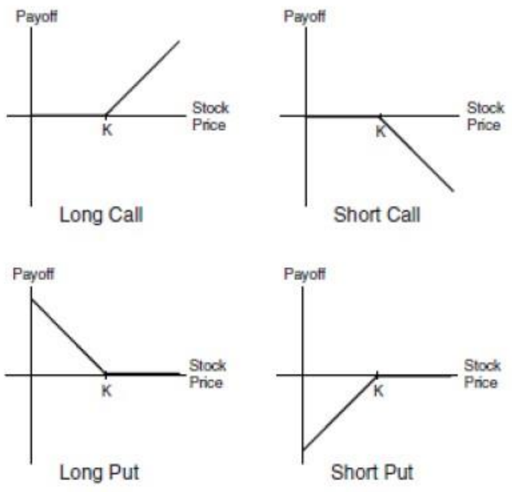

Figure 2: Payoff for standard options

Additionally, options can also be categorized as American or European. The main difference between them lies in the exercise flexibility: American options allow the holder to exercise the option at any time up to the maturity date, whereas European options can only be exercised at expiration (Cox et al., 1979).

In terms of valuation methods, three key models stand out: the Black-Scholes-Merton Model developed by Fischer Black, Myron Scholes and Robert Merton in 1973; the Binomial Model, introduced by Cox, Ross, and Rubinstein in 1979; and the Monte Carlo simulation method.

3.2 Black-Sholes-Merton Model

The Black-Scholes-Merton model was designed for European call and put options, meaning these options can only be exercised at maturity. Several assumptions were made to create ideal market conditions. It assumes that the short-term interest rate is known and remains constant over time, the stock pays no dividends or other distributions, and there are no transaction costs associated with buying or selling the stock or the option. Moreover, the stock price is assumed to follow a random walk in continuous time with a variance rate proportional to the square of the stock price, leading to a lognormal distribution of possible stock prices at the end of any finite interval. The variance rate of return on the stock is also assumed to be constant (Black & Scholes, 1973). Merton (1973) allows the existence of a constant continuous dividend yield.

These assumptions culminated in the development of the well-known Black-Scholes-Merton Formulas:

$$C = S_0 e^{-\delta t} N(d_1) - X e^{-rt} N(d_2) \tag{1}$$

$$P = X e^{-rt} N(-d_2) - S_0 e^{-\delta t} N(-d_1) \tag{2}$$

Here, C is the call option price and P is the put option price. S_0 is the current stock price, X is the strike price, r is the risk-free interest rate, t is the time to expiration and δ is the dividend yield.

Additionally,

$$d_1 = \frac{\ln\left(\frac{S_0}{X}\right) + \left(r - \delta + \frac{\sigma^2}{2}\right) t}{\sigma\sqrt{t}} \tag{3}$$

$$d_2 = d_1 - \sigma\sqrt{t} \tag{4}$$

In these equations, σ represents the volatility of the stock, and $N(d)$ denotes the cumulative distribution function of the standard normal distribution.

3.3 Binomial Model

In 1979, a significant advancement in option pricing theory occurred with the introduction of the binomial model, providing a discrete-time framework. This model also added flexibility because it took into account the American option since it can be optimal to exercise prematurely. It uses a binomial tree or lattice to represent the possible paths that the price of the underlying asset can take over time. At each node in the tree, the asset price can move up or down with specific probabilities, which are derived from the asset’s volatility and the length of the time step (Hull, 2012). *Figure 3* represents a multi-step binomial model.

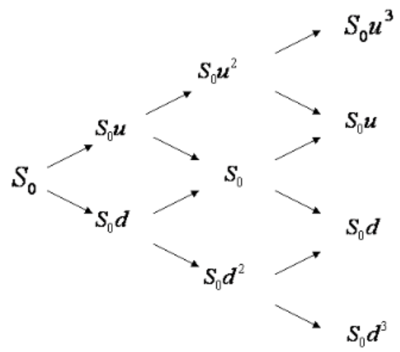

Figure 3: Multi-step Binomial Model
Source: "Option Pricing – Binomial Models" by Goddard Consulting, n.d.

The up (u) and down (d) factors are calculated as follows:

$$u = e^{\sigma\sqrt{\Delta t}} \tag{5}$$

$$d = e^{-\sigma\sqrt{\Delta t}} \tag{6}$$

where Δt is the length of the time step.

In a risk-neutral world, the expected return of the asset is the risk-free rate *r* adjusted for the dividend yield. Therefore, the upward and downward movements follow risk-neutral probabilities. The risk-neutral probability p for an upward movement is:

$$p = \frac{e^{(r-\delta)\Delta t} - d}{u - d} \tag{7}$$

$e^{(r-\delta)\Delta t}$ is the growth factor over the time step Δt. The probability of a downward movement is simply one minus *p*.

The option value at expiration is:

$$C_T = \max(S_T - X, 0) \tag{8}$$

$$P_T = \max(X - S_T, 0) \tag{9}$$

where C_T and P_T is the call option value at time T (expiration time) and the put option value, respectively.

For European options, the value of the option at each node is calculated by discounting the expected value of the option at the next time step, using the risk-neutral probabilities. Then,

$$C_i = e^{-r\Delta t}[pC_{i+1,u} + (1-p)C_{i+1,d}] \tag{10}$$

$$P_i = e^{-r\Delta t}\left[pP_{i+1,u} + (1-p)P_{i+1,d}\right] \tag{11}$$

For American options, it is necessary to compare the value of immediate exercise with the value of holding the option and take the maximum, that is

$$C_i = \max(S_i - X, e^{-r\Delta t}\left[pC_{i+1,u} + (1-p)C_{i+1,d}\right]) \tag{12}$$

$$P_i = \max(X - S_i, e^{-r\Delta t}\left[pP_{i+1,u} + (1-p)P_{i+1,d}\right]) \tag{13}$$

In these equations, i denote the specific time step within the binomial tree. $C_{i+1,u}$,$C_{i+1,d}$ $P_{i+1,u}$ and $P_{i+1,d}$ represent the option prices at time step $i+1$ in the upward and downward movements, respectively.

3.4 Monte Carlo Simulation

In 1977, Phelim Boyle made a remarkable contribution to option pricing by demonstrating that Monte Carlo simulation can be used to obtain numerical solutions to option valuation problems. This approach involves simulating numerous possible paths for the underlying asset price and averaging the discounted payoffs to estimate the option's price (Boyle, 1977).

It is assumed that the asset prices follow a Geometric Brownian Motion (GBM) process. This process assumes that the price changes are log-normally distributed and can be described by the stochastic differential equation.

$$dS = \mu S dt + \sigma S dW \tag{14}$$

S is the asset price, μ is the drift rate, σ is the volatility, and dW is a Wiener process increment. The term $\sigma S dW$ introduces the randomness into the price evolution, capturing the unpredictable fluctuations in stock prices.

Then, it is possible to generate the distribution of stock prices by forming the random variables (Boyle, 1977).

$$S_{t+\Delta t} = S_t e^{\left(r-\delta-\frac{1}{2}\sigma^2\right)\Delta t + \sigma\sqrt{\Delta t}Z} \tag{15}$$

where Z is a standard normal random variable.

A series of simulation trials is carried out following *equation 15* and at the end of each simulation; the option's terminal payoff is computed. Finally, the Monte Carlo estimate for the option value is the arithmetic average of all terminal payoffs. This value is then discounted at the risk-free rate to yield an estimate at the option value (Boyle, 1977).

$$C = e^{-rT}\mathbb{E}[\max(S_T - K, 0)] \tag{16}$$

To improve accuracy of Monte Carlo simulations, variance reduction techniques can be used. Antithetic variates is one technique that reduces the variance of Monte Carlo estimators by generating negatively correlated sample pairs, which helps balance fluctuations and provides more stable estimates. Furthermore, Control Variates is another effective method, since it leverages the known expected value of a correlated variable to reduce the variance of the estimator (Boyle et al., 1997)

For American options, which can be exercised at any time before expiration, the Least Squares Method (LSM) is used. This process, developed by Longstaff and Schwartz (2001), involves simulating multiple paths of the underlying asset price and using least squares regression to estimate the continuation value of the option.

First, a large number of possible future paths for the underlying asset price are generated using Monte Carlo simulation. Then, backward induction process is employed, starting at the last time step before expiration and moving backwards through the simulated paths to the current time. At each time step and for each path, the continuation value (the expected payoff of holding the option) is estimated using least squares regression. The immediate exercise value is then compared with the estimated continuation value. If the immediate exercise is greater, the option is exercised; otherwise, it is held. Finally, the option value is computed as the discounted average of the payoffs from the optimal exercise strategy determined by the regression (Longstaff and Schwartz, 2001).

3.5 Real Options

The term *Real Options* emerged in 1977 through the work of Stewart C. Myers, who identified two types of assets that a company can hold: real assets and real options. He explained that the market value of real assets remains unaffected by the firm’s investment strategies, whereas real options represent opportunities to acquire real assets under favorable conditions. Therefore, a corporate asset seen as a growth opportunity can be considered a call option (Myers, 1977). The real options approach extends financial options theory to non-financial assets (Schwartz, 2013).

It integrates a learning model that allows management to make more informed and strategic decisions as uncertainties are resolved over time. Traditional methods consider risk and return on investment in a static manner, often equating all uncertainty with risk and viewing it negatively. However, real options recognize that not all uncertainty equates to risk, and not all risk is detrimental. This approach considers capital investment dynamically, leveraging upside risk as a potential advantage. Furthermore, discounted cash flow analysis assumes a static investment decision, presuming that strategic choices are made at the outset with no flexibility to adapt or explore alternative pathways in the future (Mun, 2005).

