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Forecasting the Liquidity in PPA Markets in Europe

TESI DI LAUREA MAGISTRALE IN MANAGEMENT ENGINEERING

Author: **LAMA BOU AKL**

Student ID:	942471
Supervisor:	Prof. Simone Franzò
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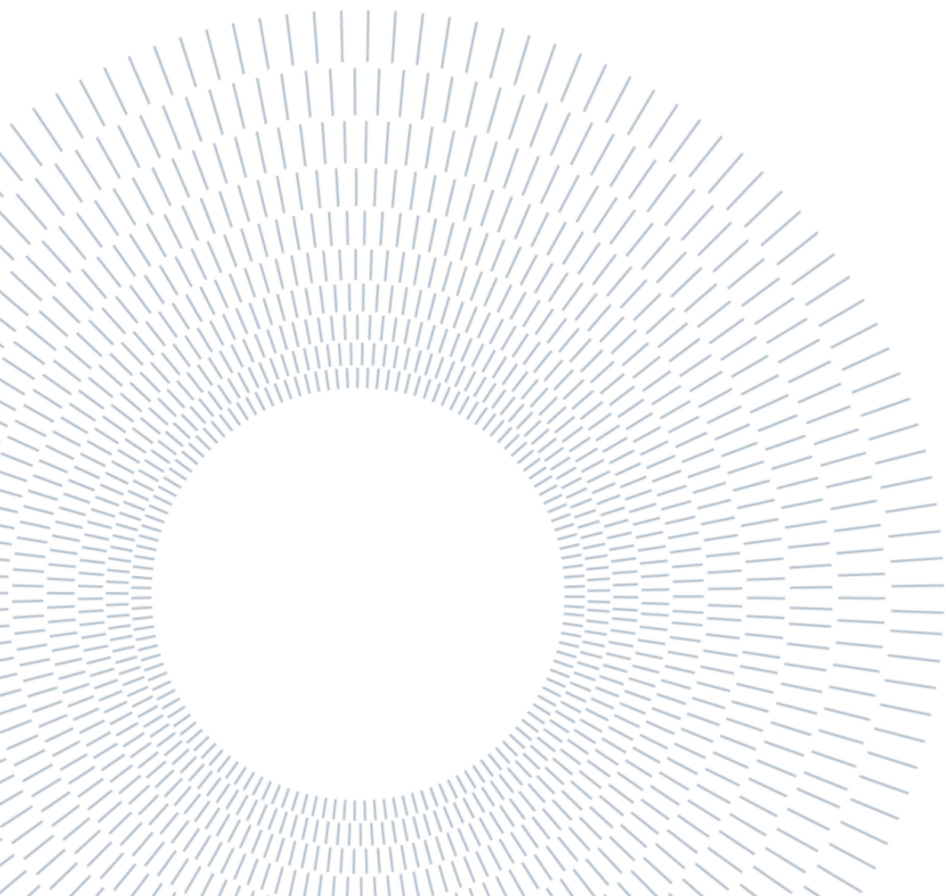

Abstract

The energy transition has been continuously a central topic at the European level discussions where all countries are urged to decrease their greenhouse gases emissions by progressively shifting towards renewable energy. When the renewable energy markets were still at their infancy, significant governmental support, through subsidies, was required to encourage investments in the rising technologies. However, as renewable energy technologies proved themselves to be competitive with other conventional energy production technologies, the governmental subsidies gradually started decreasing. As a result, several business models have emerged to ensure the bankability and execution of renewable investments, out of which Power Purchase Agreements (PPA) have proven to be the most diffused. The European PPA markets are at different levels of growth in different countries; nevertheless, all market players, starting from regulators up to corporate players realize the importance of PPAs in achieving the energy transition and hedging against electricity market fluctuation through time. Various players are interested in knowing how the future of such new markets would be in upcoming years to help guide their decisions; however, such data remains controlled by advisory firms that keep track of the market dynamics and build their own forecasting models which are kept confidential in most cases. Hence, the goal of this research was to build a model that forecasts the liquidity in PPA markets which is made public to all interested parties. Historical data was gathered along with market analysis, several models were developed and tested to identify the most accurate ones. The final result was the development of two models to forecast the future volumes in the PPA markets: one model provides rough and quick estimates for the liquidity in a PPA market while the other is more rigorous and provides results with higher accuracy. The first model is using artificial neural networks (ANN) while the second, more detailed model is through the scenario-building technique. The two models are of use on the market as each can be used in a unique situation according to the level of accuracy needed and the time needed to execute the model.

Key-words: Power Purchase Agreements, renewable energy, energy transition, Europe, forecasting, neural networks, linear regression, scenario-building

Contents

List of Acronyms and Symbols

SDGs	Sustainable Development Goals
IRENA	International Renewable Energy Agency
Power Purchase Agreement	PPA
German Energy Agency	DENA
European Union	EU
European Commission	EC
International Energy Agency	IEA
International Renewable Energy Agency	IRENA
Renewable Energy	RE
Independent Power Producer	IPP
Artificial Neural Networks	ANN
Renewable Energy Sources	RES
Mean Absolute Error	MAE
Mean Absolute Percentage Error	MAPE
Root mean-square Deviation	RMSE
Auto-Regressive Iterative Moving Average	ARIMA
Seasonal Auto-Regressive Iterative Moving Average	SARIMA
Artificial Neural Network	ANN
Neural Network	NN
Multi-layer perceptron	MLP
Mean Square Error	MSE
Coefficient of Determination	R^2
Levelized Cost of Electricity	LCOE
Data Not Found	DNF
Linear Regression	LR
Global Industry Classification Standard	GICS
Correction Factor	CF

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Executive Summary

With the agreement on the Sustainable Development Goals in 2015, the global attention has started to shift on ensuring reliable and sustainable energy for all the population on the globe. In this regard, Europe has proved to be a forerunner leading the energy transition worldwide. Starting from the unbundling of the electricity system in its member states, the European Union then started stressing on the importance of increasing investments in renewable energy. The main targets behind that was to become more sustainable, with less greenhouse gas emissions, and ensuring energy security. The unbundling of the electricity system was a major enabler for the diffusion of renewable energy as more developers, independent power producers, and utilities started investing in their own renewable energy portfolio. Hence, increasing the share of renewable energy in the various European grid systems was performed due to the additions of the small capacity done by single investors. At the infancy of the renewable energy markets, the main supporters were the European Union and local governments which provided renewable subsidies to help in increasing the competitiveness of the renewable assets in terms of the price of electricity sold on market. With time, due to the economies of learning and economies of scale achieved by the emerging technologies, such assets started to gain grid parity where their costs and profits became comparable, and even outperforming, conventional energy technologies such as coal fired plants and fossil fuel-based plants. The investment in such technologies on a large scale necessitates obtaining debt financing from financial institutions to cover the costs of the investments. To give required financing, financial institutions need to have a guarantee that the produced electricity from the asset will be sold in future years to be able to pay back its debt. While previously winning a contract through governmental subsidy schemes covered this requirement, the gradual decrease in subsidies necessitates other forms of guarantee. On this point, Power Purchase Agreements (PPAs) started gaining momentum in European countries. PPAs are bilateral contracts between energy producers and end users that guarantee for a long period of time the offtake of electricity from a renewable asset at fixed terms, often a form of a fixed price. The interest of studying PPA markets have emerged on the side of project developers and governmental bodies to help steer regulations and renewable energy investments. Although the various types and production profiles obtained through a PPA have

been studied in academic research, there is the lack of a coherent replicable model that aims at forecasting the size of European PPA markets in upcoming years. In fact, knowing the liquidity of PPA markets is essential as such agreements play a central role in helping countries and corporate players reach their renewable energy targets. Models to predict the liquidity of PPA markets are currently used in advisory firms to help guide the decisions of renewable investors. However, such companies do not disclose of their in-house created model to ensure they stay competitive on the market.

RESEARCH METHODOLOGY, GAP AND OBJECTIVE

By reviewing the available literature, forecasting related to the electricity system appeared to be a widespread topic. Researchers have been interested, for more than 10 years, in forecasting the electricity consumption and production on local, national and regional levels. Several models emerge ranging from conventional to unconventional models. However, a clear absence of a model that aims to predict the liquidity of PPA markets was identified. The presence of such model could benefit the various players in PPA markets: project developers, regulatory bodies, corporate and utility buyers, and financial institutions. Therefore, the research done aims at answering the following three research questions:

RQ1: Considering the historical corporate purchasing of PPAs in a certain market, what is the future appetite for corporate PPAs in upcoming years?

RQ2: Considering the projected projects pipeline of renewable energy investments, along with other volumes that might add to the PPA supply, what is the probable volume of assets asking for PPAs in the upcoming years?

RQ3: Under each scenario, do the projected supply and the expected demand lead to a PPA market that is balanced in the future?

To answer the above questions, insights were taken from forecasting models identified during the literature review and the most appropriate methodologies and models were adapted to forecast PPA market liquidity. Due to the absence of an already established model, there was no benchmark to compare the result of the research to; consequently, several models were tested in this research to be able to compare their performance and identify the most suitable one, in terms of explaining the variability in PPA volumes in different countries and in reducing the forecast errors. At first conventional models were utilized, represented by building linear regression models. Then, the shift to more non-conventional models was tested through using artificial neural networks.

At last, a scenario-building technique was developed to be adapted according to each market characteristics.

Linear Regression Models

The first model type tested was linear regression. Linear regression is the most favorable predicting model due to its simplicity, robustness, and low application time required. To perform linear regression, there was the need to identify independent variables that explain the liquidity in European PPA markets. By doing web research, and using the experience gained during the internship at Pexapark, along with experts' opinion, five independent variables were identified that shape the PPA market:

- Renewable Subsidies Volumes;
- Wholesale Electricity Prices;
- Renewable Energy levelized cost of electricity (LCOE);
- Renewable Energy Capacity factor;
- Renewable Energy newbuild.

Each of the five factors acts either as an enabler or deterrent for the evolution of a PPA market in a certain country. The effects of each of the factors was studied along with the degree of influence on the PPA market by studying the coefficients obtained in linear regression. Various regression models were built starting from local technology-specific models up to regional technology-neutral ones. Although technology specific models better capture the characteristics of each technology in a certain market, it is difficult to build such models now. This is true due to the limited datasets available which do not permit proper training and testing of linear regression models. As for technology-neutral models, they could be trained by larger datasets, thus allowing higher model predictability and accuracy. Among all linear regression models built and tested, the most accurate one appeared to be European-level technology-neutral model. The model was trained and tested with 28 datapoints and the obtained coefficient of determination in testing is 0.543 with a mean average error (MAE) of 0.096. Hence, with the current availability of data, this is the best linear model that can be created. The model could be used to obtain a rough estimate of the PPA market size in upcoming years.

Artificial Neural Network Models

After the failure to obtain satisfying results using linear regression, there was the attempt to create a forecasting model using artificial neural networks. To build a neural network model, only the historical data related to PPA markets is needed through the yearly contracted capacity. In this case, there is no need to identify independent variables that predict the PPA market, since the model solely builds on past data. The same assumptions and configurations to build a linear model were used for the neural network model. Also in this case, the best performing the model is the technology-neutral predictive model based on the European data. When tested, the trained model resulted in a coefficient of determination of 0.638 with an MAE of 0.081. This shows that with the same assumptions taken as in the case of the linear regression model, the neural network model turned out to be outperforming. Therefore, among all linear regression and neural network models built, this model appeared to be the most accurate with the least error. However, the model still has some forecasting errors, which are acceptable if one wishes to have a rough and quick estimate of the liquidity of PPA markets in future years. Since the best model so far is still not usable to have an in depth understanding of each European markets, the scenario-building technique was also questioned.

SCENARIO-BUILDING TECHNIQUE MODEL

With the failure of linear regression and neural network models to have accurate predictions, the scenario-building technique. It is based on building three scenarios, high, low and reference, to forecast each of the demand and supply of PPAs. The supply forecasting starts from the yearly renewable newbuild and the yearly subsidy volumes to obtain the merchant renewable volumes eligible for PPAs. As for the demand forecasting, it is based on identifying the top PPA purchasing industries in the market under study and benchmarking their renewable performance to the respective RE100 industries. In this technique, a more in-depth analysis of the market studied is needed compared to the previous two techniques to be able to do proper assumptions and build the three scenarios for both supply and demand. To better illustrate the created model, it was applied to the German PPA market where both supply and demand were forecasted. The result showed that in the most probable case, the German PPA market will be undersupplied due to the persistent subsidies and some permitting delays. In addition to the illustration on the German market, the characteristics of the top European PPA markets are listed to facilitate the replicability of the formed model.

CONCLUSION

To conclude, various models were built and tested to identify the most suitable one. One can say that the neural network model created, or even the linear regression one based on technology-neutral analysis of all European PPA markets are suitable to have a quick and rough estimate of the liquidity of the PPA market in a certain country in the future. On the other hand, if one wishes to perform an in-depth analysis of a market and obtain more accurate results, the scenario-building model is better than the other two models.

1. Introduction

1.1 Topic Overview

"Ensure access to affordable, reliable, sustainable and modern energy for all." – United Nations' Sustainable Development Goal 7

The Sustainable Development Goals (SDGs) are a set of 17 goals adopted by the United Nations' Member States in September 2015 with the aim of improving the life of present and future generations globally. To transform the goals into measurable objectives, 169 targets were further developed to be achieved by 2030, tackling the main socio-environmental and economic challenges affecting developed and developing countries worldwide (Andreoni et al., 2016). Furthermore, the set targets equally address the three well-known pillars of sustainability: economic development, environmental preservation, and social well-being. In this regard, the sustainable development roadmap endorsed by the SDGs stresses the importance of working towards the achievement of the three pillars simultaneously, as the only way to reach true sustainability is by their integrated achievement (*Progress towards the Sustainable Development Goals*, 2021). Consequently, the roadmap consists of four main elements around which the SDGs revolve (United Nations Environment Programme, 2016):

1. **Human well-being is directly connected to the well-being of its ecosystem;**
2. Global environmental challenges not only affect developing countries, but also threaten the achievement of prosperity in the long run;
3. Abolishing inequality in the distribution of resources is crucial for sustainable development;
4. **Sustainably managing natural resources is a fundamental element of long-term development.**

Examining the proposed roadmap makes it evident that two out of the four elements (elements 1 and 4) highlight the necessity of sustainable resource management in ensuring human well-being and long-term prosperity and development. At the heart of sustainable resource management emerges SDG number 7 with the need to enhance access to electricity, accelerate the adoption of renewable energy (RE) technologies and improve energy efficiency. In addition to the significant global effort towards SDG 7, more needs to be done in the upcoming years to attain its three main targets by 2030 (2):

1. Ensure universal access to affordable and reliable energy;
2. Increase considerably the share of renewable energy in the global energy mix;
3. Double the rate of improvement in energy efficiency globally.