Real options have several advantages. They enable the creation of dynamic models that allow for quantitative predictions, unlike static models, which offer only qualitative predictions that may not hold in a dynamic environment. Additionally, real options valuation encourages managers to adopt a strategic approach to investments by identifying available options and determining the optimal conditions for exercising these options. On the other hand, there are also disadvantages. This method adds complexity and reduces transparency, being highly sophisticated and potentially leading to a misplaced sense of precision. Such an emphasis on the valuation model might overshadow the importance of its underlying assumptions and inputs. Moreover, the process of identifying and valuing real options involves a degree of subjectivity. The method becomes particularly challenging when multiple state variables are introduced, complicating investments with various sources of uncertainty (Lambrecht, 2017).

There are various types of real options, such as the option to wait, the option to expand, the option to contract, the option to abandon for salvage value and the option to switch. The option to wait allows a company to defer decision-making to a future date when it can act with more information and resources. The option to expand enables a company to grow its operations, such as entering a new market, opening a new factory, or developing a new product. The option to contract allows a company to reduce its scale or exit a project if conditions become unfavorable. The option to abandon grants a business to immediately shut down a project with negative NPV or operational difficulties, liquidating assets for salvage value. Finally, the option to switch enables a company to halt operations during unfavorable conditions and resume them when conditions improve (Saravanakumar, 2024).

Luehrman (1998) demonstrated that it is possible to model a project by aligning its characteristics with the structure of a call option. The capital expenditure required to exploit an investment opportunity is analogous to the exercise price (K) of a call option. The present value of the project's cash flows at the valuation date,V_{t}, corresponds to the underlying stock price, S_{t}.The period during which the firm can defer the investment decision corresponds to the option's time to expiration $\tau \coloneqq \mathrm{T} - \mathrm{t}$, with T being the final decision date. The uncertainty about the future value of the project’s cash flows corresponds to the volatility,σ. The time value of money is given by the risk-free interest rate r and δ is the rate of return shortfall or dividend yield.

There are three main solutions for solving option valuation problems: the dynamic programming approach, partial differential equations (PDE), and the simulation approach. The Binomial model is a dynamic programming approach and is widely used for valuing simple options, but becomes inadequate for complex options with multiple influencing factors or path dependencies. Solving PDEs is particularly challenging with more than three state variables, making it unsuitable for complex real options problems. Finally, simulation is a powerful method and the most practical tool for solving real options valuation problems, since it is easily applied to multi-factor models and directly applicable to path-dependent problems, allowing state variables to follow general stochastic processes (Schwartz, 2013).

3.6 Real Options in the Renewable Energy Sector

Traditional methods for evaluating investment plans, such as the discounted cash flow (DCF), the NPV, the internal rate of return (IRR), and the payback period, have limitations. These methods typically assume investments are irreversible and must be made immediately, making them less suitable for long-term investment climates. As a result, they often fail to capture the managerial flexibility inherent in many investment decisions, potentially underestimating the true value of an investment (Lee, 2011). The net present value is calculated as follows:

$$\mathrm{NPV} = -\mathrm{CF}_0 + \sum_{t=1}^{T} \frac{\mathrm{CF}_t}{(1+k)^t} \tag{17}$$

where CF_0 is the initial investment cost, CF_t is the cash-flow at time t and k is the discount rate.

The complexities of uncertainties impacting renewable energy investments are substantial. The development and commercialization of renewable energy technologies require significant initial capital, making the research and development (R&D) phase crucial for cost reduction. R&D in this field is inherently high-risk and involves various strategic options, such as delaying, abandoning, or expanding projects. Therefore, it is essential to consider these uncertainties and options simultaneously when evaluating the economic value and determining the optimal timing for deploying R&D results (Liu et al., 2019).

Given these complexities, selecting an appropriate valuation method is critical. The Real Options Approach (ROA) is particularly effective in addressing uncertainty and incorporating managerial flexibility, making it a valuable tool for analyzing investment opportunities in the renewable energy sector. ROA leverages the principles of financial options theory to value the flexibility and choices available to managers, providing a more accurate reflection of an investment's potential value.

Advancements in renewable energy technology are hindered by high R&D costs, the challenge of recouping investments, lengthy and deferrable planning processes, substantial investment risks, and uncertain returns. Decision-makers in this field have significant flexibility in timing their investments. Policymakers can leverage this flexibility to adjust policies, ensuring that renewable energy development aligns with policy goals. ROA not only quantifies the managerial flexibility overlooked by traditional assessment methods but also reduces the likelihood of undervaluing policy initiatives. Development policies can utilize the concept of options to generate value by waiting to reduce uncertainty in policy planning (Lee, 2011).

Throughout the years, several studies have employed the real options approach in the renewable energy sector. For example, David & Owens (2003) estimated the option value of renewable electric technologies (wind energy) in the face of uncertain fossil fuel prices. They showed that the value increases with the growth of current and future R&D funding levels. Bøckman et al. (2008) proposed a real options-based model for assessing small hydropower projects subject to uncertain electricity prices. The results showed the option value and a unique price limit for initiating the project. Kim et al. (2014) evaluated the economic value of the investment in wind power R&D in Korea and optimal deployment timing of wind power technology using ROA. They identified compound options for decision-makers, such as abandoning, deploying, or continuing the R&D stage. Wang et al. (2014) developed a benefit real options model from the government's perspective to evaluate biomass power production investment in China. The study considered uncertainties in straw purchase prices, government incentives, and technological improvements.

Table 1 provides a summary of other relevant studies on the field.

Study	Uncertain Factor	Purpose of study
Venetsanos et al. (2002)	Deregulated energy market	Assessing the profitability of wind power plants
Fleten et al. (2007)	Electricity Price	Estimating the investment timing and scale of wind power
Szolgayova et Al. (2008)	Technical change and fossil fuel price	Investigating uncertain factors' impact on replacement investment decisions
Lee and Shih (2010)	Fossil fuel prices and technical change	Evaluating the policy value of renewable energy development
Lee (2011)	Electricity price	Examining the value and feasibility of renewable energy investment
Reuter et al. (2012)	Electricity price for renewable energy	Analyzing the decisions to invest into new power generating capacity, the selection of technology type and optimal operation
Boomsma et al. (2012)	Different support schemes	Analyzing investment timing and capacity choice for renewable
Monjas-Barroso & Balibrea-Iniesta (2013)	Production cost, investment cost and consumer price index	Measuring the impact of the real regulatory option on renewable energy project investment
Wesseh Jr and Lin (2016)	Non-renewable energy cost	Assessing the viability of wind energy projects
Barbosa et al. (2018)	Regulatory uncertainty	Evaluating the influence of different configurations of Feed-in tariffs programs on investment decisions on RE projects
Paxson et al. (2022)	Demand Uncertainty	Devoloping a model that determines the optimal timing and capacity choice for investments under price floors and ceilings (collars).

Table 1: Summary of relevant studies

These studies utilize various methods such as Monte Carlo Simulation, partial differential equations, and dynamic programming (decision trees). The Real Options Approach is consistently combined with traditional project evaluation methods, such as NPV, IRR, discounted payback period, levelized cost of electricity (LCOE), and return on investment (Delapedra-Silva et al., 2022).

The LCOE is defined as "The constant dollar electricity price required to cover all operating costs, to repay interest accrued on debt and initial project costs, and to pay an acceptable return to investors over the life of the plant" (Bistline et al., 2018).

According to Cali et al. (2018),

$$LCOE = \frac{\sum_{t=0}^{T} \frac{CF_{CAPEX}(t) + CF_{OPEX}(t)}{(1+k)^t}}{\sum_{t=0}^{T} \frac{netAEP}{(1+k)^t}} \tag{18}$$

where T is the lifespan of the wind farm and $\forall t \in \{1, \ldots, T\}$, $CF_{CAPEX}(t)$ and $CF_{OPEX}(t)$ are the total capital expenditure (CAPEX) cost and operational expenditure (OPEX) for the year of t, the net AEP is the estimate annual power generation of the power plant. CAPEX includes various components and respective installation, such as the wind turbine, the floating platform, the array cables, the export cable, the onshore cable, the offshore substation, the onshore substation, the mooring lines and the anchoring (Maienza et al., 2020). OPEX corresponds to the operation costs and the direct and indirect maintenance costs (Maienza et al., 2020). An investment is considered cost-competitive compared to other facilities when it generates an output at a LCOE lower than the current market price (Bistline et al., 2018).

4 Methodology

The value of a renewable energy project, such as a wind farm, is influenced by numerous factors over its lifetime. This value can be represented as the expected net present value of future cash flows. For a project with a lifetime$L$, which can be initiated in year t (where $1 \leq t \leq t_v$) and requires an investment cost of I_t , the NPV can be expressed as follows (Zhang et al., 2016) :

$$V_t = \mathbb{E}[\sum_{i=t}^{t+L} e^{-r(i-t)}\pi_i - I_t] \quad (19)$$

where t is the start year of the investment, V_t is the total net present value of the project, r is the discount rate and π_i is the cash flow in year i.

Given the stochastic nature of the investment environment for renewable energy, characterized by uncertainty and managerial flexibility, the traditional NPV method might not fully capture the project's value. Instead, the real options method is preferred as it incorporates these uncertainties and flexibilities into the investment valuation (Zhang et al., 2016).

So, the project's value is the sum of the net present value and the economic value of flexibility under uncertainty, that is

$$F = V + OV \quad (20)$$

where F is the investment value (using the real options method), V is the net present value and OV is the economic value of flexibility. This approach allows investors to optimize the timing of their investment to maximize the project's value:

$$F = \max_{0 \leq t_s \leq t_v}[\max(V_{t_s}; 0) \cdot e^{-rt_s}] \quad (21)$$

here t_s denotes for the stochastic optimal time when the investment is undertaken and t_v is the last investment period. The NPV is calculated for each period and discounted at the risk-free rate to identify the period t_s where the project generates the highest value.