Moreover, the three targets of the SDG 7 are captured by the World Economic Forum's definition of the energy transition as "a timely change towards more inclusive, secure, affordable and sustainable energy systems that provides solutions to global energy-related challenges while creating value for business and society." Put in simple words, the energy transition mainly refers to the shift in the global energy systems from polluting fossil-fuel based energy sources to renewable non-polluting energy technologies. Through the past years, the main driver behind the transition to clean energy were governmental policies. Generous subsidy schemes financially supported renewable energy projects rendering them economically competitive on electricity markets. However, with the ongoing decreasing costs of renewable technologies, the electricity sector will naturally shift towards a cleaner global energy mix ("The Global Energy Transition," 2022). In recent years, this natural shift has become evident when one examines the investment patterns in the energy sector. According to the International Renewable Energy Agency (IRENA), capacity additions to the power sector have been increasingly dominated by renewable technologies. In the year of 2020, renewable energy installations formed 82% of the total newbuilt capacity, leading to around a 10% increase compared to the previous year (La Camera, 2021). In addition to increasing renewable energy installations, market trends show that the energy transition is affecting various stakeholders in the economic value chain, ranging from financial institutions and asset managers up to energy consumers and industrial sectors. To start with, more than 80 influential asset managers and financial institutions have declared to transforming their financing into net-zero emissions by 2050, with clear intermediate goals every five years. Their commitment stems from the clear ability of green electricity to outperform coal production and from the need to reduce greenhouse gas emissions. Consequently, the financing of polluting projects and activities which are not consistent with the energy transition path will progressively diminish in the upcoming years. Similarly, many sectors are already taking their role in reaching a greener world, motivated by economic grounds and by a sense of moral and social responsibility. With the shifting mindset of financial institutions and corporate players, long-term renewable energy contracts, known as Power Purchase Agreements (PPAs), have emerged to support the financing and procurement of clean electricity. In the past few years, PPAs have gained an increasing attention in energy transition discussions as many reputable energy sellers and buyers are signing such agreements for long periods ranging from 10 to 20 years. Well-known corporates, such as Google and Amazon, have led the energy transition by signing PPAs in various regions for their data centers and operating sites (Salame, 2021). This has greatly encouraged other players to take similar steps and capture the economic opportunities presented by such contracts. Similarly, utilities have entered into PPAs with the ultimate goals of fixing their energy goals and meeting their emissions reductions obligations. Although PPAs play a pivotal role in the decarbonization of the electricity system, existing literature still lacks clear analysis of market trends and evolution, which is the main aim for the research presented in this document.

1.2 Thesis Development Methodology

The research presented in this document is the result of a one-year extensive experience at the Transactions team in the Swiss startup company, Pexapark. Pexapark provides software and advisory services for renewable energy projects and assists in their risk management. Since 2018, the company has established itself as the leader in empowering renewable energy investors to manage their assets in a post-susbidy world. In fact, the company's continued success has materialized through several awards given by reputable associations and bodies, the latest being the Swiss Innovation Agency. In March 2022, Pexapark has won the Innosuisse Scale-Up Award based on its promising growth potential and innovative business model. The company's transactions team performs market research, reaches out to potential energy buyers, and supports clients in the negotiations of PPAs. As part of the advisory team, the internship involved taking on several tasks which helped in developing an in depth understanding of the PPA market dynamics, including:

- Researching and analyzing European power markets in the context of PPAs and preparing "Key Market Insights" reports for clients covering various European countries;
- Writing monthly articles summarizing European PPA activity in the company's public news digest "PPA Times";
- Research on specific topics enabling the advisory team to conduct business such as renewable subsidy schemes in various European countries, grid connection costs in European countries.

The above-mentioned tasks were accompanied by an extensive literature review. The literature review included several scopes including academic papers, books, and reports published by competitors and international bodies. A clear gap was found in the research and the aim of the work is to tackle it by forecasting the liquidity of PPA markets at the European level. It is noteworthy to mention that part of the developed work has been adopted by the German Energy Agency (DENA) and will be published in German by the time of the presentation of the work at Politecnico di Milano.

1.3 Thesis Delimitations

This research focuses on renewable business development by specifically analyzing the potentiality of the evolution of PPA markets. Therefore, the main target of the research is to identify factors that potentially affect the capacity of PPA deals signed in upcoming years. Then, identified factors are utilized to identify the best possible solution to model the liquidity of PPA markets in terms of both, demand, and supply. As any other research study, there are certain delimitations imposed by the scope of the analysis and the available data given that PPA markets are still an emerging phenomenon whose dynamics is still not comprehensively studied by scholars. PPAs are becoming abundant in different regions of the world: ranging from the United States up to European, Middle Eastern and African countries (renewableenergyworldcontentteam, 2021). Specifically, the European Commission (EC) endorses PPAs as an instrument to decrease the greenhouse gas emissions in the continent and protect European businesses from electricity market volatility. European countries are becoming a model of success, setting the role for other green-aspiring regions and countries ("European Commission endorses corporate renewable PPAs as part of the answer to surging energy prices," n.d.).The beforementioned fact, in addition to Pexapark's main markets being European, has steered the direction of the research to be fully focused on the liquidity of PPA markets in Europe. In later sections, the focus of the study further narrows down to Germany to be able to fulfill the request of DENA in analyzing the German PPA market and since Germany is considered one of the leading markets in both solar and wind technology PPAs at the European level. The rising interest in PPAs in Germany mainly stems from the high presence of energy-intensive industries in the country, the high environmental responsibility taken on by its population, and other market-specific dynamics ("European power purchase agreement (PPA) energy market grows in Europe despite COVID-19," 2021). Therefore, the significance in a deep analysis of the German market is high.