The value of the project is the sum of all expected cash flows discounted at a certain rate. It is possible to simplify the model in order to calculate the cash flows, that is

$$CF = (Price\ of\ electricity - LCOE) \times AEP \quad (22)$$

where AEP is the annual energy production. The Price of Electricity is the market price at which the generated electricity is sold.

The AEP can be calculated as it follows (Wind Energy and Power Calcuations, n.d.):

$$AEP(Mwh) = Capacity\ (Mw) \times Number\ of\ hours\ in\ a\ year\ (H) \times Capacity\ Factor\ (\%) \tag{23}$$

Therefore, the project's cash flows depend on the price of electricity, the LCOE and the AEP. These three variables are uncertain factors.

The stochastic process is an appropriate technique for describing the uncertain factors, so it is assumed that these uncertain variables follow a Geometric Brownian Motion (GBM) (Zhang et al., 2016).

$$dS_t = \alpha S_t dt + \sigma S_t dz \tag{24}$$

where S_t is the uncertain variable, α represents the variable's drift and σ represents the volatility. Additionally, dz represents the independent increment of Wiener process, where $dz = \varepsilon\sqrt{dt}$, ε is a normally distributed random variable with zero mean and unit standard deviation. Besides that, $\mathbb{E}[S_t] = S_0 e^{\alpha t}$. For simplification, it is assumed that all uncertain variables are independent and uncorrelated.

The method outlined in Zang et al, 2016, is a combination of the backward dynamical programming and the least-squares Monte Carlo method. The backward induction begins from the last decision point, working back to the starting decision point and comparing exercising investment versus the continuation value. On the other hand, the Least-Squares Monte Carlo approach is based on the Monte Carlo simulations and the least squares regression model. It is used to calculate the continuation value and the optimal investment rules. The result of the Least-Squares regression is an efficient unbiased estimator of the conditional expectation function and allows accurately estimating the optimal stopping-rule for the options.

The model consists in five steps.

1. It is necessary to define the number of simulation paths (W) and the number of decision points per path (N):

$$N = \frac{t_v}{\Delta t} \tag{25}$$

where Δt represents the step size.

2. Then, simulate the change paths of the uncertain factors based on their discrete approximations.
3. For any path j, it is calculated the expected net present value of the project at each discrete decision point during the validity period of investment (t_v). For any path j, the problem can be solved by dynamic programming. At the final observation date of the

validity period ($t = t_v$), conditional on not having invested in the previous periods, it is possible to obtain:

$$F_{t,j} = \max\{V_{t,j}; 0\} \tag{26}$$

$$\Gamma_{t,j} = \begin{cases} 1, V_{t,j} \geq 0 \\ 0, Otherwise \end{cases} \tag{27}$$

Therefore if $\Gamma_{t,j}$ is equal to one, it represents immediate investment. Otherwise, the investment is delayed.

4. For every period ($1 \leq t \leq t_v$), it is mandatory to evaluate whether it is better to invest immediately or delay the investment by comparing the expected net present value from immediate investment with the expected investment opportunity value from delaying the investment, that is

$$F_{t,j} = \max\{V_{t,j}; e^{-r\Delta t}\,\mathbb{E}[F_{t+1,j}]\} \tag{28}$$

$$\Gamma_{t,j} = \begin{cases} 1, V_{t,j} \geq e^{-r\Delta t}\,\mathbb{E}[F_{t+1,j}] \\ 0, Otherwise \end{cases} \tag{29}$$

5. The recursion proceeds by rolling back in time and repeating the procedure until the exercise decisions at each possible exercise time along each path has been determined. t_j is the optimal investment timing in path j. The optimal investment timing (t_s) is the one with the highest frequency. The investment value is computed by taking the average value over all paths. Therefore,

$$t_j = \inf\{t \mid \Gamma_{t,j} = 1\}, 1 \leq t \leq t_v \tag{30}$$

$$F = \frac{1}{W}\sum_1^W \left(e^{-rt_j} F_{t,j}\right), j = 1, \ldots, W \tag{31}$$

5 Data Collection

This section outlines the sources of data, the rationale behind selecting these data points, and how they were utilized in the model.

The historical electricity price data were sourced from Ember Climate, which provides comprehensive energy data for European countries, including Portugal. This dataset covers the period from January 2015 to January 2020. The data was used to model the evolution of electricity prices over time using a Geometric Brownian Motion (GBM) approach, reflecting the uncertainty and volatility in electricity markets. These price simulations were carried out over a 40-year period, corresponding to the potential lifespan of the projects.

In order to estimate the AEP for both onshore and offshore wind farms in Portugal, historical data on energy output were obtained from Statista. This data was combined with information on installed capacity, sourced from the IEA Wind Report, to calculate the capacity factors, which represent the efficiency of wind turbines in converting wind energy into electrical power. For onshore wind farms, additional capacity and capacity factor data were obtained from WindEurope's Annual Statistics. For offshore wind farms, the capacity and capacity factor data were based on the WindFloat Atlantic project.

The CAPEX and OPEX data for onshore wind projects were sourced from IEA Wind. Although these data are relative to the 28 European countries, they serve as a good proxy for the Portuguese context. The CAPEX and OPEX data for offshore wind projects were obtained from the National Renewable Energy Laboratory (NREL). Due to the scarcity of information, the values used in the model were an average of three different scenarios: conservative, moderate, and advanced.

The valuation model was conducted in R Studio, incorporating both backward induction and Monte Carlo simulations to model uncertainties and determine the optimal investment decision. The model included 15 possible investment periods, corresponding to the years in which the investment could be initiated, with each investment period being evaluated over the 25-year operational lifespan of the project. To capture the variability in the model's inputs, 5000 different paths were simulated, ensuring that the analysis was free from path dependencies.

6 Results

6.1 Uncertain Variables Evolution

To accurately compute the cash flows of both onshore and offshore wind energy projects, it is essential to account for several uncertain variables. These include electricity prices, annual energy production, onshore LCOE, and offshore LCOE. This section outlines the methodologies used to estimate each of these variables, considering the inherent uncertainties associated with them. As stated previously, it is assumed that all uncertain variables are independent.

6.1.1 Electricity Prices Estimation

As mentioned earlier, the uncertain variables in the model follow a stochastic process, which is mathematically represented using the Euler-Maruyama method:

$$P(t + \Delta t) = P_t + \alpha \cdot P_t \cdot \Delta t + \sigma \cdot P_t \cdot \sqrt{\Delta t} \cdot dz \tag{32}$$

To estimate the drift and volatility parameters, historical electricity price data from 2015 to 2020 were used. This period was chosen deliberately to exclude the years following 2020, which were affected by atypical events such as the COVID-19 pandemic and the war in Ukraine, leading to significant disruptions and price anomalies in the electricity markets. By focusing on the pre-2020 period, the analysis aims to provide a more stable and representative estimate of the underlying trends in electricity prices.

The historical data retrieved were on a monthly basis. To align with the annual time step used in the model, the mean of the monthly prices was calculated to obtain a single representative value for each year. This approach helps smooth out short-term fluctuations and provides a more accurate reflection of the annual trends.

For simplification purposes, a cap and floor were also applied to the simulated electricity prices to ensure they remain within a realistic and desirable range of 45€ to 90€ per Megawatt hours (MWh). The cap and floor prevent the model from producing extreme values that could skew the results and lead to unrealistic project valuations.

For the initial price used in the simulations, the mean of the historical data was considered, resulting in an initial value of 46.65€. The drift rate was calculated at -7.17%, and the volatility rate was 26.08%.

Figure 4 illustrates the simulated evolution of electricity prices from 2024 to 2064, showing that the average of all 5000 simulated paths stabilizes within a range of approximately 50€ to 55€ per MWh after an initial period of adjustment.

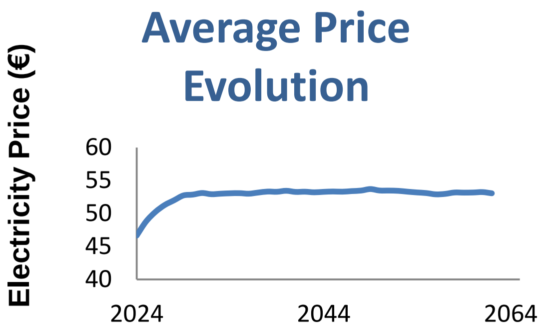

Figure 4: Average Price Evolution

6.1.2 Annual Energy Production Estimation

The estimation of the Annual Energy Production follows a stochastic process similar to that of electricity prices, modeled by the following equation:

$$AEP(t + \Delta t) = AEP_t + \alpha \cdot AEP_t \cdot \Delta t + \sigma \cdot AEP_t \cdot \sqrt{\Delta t} \cdot dz \tag{33}$$

The AEP is influenced by both the capacity factor and the installed capacity of the wind farms. For onshore wind farms, the capacity factor is set at 35%, with an installed capacity of 3.1 MW. For offshore wind farms, the capacity factor is 44.5% with an installed capacity of 8.4 MW.

The drift and volatility parameters were calculated using historical data on the total energy output per hour in Portugal, divided by the installed capacity in the country. The initial parameters used for the simulation were as follows: for onshore AEP, the initial value was 9 504.6 MWh, while for offshore AEP, it was 32 744.88 MWh. The drift rate was 1.02%, and the volatility rate was 7.90%.