2. Research Background

2.1 Evolution of the Energy Transition in Europe

In the aftermath of World War II, the topic of energy formed a central pillar in the unification of the European countries. In this regard, the evolution of energy discussions in the European Union (EU) can be divided to three main phases. In the first phase of the European integration, one of the main concerns of European countries was to ensure energy security. Member states were convinced that building strong and resilient economies is based on a stable and abundant supply of energy (Pilloni, 2022). For this reason, countries unified their efforts to create unions and communities to organize their energy production and decrease their dependence on external countries. For example, in 1951, the European Coal and Steel Community was created with the aim of organizing the production of European coal which was the main energy source for most member states (Hafner and Raimondi, 2020). Starting in the 1980s, the second phase of energy discussions in Europe emerged wherein European countries started considering creating a fair competition throughout the European electricity markets. Through this time, several directives were introduced resulting in the liberalization of the electricity markets in European countries creating an increased competition in the energy value chain. The goal of the liberalization was to increase competition in the generation and retail of electricity, while keeping the distribution and transmission regulated. This process was initiated to facilitate electricity prices reduction through competition and encourage electricity generators to invest in low-cost technologies (Pepermans, 2019). Lastly, the third phase of energy policy evolution at the European level started in the year 2000, when the topics of sustainability and climate policy started gaining an increasing momentum at both, global and European levels. As a starting point, the first discussions of the need to combat climate change were initiated on a global scale since 1992 with the "Earth Summit" in Rio de Janeiro followed by the Kyoto Protocol in 1997 (Hafner and Raimondi, 2020). Shortly afterwards, the EU made its stance on climate topics clearly visible to other regions through its active participation in international climate conferences and through specific policies and targets that aim to combat climate change and support the energy transition. One of the earliest targets set by the European Union dates to 2009 through the "European strategy for sustainable, competitive and secure energy", also known as the Green Package, which sets three goals summarized by the "20-20-20" by 2020. The three goals are reaching 20% renewable energy, 20% greenhouse gases reduction and 20% energy efficiency by the year 2020. Also in 2009, the European Commission announced the Effort Sharing Decision through which it has set intermediary targets for greenhouse gas reduction for each member state starting from year 2013 and up to 2020. The targets are sector-specific and focus on the sectors that are not tackled in the Emissions Trading system including transportation and residential use. Collectively, the sectors in the member states would help achieving a 10% reduction in the greenhouse gas emissions of the EU compared to 2005 levels of emissions. Few years later (2014), the 2030 Climate and Energy Framework was suggested by the European Commission. This proposition included three main objectives to be achieved by 2030 at the EU level: reducing greenhouse gas emissions by 40% with the year 1990 as baseline, increasing renewable energy in final energy mix to at least 27%, and increasing energy efficiency by 27% compared to 2007 levels. In addition to regional efforts, the European Union played an integral role in international efforts to combat climate change. For instance, the EU member states were among the signees of the Paris Agreement which was adopted at the Paris climate conference (COP21) in December 2015 ("Paris Agreement," n.d.). The Paris Agreement is a legally binding international agreement centralized on climate change. The goal of the agreement is to limit global warming to below 2 degrees Celsius with pre-industrial levels as a baseline. This agreement marked the first binding international efforts to fight climate change and limit global warming effects. It entered into force in November 2016, and the EU ratified the agreement with key legislations to ensure its implementation by 2018. Unlike other parties which failed in taking political decisions to ensure their commitment to the agreement, the European Union's efforts extended through the years, and the EU became a leading example in combating climate change for other regions. In 2019, the EU presented the "Clean energy for all Europeans" in which it set stricter green goals to ensure its member states can fulfill the obligations ratified in the Paris Agreement. One of the legislations in the new package binds member states to have a renewable share in their energy mix not below 32% by 2023. In 2020, the European Commission studied the progress of member states in reaching the set green targets with the measuring baseline being year 1990. The main takeaway was that member states are on the road to sustainability by successfully starting to decouple the growth of their economies from resource use. Between the year of 1990 and 2018, the European economy witnessed a growth of 61% coupled with a 23% reduction in greenhouse gas emissions. To ensure that this trend continues in upcoming years, the European Green Deal program was announced with the ultimate state having a net-zero European economy by 2050. In addition, the European Commission recognized that the factor that might hinder the achievement of a net-zero economy is the industrial emissions which account for 20% of the total region's emissions. Hence, the main efforts in the upcoming years should be focused on facilitating and supporting the transition of various industries in Europe. To be able to do so, high financial resources should be mobilized which led to the creation of the "Sustainable Europe Investment Plan" along with the Green Deal. Through this plan, the EU plans to make available an amount of at least 1 trillion Euros for sustainable development in the coming 10 years. However, with the COVID-19 outbreak, the energy transition and climate actions have been negatively affected, similarly to many other pillars of worldwide economies. In July 2020, EU member states have agreed on a 1.8 trillion euros joint fund to help boost the European economies in the aftermath of COVID-19 and help in increasing the pace of the energy transition. In fact, 30% of the total fund expenditures are strictly reserved for climate change combatting investments and actions. This came with the European Commission's certainty that investing in low-cost energy technologies would be a major enabler for the European industries and economies to recover in the post-pandemic era. Amid the promising targets and actions taken by the European Union and European Commission, it is important to keep in mind that the actual energy transition in Europe will only be viable if individual member states exert concrete efforts in transitioning their energy mix and supporting energy efficiency investments. This would be made possible through in line governmental legislations and support schemes. Below, in Figure 2-1: Timeline of European Green Agreements, a timeline with the main agreements and packages that are shaping the European efforts with regards to the energy transition can be seen:

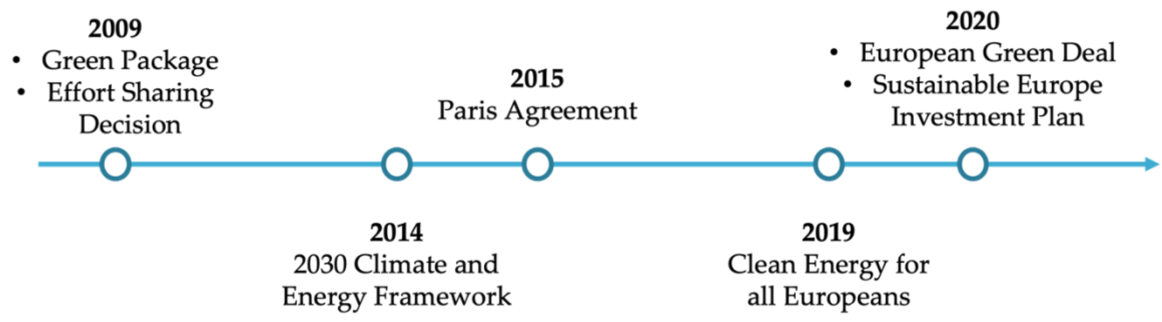

Figure 2-1: Timeline of European Green Agreements

2.2 European Diffusion of Renewable Energy

With the initiation of the European Green Deal, the main objective of European member states became evident: to become a worldwide leader in the energy transition with zero emissions by 2050. Additionally, countries acknowledged the potential of renewable energy in creating benefits at various levels in society. Firstly, the increased diffusion of renewable sources would ensure a reduction in greenhouse gas emissions along with decreasing the dependency of the European Union on fossil fuels, which implies a decreased dependence on non-EU countries. Secondly, investments in renewable energy would create new job opportunities in the renewables value chain, hence improving employment rates. Being a forerunner in the energy transition, the European progress has become a hot topic for global and regional agencies to study and forecast. Some of the research bodies that regularly provide updates on the European energy transition include: Eurostat, European Environment Agency, International Energy Agency (IEA), International Renewable Energy Agency (IRENA), and finally, the European Commission. According to Eurostat, the share of renewable energy in the gross final energy consumption in the EU member states more than doubled from 2004 till 2020 ("Renewable energy statistics," 2022). The evolution of the share of the renewable energy in the final energy consumption in the EU could be seen in depth in Figure 2-2:

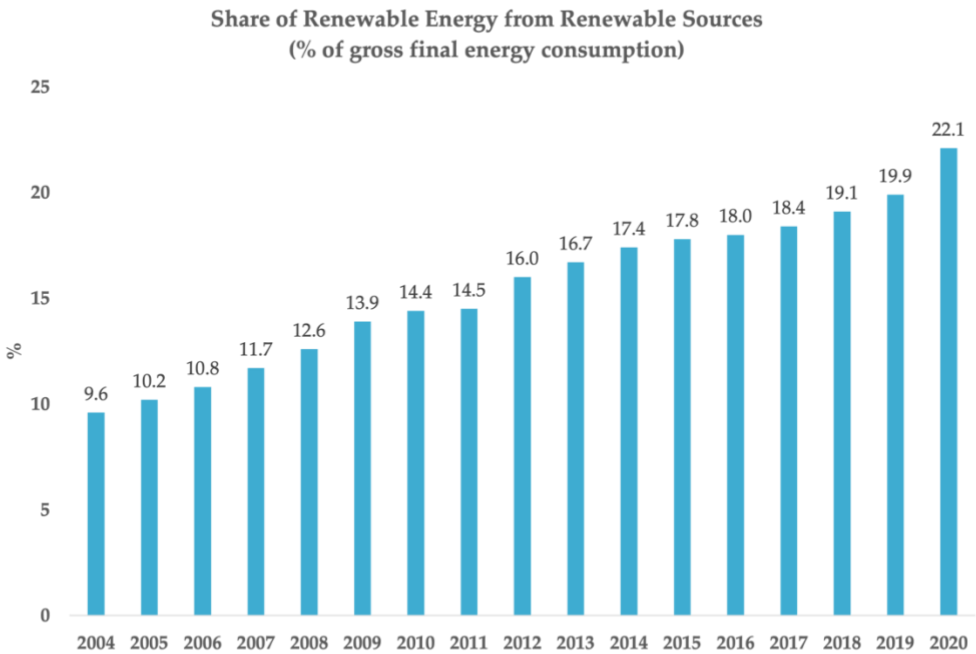

Figure 2-2: Share of RE from Renewable Sources in Europe (2004 – 2020)

Moreover, 2020 marked the first time in which the EU exceeded its annual target with renewables achieving 22.1% of the energy consumed as compared to the target of 20%. This achievement stemmed from the consistent effort put by different member states in decarbonizing their electricity markets, although examining individual countries shows unequal efforts by different states. While some countries managed to exceed their set 2020 targets, such as Sweden and Germany, others, like France failed to do so. Another facilitating factor for exceeding the 2020 target was the disruption in several industries caused by COVID-19 pandemic. Due to lockdowns enforced in almost all European countries, industries had to stop their production for extended periods which led to a decrease in the energy consumption; and therefore, the increased share of renewables in final energy consumption ("Share of energy consumption from renewable sources in Europe," 2022). In the aftermath of the pandemic, year 2021 emerged as a decisive year for the European energy transition. Investing in renewable energy was seen as an essential element in paving the path for climate neutrality and a response to the economic impacts of the pandemic (*State of the Energy Union 2021*, 2021). In this year, the cumulative electricity produced from RE in the EU recorded a new high of 1068 TWh, constituting 37% of the total electricity produced. In terms of energy produced, this represents a 9% increase compared to 2019 levels. Since the year 2019, wind and solar energy comprise the bulk of the renewable energy growth. In fact, 2021 marked the first year in which the combined production of those two energy sources, 547 TWh, outperformed the production from natural gas, 524 TWh in Europe (Moore, 2022). However, one common aspect seen in the analysis of the RE diffusion is the fluctuation in the percentage of RE in the final energy consumption which is caused by the nature of such production technologies, variable and non-programmable. This will be solved in upcoming years with the diffusion of storage solutions which ensure energy security amid an increasing RE share in the energy mix. Below is a summary of the status of development of both, solar and wind projects, at the European level.

2.2.1 Solar Expansion

Driven by relatively low investment costs, solar installations were among the first renewable technologies to gain momentum in Europe. Unlike other renewable technologies, solar power is a booming market in the EU at residential and utility scale. 2021 witnessed a 34% increase in solar installations compared to its precedent year with 25.9 GW new solar installations in Europe. Examining the individual countries' contribution to the total installed capacity, the top five countries in solar installations in 2021 are the following: Germany (5.3 GW), Spain (3.8 GW), the Netherlands (3.3 GW), Poland (3.2 GW) followed lastly by France with 2.5 GW. On a cumulative level, the total solar installations in the EU added up to 164.9 GW by the end of 2021with 25 member states installing more capacity compared to their respective 2020 levels. The latest figures of solar installations in top European markets can be seen in Figure 2-3 ("Solar boom," 2022):

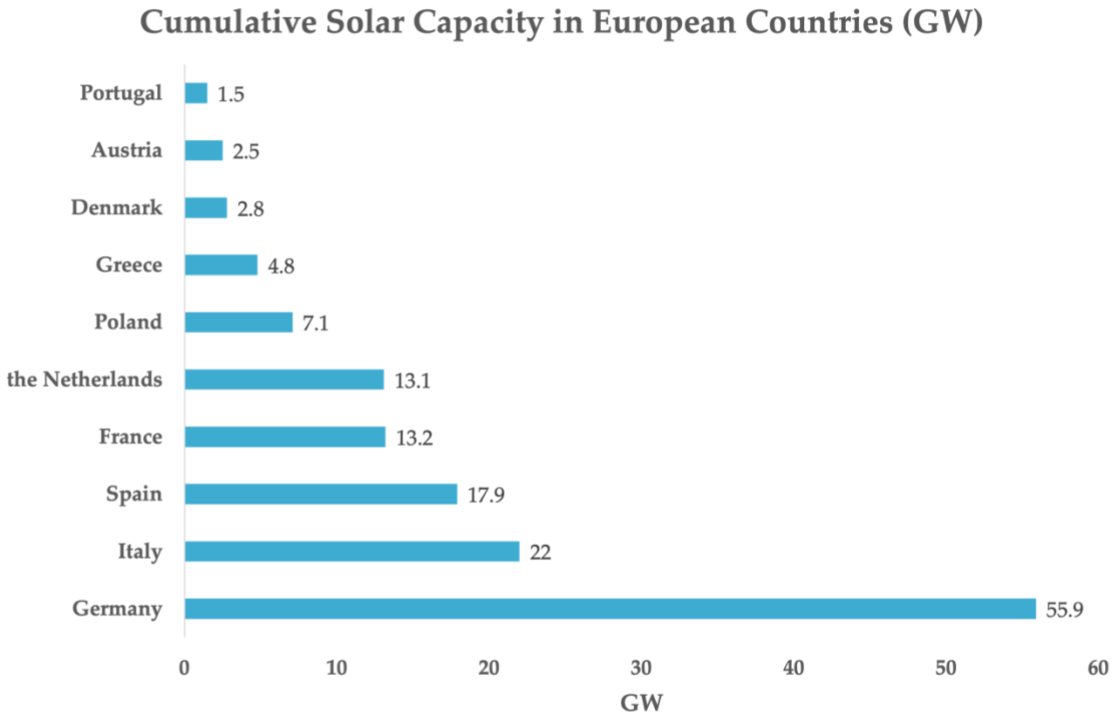

Figure 2-3: Solar Capacity in European Countries

As seen in the above graph, Germany is the European leader in solar capacity with a total of 55.9 GW installed projects by the end of 2021. In the second place comes Italy; although as seen in the Figure 2-3, Italy possesses less than half of the capacity installed in Germany (22GW). In the following ranks come Spain, France and the Netherlands which have a comparable market size. Researchers expect a continued dominance of solar technology at the European level in upcoming years. However, concerns still arise regarding a possible slowdown caused by grid connection issues and complicated permitting processes in some member states ("Solar boom," 2022).

2.2.2 Wind Expansion

Despite the on-track expansion of solar technology, investments in wind projects are relatively weak. In 2021, 17 GW of new wind buildout was installed in Europe. According to WindEurope, Europe should have at least doubled this capacity in 2021 to make sure it is on track with its 2030 Climate and Energy goals. Out of this 17 GW, 81% refers to onshore wind installations with Sweden, Germany and Turkey having the highest onshore wind build out among the member states ("Wind energy in Europe," 2022). A study done by WindEurope in 2022 shows that the factors delaying the wind expansion at the European level are the delays in permitting processes and bottlenecks in wind supply chains globally. The cumulative wind installed capacity in the main European markets can be seen in Figure 2-4:

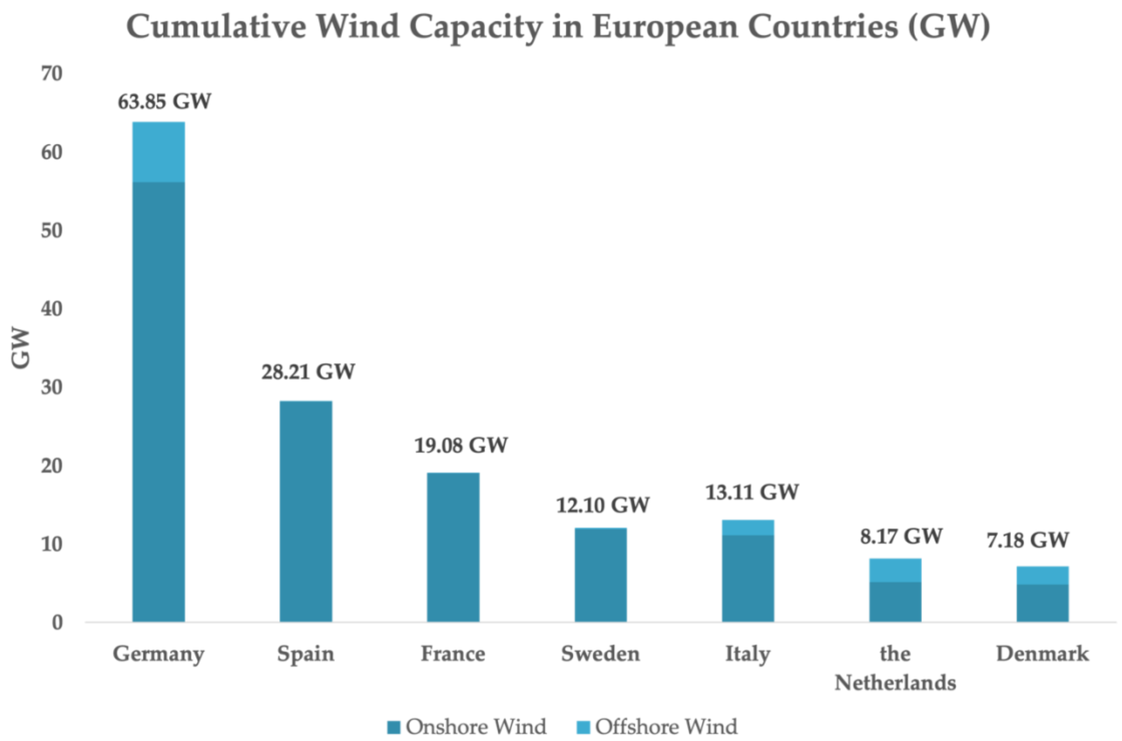

Figure 2-4: Wind Capacity in European Countries

As seen in the above figure, Germany is also the European leader in the wind industry with a total of 63.85 GW of installed capacity, out of which more than 90% refers to onshore wind projects. Germany is followed by Spain, France, and Sweden, all of which are dominated by onshore wind with a negligible amount of offshore installations (in the megawatts range). However, despite increasing installation rates for both onshore and offshore wind, Europe lags behind its forecasted expectations. It needs to install around 25 GW per year of onshore wind and 8 GW of offshore wind in the upcoming four years to be able to reach its 2030 set targets ("Wind energy in Europe," 2022).

2.3 Financing of RE Projects in Europe

The financing of renewable energy technologies plays a key role in the diffusion of the low-emissions energy production and in achieving the energy transition. In earlier years, when the costs of renewable energy projects were relatively high compared to other energy production methods, governmental support played an integral part in facilitating the diffusion of such technologies. However, with the continuously decreasing cost of production of green energy, the financing of renewable energy has expanded to include a multitude of actors ranging from governments, banks, investment funds, and even corporates (Iskandarova et al., 2021). In their study of renewables financing mechanisms, Iskandarova et al. studied European countries including Poland and the Netherlands, and, subsequently, divided the financing mechanisms into governmental financial instruments and market-based mechanisms. Moreover, governmental instruments could be either European, regional, or state-based funds. Such type of support can be given through various ways including Green Certificates, Renewable Obligations, tax relief schemes and auctions to grant contract for difference. On the other hand, market-based mechanisms have appeared in recent years and include preferential bank loans for green projects, private funds and investments, and power purchase agreements (PPAs). In addition, the paper examines the evolution of the financing of RE through time, which is comparable to other European countries which started investing in renewables in the early 2000s. For such countries, the timeline for financing can be roughly generalized as follows:

Phase 1: *Until the early 2000s, most European countries suffered from a complete absence any supporting mechanism for RE investments.*

Phase 2: *From the early 2000s until around 2015, climate change topics formed a big part of European discussions. Most of renewable energy investments during this period were supported through EU funds.*

Phase 3: *From 2015 and up till 2019, almost each member state created its own support mechanisms and subsidies. Renewable energy investments enjoyed various governmental financial support schemes during this period which helped in the rapid expansion of mostly solar and wind projects*

Phase 4: *Starting 2019, a common trend observed at the European level is the decrease in the governmental support. Therefore, new renewable energy investments search for market-based mechanisms to help in their realization, including PPAs.*