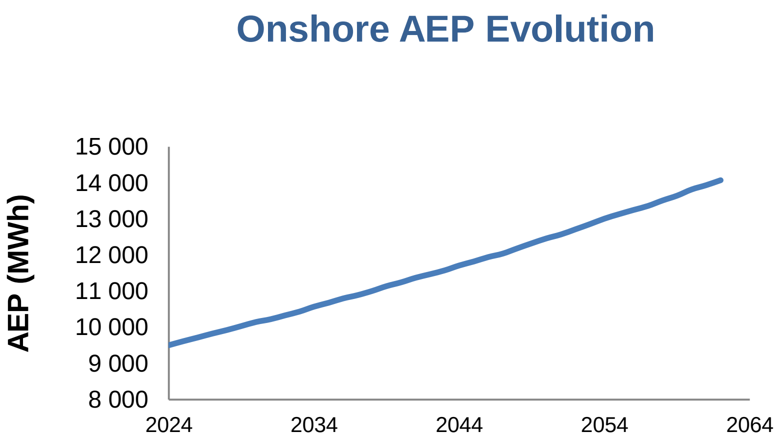

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Figure 5: Onshore annual energy production evolution

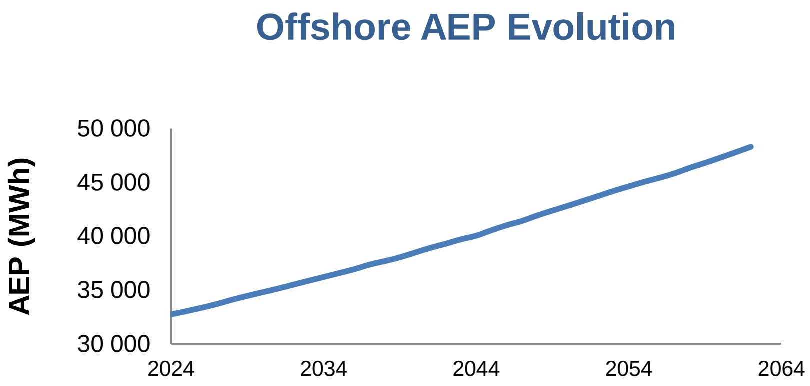

Figure 6: Offshore annual energy production evolution

Figures 5 and *Figure 6* show that the difference between the AEP estimation for onshore and offshore wind farms lies in the initial values, which are significantly influenced by the differing capacity factors and installed capacities. The higher capacity factor and installed capacity of offshore wind farms account for the much larger initial AEP value compared to onshore projects.

6.1.3 Onshore Levelized Cost of Energy Estimation

Onshore LCOE is determined by both the costs associated with the project and the AEP. The dynamics of AEP have already been discussed. In terms of costs, the focus is on Capital Expenditure and Operational Expenditure. Both of these variables follow the stochastic process outlined below:

$$CAPEX(t+\Delta t) = CAPEX_t + \alpha \cdot CAPEX_t \cdot \Delta t + \sigma \cdot CAPEX_t \cdot \sqrt{\Delta t} \cdot dz \tag{34}$$

$$OPEX(t+\Delta t) = OPEX_t + \alpha \cdot OPEX_t \cdot \Delta t + \sigma \cdot OPEX_t \cdot \sqrt{\Delta t} \cdot dz \tag{35}$$

In this context, CAPEX is a one-time cost that occurs during the 15-year investment period, whereas OPEX is incurred annually, starting from the year immediately following the investment year. Both CAPEX and OPEX were multiplied by the installed capacity (3.1 MW) since the initial data provided was the cost per MW of installed capacity. Because CAPEX only occurs once, it is only estimated for a period of 15 years, spanning from 2024 to 2038.

According to the analysis presented on the Wind Energy - The Facts website, the discount rate typically applied in renewable energy projects falls within a range of 5% to 10%. This reflects the inherent uncertainties and risks associated with such projects, including fluctuating energy prices, technological advancements, and policy changes. Given these considerations, I have chosen to use a discount rate of 7.5%, which strikes a balance between risk and return, aligning with industry standards while accounting for the moderate level of uncertainty in my project. This rate is sufficiently conservative to reflect potential project risks without being overly cautious, ensuring a robust financial evaluation.

Regarding CAPEX evolution, the initial parameters are an initial CAPEX of 4 479 500€, a drift rate of -4.71%, and a volatility rate of 7.24%. These parameters reflect the expected decline in costs due to technological improvements (negative drift) and the uncertainty associated with future costs (volatility).

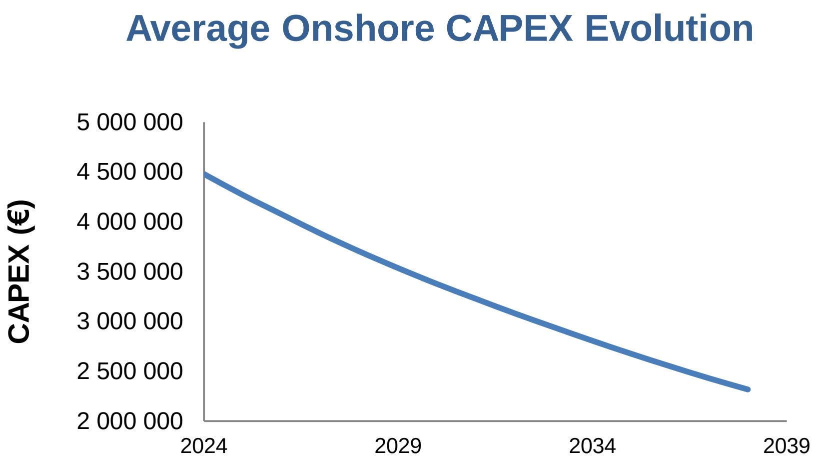

Figure 7: Average onshore capital expenditures evolution

As shown in *figure 7*, the decline in CAPEX over time demonstrates the cost-saving potential of delaying the investment, as future expenditures are expected to be lower due to ongoing improvements in technology and reductions in installation and material costs. The graph provides a visual representation of how the expected reduction in costs over time could influence the timing of investment decisions for an onshore wind project.

The OPEX for the onshore wind project is characterized by an initial value of 216 609€. This OPEX is subject to a negative drift rate of -2.56% per year, indicating an anticipated decrease in operational costs over time, likely due to efficiency improvements. The volatility rate of 5.19% reflects the expected variability in these costs, accounting for potential fluctuations in maintenance expenses, labor costs, and other operational factors.

Unlike CAPEX, OPEX occurs annually, starting from the year immediately following the investment. Therefore, to ensure a comprehensive analysis that covers the entire potential operational lifetime of the project, OPEX is estimated for each year from 2024 to 2062. *Figure 8* shows a consistent decline in OPEX which aligns with expectations that operational efficiencies and advancements in technology will help lower the expenses associated with maintaining and operating the wind farm.

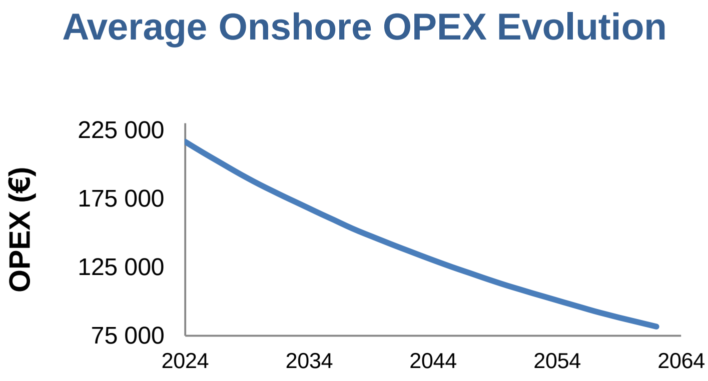

Figure 8: Average onshore operating expenses evolution

The LCOE for onshore wind projects has been computed based on the evolution of CAPEX, OPEX, and AEP over time. As mentioned earlier, the LCOE is assumed to remain constant throughout the entire operational lifetime of the project, which spans 25 years. This means that if the project begins in a specific year, such as 2024, the LCOE calculated for that year will apply to the entire 25-year lifespan of the project. Therefore, the LCOE remains fixed from the time of investment onward. Given the 15-year investment window, the LCOE is only calculated for the years 2024 to 2038. This ensures that for any project started within this investment window, the respective LCOE remains consistent over the full operational period of 25 years.

The results, as illustrated in *Figure 9*, show that the LCOE for onshore projects decreases over time. This decline can be attributed to the reduction in both CAPEX and OPEX, coupled with relatively stable AEP values. By 2038, the LCOE reaches a low of approximately 28.91€ per MWh, making the investment increasingly cost-effective as time progresses. This trend highlights the potential for improved financial returns on onshore wind investments if the project is initiated in later years within the investment window.