In its Renewables 2021 report, the IEA expects an expansion of 45% in the renewable capacity at the European level till 2026. On this matter, it acknowledges the pivotal role that corporate PPAs will play in this expansion due to several reasons including the increasing competitiveness of solar and wind energy prices, and the concrete sustainability goals set by several European industries (Bahar, 2021). In fact, the importance of PPAs in the energy transition is not only acknowledged by research institutions and academia, but also from regional regulatory bodies. In October 2021, the European Commission presented its member states with a toolbox that guides them amid the rising electricity prices. Among the presented solutions, the Commission endorses PPAs as a tool to increase renewable energy investments which guarantee lowered electricity prices. Member states governments should recognize their role in growing their PPA markets by helping small to medium enterprises in signing PPAs through demand aggregation. Lastly, the European Commission announced its intention of publishing additional guidelines on expanding Member State's PPA markets by 2023 ("European Commission endorses corporate renewable PPAs as part of the answer to surging energy prices," n.d.). This move by the European Commission reflects the importance of market-based support mechanisms in the further development of renewable energy markets at the European level.

3. Technical Background

3.1 Definition of PPAs

A PPA is a contractual agreement between two parties, where one is an energy generator, and another is an electricity buyer, that involves the long-term supply of electricity. PPAs are mostly present for renewable energy sources and the length of the contract varies usually from 10 to 20 years. There are several key terms that refer to the parties involved in a PPA. The energy seller could be also named the generator, asset owner or independent power producer (IPP). As for the energy buyer, the most common nomenclature is energy offtaker (Niklaus, n.d.). As mentioned in Section 2.3, the emergence of PPAs started with the decrease in governmental financial support to renewable energy projects. With the decreasing costs of renewable energy, subsidy schemes are progressively decreasing in most countries. However, investors still struggle in finding securities to their investments, and thus, they refer to PPAs to ensure stable revenues through time. In addition to the buyer and seller, there might be secondary actors, such as lenders, which might affect the PPA negotiation process and terms. In almost all cases, utility-scale renewable energy projects require high amount of capital which cannot be borne alone by the independent power producer. In such cases, the IPP refers to a borrowing money from financial institutions to facilitate the financing of the project. As lenders need to guarantee that the investment will be able to pay back the borrowed money, they put certain conditions for the PPA terms to be considered as bankable. In case the negotiated PPA does not meet the required criteria, a renegotiation would be asked by the lender before giving out the loan (Ross, 2020). In fact, the negotiation of PPAs in most cases takes months before the two parties agree to sign a final agreement. The two parties enter into back-and-forth negotiations and discussions of the contracts, and the most commonly negotiated terms in a PPA are summarized below:

- **Commercial Structure:** The commercial structure of the PPA defines the distribution of risks between the energy buyer and seller. The two most common structures are pay-as-produced and baseload, either monthly or annual. In a pay-as-produced PPA, most of the volume risk is borne by the buyer since he has to pay a fixed price for any volume of energy produced. Therefore, he is the party mostly affected in the case of either overperformance or underperformance. On the other hand, a baseload structure defines the amount of energy that should be delivered in each interval of time. This shifts the volume risk to the seller, who, for example, in case of underperformance, needs to buy the missing energy from the electricity markets and deliver it to the offtaker.

- **Distribution of risks:** There are several risks present in energy contracts which should be carefully studied by the two parties to ensure a fair PPA pricing. Those risks include price, liquidity, volume, profile, and balancing risks. Buyers and sellers should be aware that certain commercial structures could help in shifting the risk from one party to another, and therefore influence the PPA price that is negotiated. For example, in a pay-as-produced structure, most of the volume risk is carrid by the energy investor; therefore, such structure might lead to lower prices achieved through a PPA.
- **Contract Duration:** One of the first negotiated aspect of any PPA refers to the contract duration, usually referred to as PPA term. The contract duration could be affected by several factors such as the possibility to renegotiate the PPA price before the term ends, and the duration for which the parties are willing to fix the PPA price.
- **Price:** The PPA price is a complex aspect of the PPA negotiation that is influenced by several factors including the distribution of risks, the commercial structure and the contract duration. Since the closing of a PPA deal usually takes months, there will undoubtedly be changes in the market prices, which should be considered before closing the deal. To avoid complexity in the negotiations, parties often refer to a reference price during their negotiation provided by service companies, such as Pexparak's software "PexaQuote".
- **Credit Risk:** This risk refers to the possibility that either the buyer, or seller will not be able to meet their contractual obligations with time. To protect themselves against this risk, each party defines certain financial guarantees to be provided by the counterparty to protect itself in case of default.
- **Settlement:** PPAs could be of two types: physical or financial. A physical PPA involves the physical delivery of the produced electricity while a financial PPA is similar to a financial derivative. In a financial PPA, the produced electricity will be traded on the market through a Transmission System Operator.
- **Performance Guarantees:** Performance guarantees refer to the guarantees put in place in case either of the two parties fails to meet its contractual obligations. Guarantees define the settlement that would take place in such an event.

- **Termination:** In the PPA contract, the possibility of early termination of the PPA should be defined, along with its acceptable circumstances and the process related to it.

Those are the main terms negotiated in the PPA contract, however, there are several other details that are discussed and that differ case by case.

3.2 Importance of PPAs

The phasing out of subsidy schemes in most European countries is shifting the dynamics of renewable energy investments. While in the past investors relied on support schemes to ensure stable revenues throughout their project lifetime, the phasing out of governmental support is increasing various stakeholders' attention towards PPAs. Long-term PPAs are now an essential hedging tool in the electricity value chain for project developers, utilities, energy traders, and corporate players. For investors in renewable energy, PPAs provide guaranteed returns for their project, and hence, facilitate project bankability (Kalam, 2021). Bankability refers to the ability of a project to receive a loan from a financial institution. In addition, the scope of bankability includes the capability of an asset or project to be financially attractive to diverse financial institutions including commercial banks, development banks and equity funds. Since PPAs define the future cash flows related to an energy investment, they facilitate the bankability of an investment when the terms ensure guaranteed revenue stream, for example through a creditworthy offtaker. In this regard, PPAs are central to renewable energy investments since they tackle two important uncertainties which are demand and pricing uncertainties. To begin with, unlike other commodities which can be produced and sold in different regions (e.g., hydrocarbons), the production of electricity from renewables should be used to meet the local demand of the market in which the production occurred. This poses high demand uncertainty related to the produced electricity. PPAs solve this issue by obligating the energy buyer with the long-term purchase of the generated electricity. Secondly, electricity prices in markets are characterized by high volatility since they are affected by market factors and not by demand-supply interactions. Hence, a PPA secures stable electricity prices over the contract duration (Ross, 2020). The beforementioned aspects reflect the importance of PPAs for energy sellers.