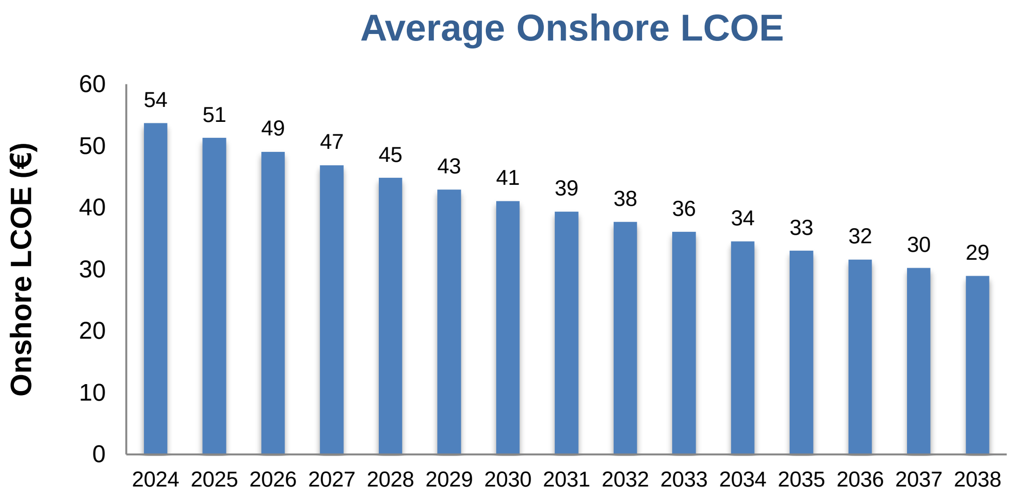

Figure 9: Average onshore levelized cost of energy

6.1.4 Offshore Levelized Cost of Energy Estimation

The estimation of LCOE for the floating offshore wind project is particularly challenging due to the emerging nature of this technology and the associated scarcity of detailed cost data. The LCOE for the floating offshore project will follow a stochastic process, expressed as:

$$LCOE(t + \Delta t) = LCOE_t + \alpha \cdot LCOE_t \cdot \Delta t + \sigma \cdot LCOE_t \cdot \sqrt{\Delta t} \cdot dz \tag{36}$$

For the initial value of the LCOE, the following considerations were made:
The initial OPEX was calculated to be 895 014€, which represents an average of three different possible scenarios (conservative, moderate, and advanced), as discussed earlier. This average value was then multiplied by 8.4, reflecting the average capacity of the offshore wind turbine. It is assumed that OPEX will decrease at a rate of 1% annually. This assumption is based on the expectation that operational efficiencies will improve over time as the technology matures, leading to cost savings.

The initial CAPEX used for the LCOE calculation was 30 499 994€. This value, like the OPEX, was derived from an average of the three scenarios and was also multiplied by 8.4 to reflect the full turbine capacity.

The net present value of all costs was computed for a 25-year project lifespan, incorporating the CAPEX in the first year and the OPEX for each subsequent year. The NPV of the AEP was also calculated using the average AEP for the offshore project, as previously demonstrated. The initial LCOE for the floating offshore project was then calculated to be 93.92€ per MWh.

I considered a drift rate of -7%, which reflects the expected decrease in LCOE over time due to technological advancements and cost reductions, as the technology becomes more widespread and operational efficiencies are realized. The volatility rate of 10% that I assumed accounts for the uncertainties associated with this relatively new floating offshore wind technology, including potential variations in OPEX, changes in regulatory frameworks, or unforeseen operational challenges.

As previously mentioned, the LCOE is estimated only for the 15 years corresponding to the investment window, reflecting the assumption that it will remain constant over the operational lifetime of the project.

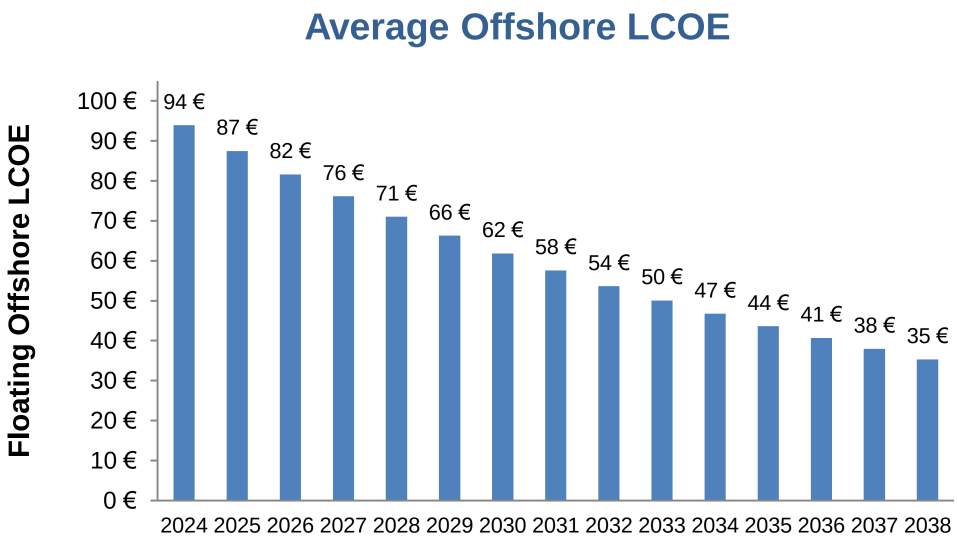

Figure 10: Average offshore levelized cost of energy

As illustrated in *Figure 10*, the LCOE for floating offshore wind farms also decreases over time, reaching 35.32€ per MWh in 2038.

6.2 NPV Valuation

The traditional NPV analysis was performed for both the onshore and floating offshore wind projects, where cash flows were calculated as:

$$CF = (Price\ of\ Electricity - LCOE) \cdot AEP \tag{37}$$

and then discounted over the project's lifespan.

For the onshore project, the average NPV across all 5000 simulation paths, with negative values set to zero, results in an NPV of 503 086€ in 2024, increasing significantly to 3 910 657€ by 2038.

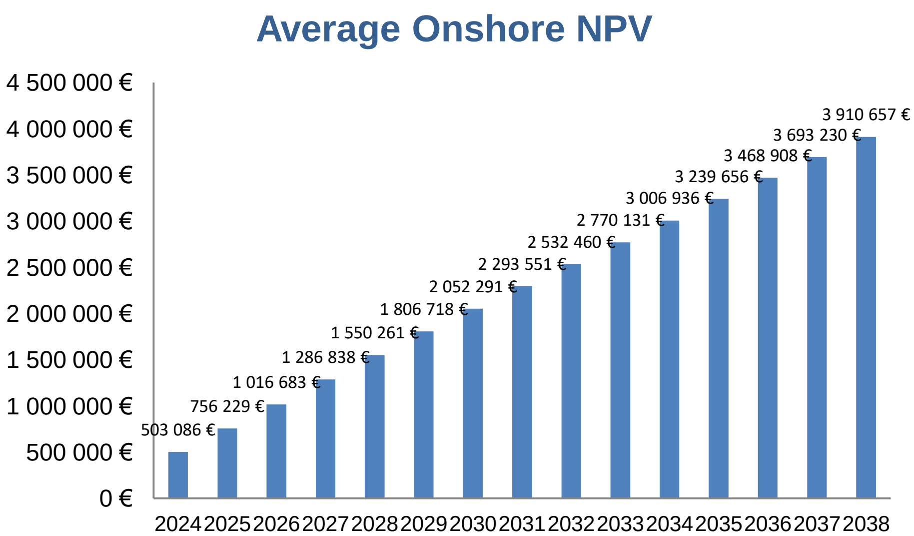

Figure 11: Average onshore net present value

According to the NPV method, the optimal year to invest in onshore wind projects is 2024. Out of the 5000 paths simulated, there are only 186 scenarios where it is not worth investing in any of the possible investment years.

Optimal Year	Onshore
2024	**2201**
2025	598
2026	446
2027	355
2028	265
2029	228
2030	165
2031	129
2032	103
3033	76
2034	61
2035	57
2036	52
2037	46
2038	32

Table 2: Optimal year onshore – NPV valuation

On the other hand, the floating offshore project presents a different scenario. The average NPV for the 5000 paths in 2024 is 0€, indicating that the project is not worth investing in 2024. However, by 2038, the average NPV rises to 9 242 606€, indicating a favorable investment opportunity.

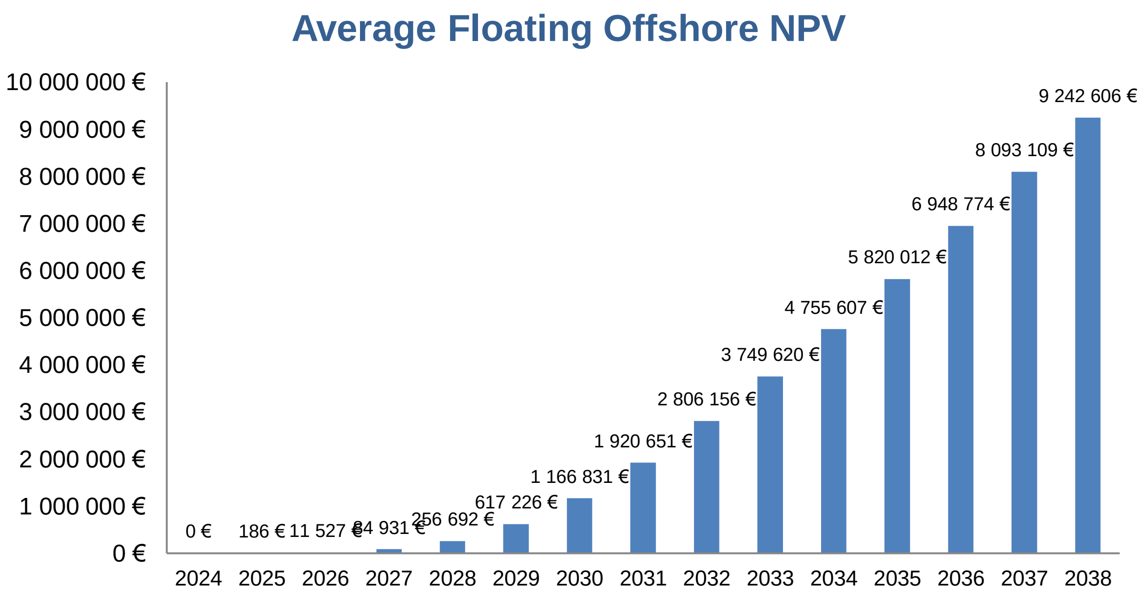

Figure 12: Average floating offshore net present value

For the floating offshore project, the optimal investment timing is identified as 2030. Unlike the onshore project, the offshore project has 427 paths where investing is not considered worthwhile during any of the possible investment periods.

Optimal Year	Floating Offshore
2024	0
2025	1
2026	38
2027	172
2028	296
2029	518
2030	**642**
2031	596
2032	539
3033	475
2034	389
2035	320
2036	261
2037	194
2038	132

Table 3: Optimal year floating offshore – NPV valuation

6.3 Real Options Valuation

In the real options valuation, following the methodology outlined by Zhang et al. (2016), the optimal investment year for both the onshore and floating offshore wind projects is identified as 2038. This analysis incorporates the inherent flexibility of delaying the investment decision, which allows the project to capture more favorable market conditions and cost efficiencies over time. By considering the uncertainty and the potential benefits of postponing the investment, the real options approach provides a more dynamic and robust framework for decision-making compared to the traditional NPV method.

Optimal Year	Onshore	Floating Offshore
2024	2	0
2025	34	0
2026	83	1
2027	153	1
2028	243	7
2029	261	16
2030	336	47
2031	335	88

2032	291	154
2033	349	192
2034	377	282
2035	399	388
2036	421	558
2037	458	829
2038	**1072**	**2010**

Table 4: Optimal year onshore and floating offshore – RO valuation

For the onshore wind project, the Real Options analysis reveals that delaying the investment until 2038 maximizes the project's value, despite the traditional NPV analysis suggesting an earlier investment in 2024. This delay allows the project to benefit from anticipated decreases in LCOE and potential increases in electricity prices, thereby enhancing overall project profitability.

Similarly, for the floating offshore wind project, the optimal investment year is also identified as 2038. This timing allows the project to take advantage of expected technological advancements and cost reductions, which are crucial for the economic viability of this relatively new and innovative technology.

6.4 Value of Waiting

The concept of "waiting" in project investment decisions refers to the strategy of delaying an investment to maximize potential returns by accounting for future uncertainties. In renewable energy projects, especially wind farms, this means considering whether it is more advantageous to invest immediately or wait for more favorable conditions, such as lower costs, higher energy prices, or improved technology. This decision can significantly affect the project's overall value.

For onshore wind projects, the traditional NPV method indicates that the optimal investment year is 2024, with a project value of 503 085 70€. However, using the Real Options method, which accounts for the flexibility of delaying investment under uncertainty, the optimal year shifts to 2038. In that year, the project is valued at 3 910 657€. When the project value in 2038 is discounted back to 2024 using the appropriate discount rate, the discounted value amounts to 1 368 487€. This indicates that by waiting until 2038 to invest, the additional value derived from flexibility is 865 401€ (1 368 487€ minus the NPV of 503 086€). This value represents the economic benefit of waiting and highlights the potential gain from delaying investment rather than committing immediately in uncertain market conditions.

For offshore wind projects, the NPV method suggests the optimal investment year is 2030, with a project value of 1 166 831€. When this value is discounted back to 2024, the present value becomes 744 004€. Using the Real Options method, the optimal year for investment is 2038, with a project value of 9 242 606€. Discounted back to 2024, this value is 3 234 337€. The value of waiting until 2038, therefore, amounts to 2 490 333€, representing the gain from delaying the investment compared to following the NPV approach.

In conclusion, the real options approach demonstrates that waiting can add significant value to both onshore and offshore wind projects. For the onshore project, the value of waiting is 865 401€, while for the offshore project, it is 2 490 333€. This highlights the importance of considering flexibility and future uncertainty when making investment decisions in renewable energy projects. By allowing for future market developments and adjusting to uncertainties, the real options method ensures a more optimal and financially beneficial investment strategy.

6.5 Sensitivity Analysis

Sensitivity analysis is a crucial step in project valuation. It allows for an examination of how changes in key input variables affect the overall outcome, providing a clearer understanding of the project's risk and robustness. In the context of wind energy, factors such as the discount rate, project costs (CAPEX and OPEX), and the annual energy production play a significant role in determining the value of the project. By conducting a sensitivity analysis, it is possible to assess how fluctuations in these variables impact the net present value and real options outcomes. This approach helps identify critical thresholds and informs decision-makers of the project's sensitivity to changes, thereby supporting better strategic planning. This analysis will focus on three key variables: the discount rate, project costs, and AEP, to evaluate their effects on the investment value and the optimal timing of investment decisions. Further details are provided in the annexes. **Annex A** presents the scenario for a low discount rate, **Annex B** explores the high discount rate scenario, **Annex C** contains information on the assumption of a constant annual energy production and **Annex D** focuses on the case of constant project costs. These annexes provide the NPV values and the optimal investment year according to both NPV and real options (RO) valuations for each scenario.

6.5.1 Discount Rate

The discount rate is a fundamental variable in the valuation of long-term projects, as it reflects both the time value of money and the risk associated with the investment. In renewable energy projects, where cash flows span several decades, the choice of the discount rate can significantly affect the net present value and real options value. A lower discount rate typically favors earlier investments by reducing the present value of future cash flows less aggressively, while a higher discount rate pushes the value of the project further into the future, emphasizing risk and uncertainty.

For onshore wind projects, which are a more established and well-understood technology, I will apply a conservative discount rate of 5%. This lower rate reflects the relative maturity of the technology and the lower perceived risk associated with such projects.

The results of applying a 5% discount rate to the onshore project show a clear preference for earlier investments. According to the NPV valuation, the optimal investment year is still 2024, with 3 736 paths out of 5 000 indicating that this is the most favorable time to invest. The project value in this case reaches 1 433 353€. Furthermore, only 78 scenarios suggest that it is not worth investing in any of the possible years, highlighting the robustness of the project under a lower discount rate. By contrast, when using the Real Options (RO) method, the optimal investment timing shifts to 2038, with 1 409 paths supporting this conclusion. The higher number of paths favoring later investment highlights the greater value that managerial flexibility holds in this scenario, as the lower discount rate reduces the penalty for waiting.

The time value of waiting further illustrates these differences. With a 5% discount rate, the value of waiting for the optimal investment year (2038) amounts to 1 327 695€. In contrast, with a 7.5% discount rate, the value of waiting is 865 401€, as future gains are more heavily discounted and, therefore, hold less value.

Project Value	**Onshore**
NPV	1 433 353€
RO Value	2 761 048€
Value of Waiting	**1 327 695€**

Table 5: Value of waiting – low discount rate scenario (onshore)

For floating offshore wind projects, a higher discount rate of 10% was applied. This rate takes into account the elevated risks and uncertainties with an innovative and pilot technology. Floating offshore wind is still in the early stages of deployment, and the uncertainty surrounding future costs, technology reliability, and potential operational challenges justifies a more aggressive discount rate.

At this rate, the net present value analysis shows that in the first two years, it is not financially viable to invest, with the optimal investment year being 2033. Out of the 5 000 simulated paths, 543 paths suggest 2033 as the best year to invest, and 904 paths indicate that investing in any year is not worth it. The real options valuation points 2038 as the optimal year to invest, with 1 882 paths supporting this conclusion.

When compared to the results with a 7.5% discount rate, the differences are striking. With a lower discount rate, the NPV valuation suggests that 2030 is the optimal investment year, and the RO valuation also points to 2038. Moreover, with a 7.5% rate, only 427 paths suggest that it is not worth investing in any year, significantly fewer than the 904 paths at the 10% rate.

A higher discount rate places more emphasis on the risks and uncertainty in future cash flows, causing the NPV to decrease. The value of waiting is also substantially lower at 10% (728 149€) compared to 7.5% (2 490 333€), reinforcing the notion that higher discount rates reduce the attractiveness of delaying investment due to the more aggressive discounting of future returns.

Project Value	Floating Offshore
NPV	694 943€
RO Value	1 423 092€
Value of Waiting	**728 149€**

Table 6: Value of waiting - high discount rate scenario (floating offshore)

6.5.2 Costs

In this chapter, the sensitivity analysis focuses on the impact of cost changes, specifically for onshore wind projects. Given the limited data availability for floating offshore projects, this analysis will only be conducted for onshore projects. In the initial scenario, the results show a reduction in costs over the years, which may not accurately reflect reality. The assumption of declining costs could be overly optimistic, as future cost reductions are not guaranteed and could be impacted by unforeseen factors such as supply chain disruptions, inflation, or changes in market conditions.

To examine an extreme scenario, I set both the drift and volatility of CAPEX and OPEX to 0%, meaning that costs remain constant throughout the years. This approach allows us to evaluate how the project behaves under a stable cost environment, devoid of any cost reductions or increases over time. By comparing this with the initial scenario, we can better understand the impact of cost assumptions on the financial viability and optimal investment decisions of the project.

The results indicate that even under a scenario of fixed costs, the NPV still increases over the investment period, though at a slower rate than in the initial analysis. In this case, the NPV rises from 520 191€ in 2024 to 1 692 912€ in 2038, as opposed to the more pronounced growth observed in the original scenario. Despite the constant cost assumption, the optimal investment timing remains the same: 2024, according to the NPV valuation, and 2038, according to the (RO) valuation.

However, one significant difference in this scenario is the number of cases where it is not worth investing in any of the potential years. With constant costs, there are 1 548 paths where investment is not financially viable, a stark increase from the 186 cases in the initial scenario. This suggests that cost variability plays a crucial role in determining the viability of the project, as the original scenario's cost fluctuations made investment more attractive in a larger number of cases.

Additionally, the value of waiting diminishes considerably in this constant-cost scenario. The value of waiting falls from 865 401€ in the original analysis to just 72 222€, reflecting the reduced flexibility and diminished potential gains from delaying investment in a scenario where costs remain static over time.

Project Value	Floating Onshore
NPV	520 191€
RO Value	592 414€
Value of Waiting	**72 222€**

Table 7: Value of waiting – constant costs (onshore)

6.5.3 AEP

In this chapter, the sensitivity analysis focuses on the impact of changes in Annual Energy Production for both onshore and offshore wind projects. In the initial scenario, AEP increases over the years for both onshore and offshore projects, reflecting assumptions of technological improvements and enhanced operational efficiencies. However, this assumption may not hold true in reality. Factors such as fluctuating wind speeds, mechanical wear and tear, or other operational challenges could prevent significant gains in AEP over time. AEP not only impacts revenue directly but also affects the LCOE, as higher AEP lowers the cost per unit of energy, thus influencing the overall project economics.

To explore an alternative scenario, I set both the drift and volatility of AEP to 0%, effectively assuming no technological improvements or operational enhancements over the project's lifetime.

In the case of onshore wind projects, setting AEP to remain constant alters the optimal investment timeline. According to the NPV valuation, the optimal year to invest shifts to 2026, while the real options valuation still points to 2038 as the optimal year. In this scenario, only 28 paths out of 5000 show that it is not worth investing in any year. Comparatively, in the initial scenario, with increasing AEP, the optimal year to invest according to the NPV valuation was 2024, and there were 186 cases where it was not worth investing at all.

The value of waiting also diminishes in this scenario. The value of waiting is 550 490€, compared to 865 401€ in the initial scenario. This reduction suggests that in a stable AEP environment, delaying investment has less benefit because the potential for future revenue growth is limited, making immediate investment a more favorable option in many cases.

Project Value	Onshore
NPV	260 741€
RO Value	811 231€
Value of Waiting	**550 490€**

Table 8: Value of waiting – constant annual energy production (onshore)

For offshore wind projects, the effect of a constant AEP is even more pronounced. In the first two years, it is not worth investing at all, similar to the initial scenario. However, the optimal year to invest according to the NPV valuation shifts to 2031, while the RO valuation remains the same at 2038. In this scenario, 670 paths out of 5000 show that it is not worth investing in any year, a noticeable increase from the 427 scenarios in the initial scenario.

The increase in unviable paths reflects the higher dependency of offshore projects on technological advancements and improvements in AEP to offset their higher initial costs.

The value of waiting also decreases in this scenario, with the waiting value falling to 1 608 963€, compared to 2 490 333€ in the initial scenario. Similar to the onshore projects, the reduced value of waiting implies that the benefits of postponing investment are diminished when AEP remains constant, as there is less potential for future improvements in energy production to increase project value.

Project Value	Floating Offshore
NPV	684 243€
RO Value	2 293 206€
Value of Waiting	**1 608 693€**

Table 9: Value of waiting – constant annual energy production (floating offshore)

7 Conclusion

This thesis investigated the application of real options theory to assess the financial viability and strategic timing of wind energy investments in Portugal, focusing on both onshore and floating offshore wind projects. Through the incorporation of uncertainties such as electricity prices, advancements in wind technology, and the variability in project costs, a dynamic model was developed to move beyond the static nature of traditional net present value analysis. This approach allowed the evaluation of investment decisions in a way that accounted for future flexibility, a critical aspect when dealing with long-term projects in rapidly evolving sectors such as renewable energy.

The research highlighted the unique economic potential of both onshore and offshore wind energy in Portugal. A key takeaway is the distinct difference in the timing of investment between these two types of projects. Onshore wind, while having an optimal investment year of 2038 according to real options analysis, shows potential for earlier or even immediate investment due to its technological maturity and relatively low costs. The value of waiting is less significant compared to offshore projects, meaning that investors could still consider earlier deployment to take advantage of the existing infrastructure and lower risk. This underscores the importance of continued support for onshore wind energy, as it remains a highly viable and lower-cost option for renewable energy expansion in the near term.

In contrast, floating offshore wind projects, though initially costlier, exhibit significant economic potential if investment decisions are strategically delayed. As technology evolves and costs decrease, the return on investment for offshore projects becomes increasingly favorable. The flexibility to wait for improved conditions, a core element of real options theory, proves to be a valuable strategy for offshore wind projects.

The findings underscore the importance of optimizing the timing of investments to maximize financial returns, especially in sectors where technological advancements are anticipated. For policymakers, the results advocate for the development of frameworks that support both immediate and delayed investments. For instance, targeted subsidies, tax incentives, or accelerated permitting processes for onshore projects could facilitate quicker deployment, while long-term support mechanisms for offshore wind, such as R&D funding and infrastructure investment, could enhance the sector's growth potential.

Despite these valuable contributions, this thesis has certain limitations that should be acknowledged. The use of geometric Brownian motion to model uncertainties such as electricity prices, technological progress, and project costs may not fully capture the complexity of real-world market behavior. Real energy markets are subject to sudden and unpredictable shocks, including geopolitical events, natural disasters, or policy shifts, which could have a profound impact on renewable energy investments. The model's reliance on historical data, while necessary for simulation purposes, may not fully account for such extreme disruptions, especially in light of the unprecedented changes seen in recent years, such as the global energy crisis triggered by the COVID-19 pandemic and the ongoing geopolitical tensions. Future models could benefit from incorporating scenario analysis or sensitivity testing to better handle these risks.

Additionally, the geographic scope of this thesis is limited to Portugal. While Portugal's wind energy sector is a promising case study due to its unique geographical and policy advantages, the findings may not be directly applicable to other countries with different economic conditions, regulatory environments, or energy infrastructures. For example, nations with less developed energy grids, fewer policy incentives, or harsher environmental conditions may not experience the same economic outcomes from wind energy investments. The global applicability of real options theory in renewable energy investment thus requires further exploration across various contexts, including countries with different levels of market maturity or government support for renewables.

Future research should address these limitations by expanding the scope and depth of analysis. One key area for future work is the integration of more sophisticated stochastic models that account for a broader range of variables and interactions. For example, the use of models that incorporate mean-reverting processes or jump diffusion could provide a more accurate reflection of price behavior in energy markets. Additionally, research could explore how specific external factors, such as carbon pricing, green bonds, or emerging regulatory frameworks, impact the value of wind energy investments over time.

Furthermore, the scope of this thesis was restricted to wind energy, both onshore and offshore. Future studies could broaden the analysis to include other renewable energy sources, such as solar and hydroelectric power, which are also vital to Portugal's energy transition. A comparative analysis of these technologies, considering the respective costs, technological advancements, and uncertainties, would offer a more comprehensive view of the optimal mix of renewable energy investments. Additionally, research could focus on hybrid renewable systems, where wind, solar, and storage technologies are integrated to provide a more stable and efficient power supply.

The role of policy incentives and regulatory frameworks is another critical area for future investigation. The evolving policy landscape, both at the European Union level and within Portugal, has a profound influence on the financial feasibility of renewable energy projects. Future research could examine the potential impacts of new policy instruments, such as carbon markets or renewable energy certificates, on investment timing and profitability. Additionally, exploring how public-private partnerships and cross-border collaborations could enhance the development of large-scale offshore projects would add depth to the conversation on scaling renewable energy solutions.

In conclusion, this thesis contributes to the growing body of knowledge on renewable energy investments by applying real options theory in the context of Portugal's wind energy sector. The findings emphasize the importance of flexible and adaptive investment strategies in the face of uncertainty. By highlighting the critical role of timing and technological progress, this work offers a perspective on how real options theory can be used to optimize investment decisions and support the global transition to sustainable energy systems. Despite its limitations, the thesis lays the groundwork for future research, which can expand on these findings to further enhance the strategic value of renewable energy investments in a rapidly changing world.

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ANNEX A: Low Discount Rate Scenario

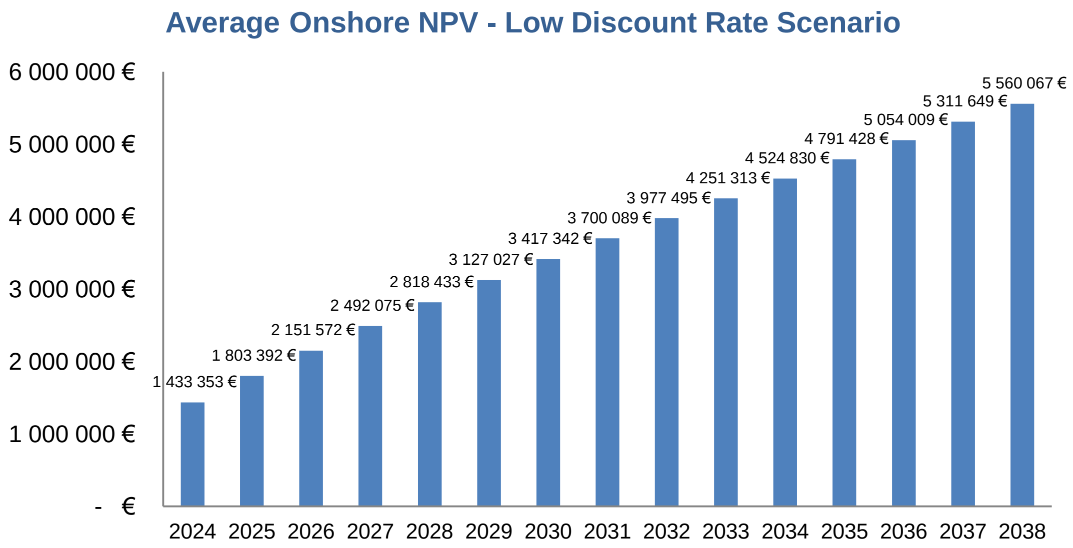

Figure 13: Average onshore net present value – low discount rate scenario

Optimal Year	Onshore – NPV Valuation	Onshore – RO Valuation
2024	**3736**	8
2025	324	41
2026	217	105
2027	157	143
2028	99	217
2029	70	226
2030	66	281
2031	60	297
2032	49	265
2033	29	318
2034	32	325
2035	31	348
2036	18	436
2037	18	503
2038	16	**1409**

Table 10: Optimal year onshore – low discount rate scenario (NPV and RO)

ANNEX B: High Discount Rate Scenario

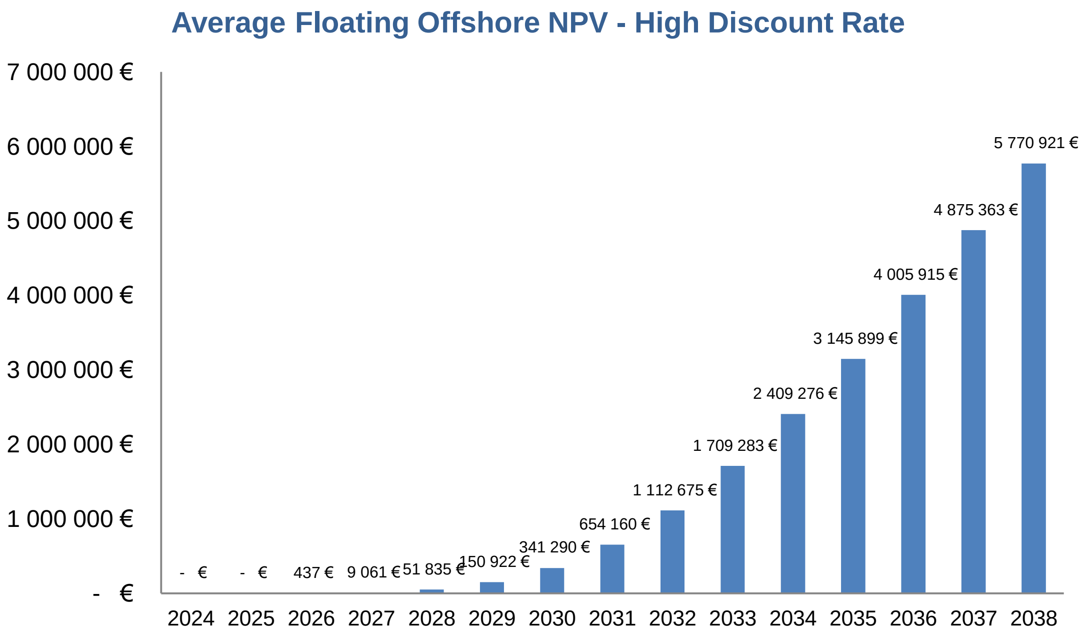

Figure 14: Average floating offshore net present value – high discount rate scenario

Optimal Year	Floating Offshore – NPV Valuation	Floating Offshore – RO Valuation
2024	0	0
2025	0	0
2026	1	0
2027	39	0
2028	92	5
2029	209	15
2030	356	44
2031	492	54
2032	527	86
2033	**543**	168
2034	479	239
2035	428	349
2036	371	487
2037	300	767
2038	259	**1882**

Table 11: Optimal year floating offshore – high discount rate scenario (NPV and RO)

ANNEX C: Constant Costs Scenario

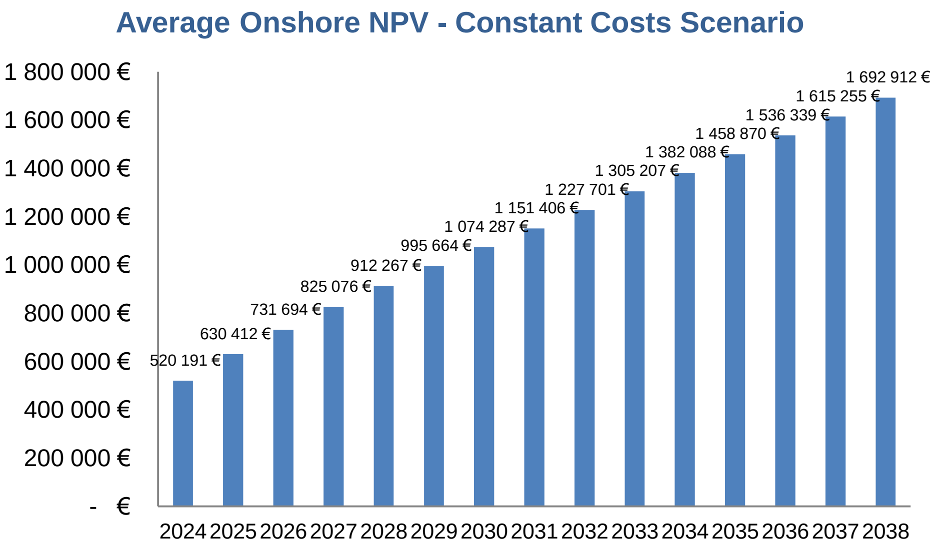

Figure 15: Average onshore net present value – constant costs scenario

Optimal Year	Onshore – NPV Valuation	Onshore – RO Valuation
2024	**2274**	0
2025	170	186
2026	151	242
2027	98	253
2028	121	223
2029	92	218
2030	81	205
2031	79	208
2032	51	171
2033	69	178
2034	65	155
2035	46	173
2036	53	171
2037	51	192
2038	51	**877**

Table 12: Optimal year onshore – constant costs scenario (NPV and RO)

ANNEX D: Constant AEP Scenario

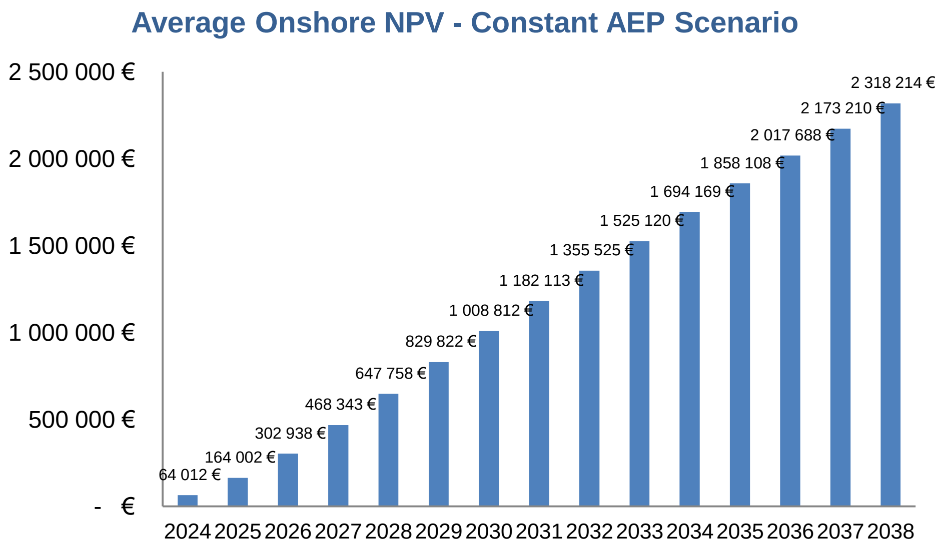

Figure 16: Average onshore net present value – constant AEP

Optimal Year	Onshore – NPV Valuation	Onshore – RO Valuation
2024	730	3
2025	795	28
2026	**912**	61
2027	780	90
2028	571	155
2029	425	192
2030	260	289
2031	157	331
2032	124	309
2033	74	368
2034	57	422
2035	35	482
2036	27	544
2037	16	570
2038	9	**1128**

Table 13: Optimal year onshore – constant AEP scenario (NPV and RO)

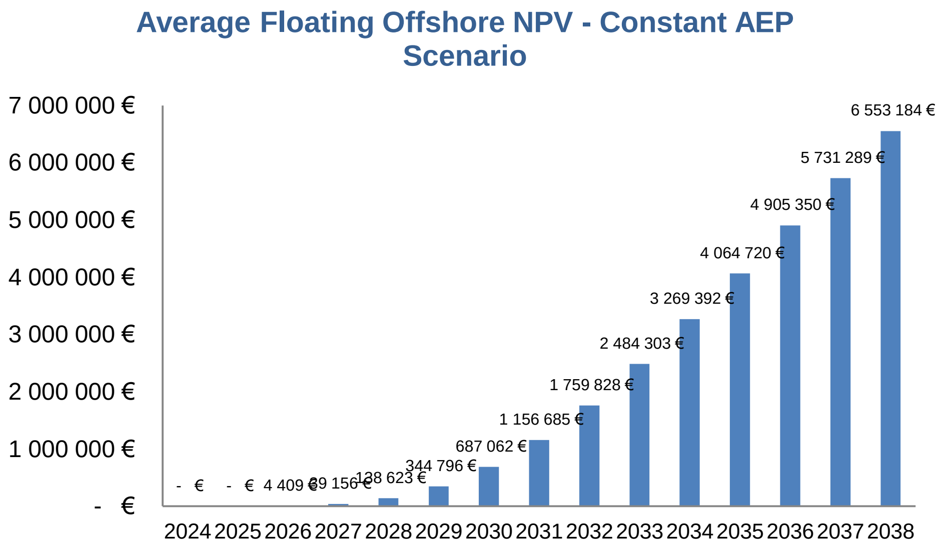

Figure 17: Average floating offshore net present value – constant AEP

Optimal Year	Floating Offshore – NPV Valuation	Floating Offshore – RO Valuation
2024	0	0
2025	0	0
2026	17	0
2027	89	1
2028	209	4
2029	376	16
2030	487	30
2031	**554**	70
2032	536	107
2033	531	185
2034	434	268
2035	353	348
2036	297	507
2037	231	798
2038	216	**1996**

Table 14: Optimal year floating offshore – constant AEP scenario (NPV and RO)