Moreover, PPAs are essential for buyers, whether they are utility players or corporates. On the buy-side, economic and environmental reasons persist to be the main motives for signing PPAs. PPAs help a corporation in meeting its sustainability commitments. In recent years, many corporates have publicly announced ambitious targets for their emissions reductions, whether through their participation in global initiatives, such as RE100, or in a self-standing manner. To reach their renewable energy targets, companies have several solutions to secure green energy: procure renewable energy directly through their utilities, purchase renewable energy certificates that cover their renewable needs or enter through long-term renewable energy purchase agreements ("Corporate renewable PPAs," 2017). Although in the past, corporate buying of PPAs was limited to big data centers, the market witnessed a rapid expansion to include various sectors that are concerned about their carbon footprint (Luther-Jones, 2019). Banks, oil companies, retailers and telecommunications giants began to realize their role in making renewable energy investments feasible by ensuring the long-term energy purchase. To illustrate, studies by the IEA show that global corporate PPAs have been continuously rising through the years, with an approximate increase of 750% in contracted capacity between the years 2014 and 2019 (Nicholls, 2020). This is illustrated in Figure 3-1:

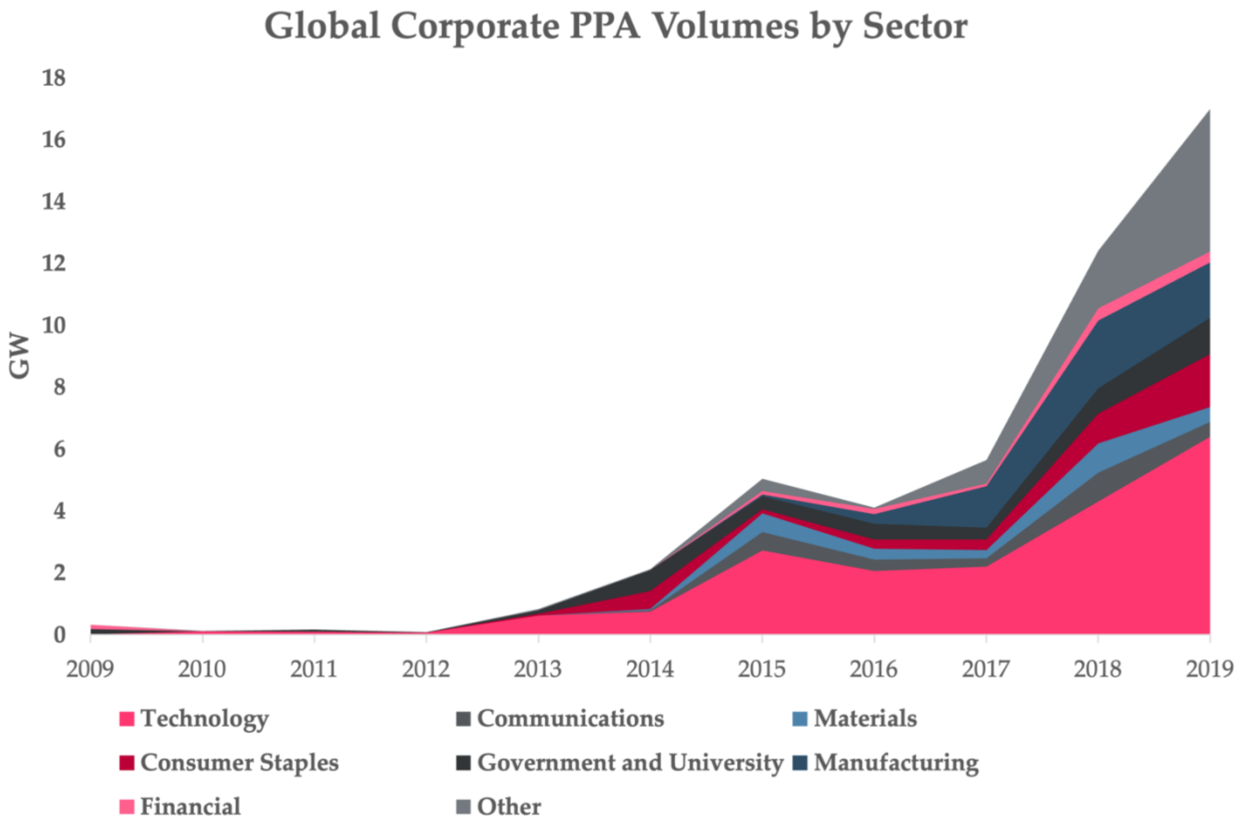

Figure 3-1: Global Corporate PPA Volumes by Sector (GW)

From the above figure, one can say that a general trend in corporate PPA purchasing is an increasing one, although in some years some sectors witness a decreased contracted capacity compared to previous year. Additionally, another clear trend is that through the years, the sectors that are involved in PPA purchasing is increasing, which reflects the rising interest of various industries in achieving carbon neutrality. In total, the global corporate purchasing of PPAs was around 18 GW in 2019. Other than meeting their social obligations, corporates enter PPAs to hedge themselves against volatile, and mostly rising, electricity prices. At the early stages of corporate PPAs purchasing, the most common pricing structure was the fixed price where the price Is fixed through the years, and it can escalate to account for inflation. However, with the increased volatility in electricity markets, a common structure nowadays is the floating price where the two parties set a cap and a floor for the price through the years to hedge both against possible market movements ("Corporate renewable PPAs," 2017). In fact, utilities enter PPAs for the same reasons mentioned above. With the rising environmental concerns, governments are enforcing regulations on utilities, obliging them to have a certain percentage of their overall supplied energy coming from renewables. This percentage could be either in line with the utility's supply market size, or with the overall country renewables targets. Nevertheless, some utilities independently decide to enter PPAs with renewable projects as a way to hedge against future unstable electricity prices. On this matter, it is worthwhile to mention that most studies and statistics available focus on corporate purchasing of PPAs since corporates tend to be more open about such contracts. As a matter of fact, many corporates enter into such agreements to highlight their green actions as this might highly serve their company and brand image. On the other hand, many utilities prefer to conceal their signed deals, or details related to their agreements for competition reasons. Hence, due to the openness of corporates regarding their PPA deals, the main focus of the demand forecasting in upcoming parts of this report will be on corporate PPAs, with less emphasis on forecasting future utilities' behavior.

4. PPA Diffusion in Europe

In this section, the focus is the analysis of the European PPA market. The analysis could be done focusing on certain regions, buyers, sellers, or even technologies. Through each lens of study, different characteristics and various conclusions could be taken from the available data. The European PPA market has started to emerge since the year 2018, with some countries being forerunners in this rising trend, while others still lagging behind. A common view by researchers and consulting companies is that most mature PPA markets occur in Western European countries while Eastern PPA markets are still in early stages of development. According to S&P Global, out of the 33.4 GW newly built assets in 2020, one fifth have signed a PPA in Europe. Moreover, more than 20% of new offshore wind installations and more than 25% of onshore wind and solar assets built during this year are covered by PPAs ("European power purchase agreement (PPA) energy market grows in Europe despite COVID-19," 2021). The mentioned statistics reflect the increasing importance of PPAs in the European electricity markets. Below, a deeper analysis of this market will be performed where the raw data is taken from Pexapark's PPA Deal Tracker which is available online on their software, "PexaQuote". To get an overall picture of the European PPA market development through the past years, it is crucial to examine the evolution of number of deals and their capacity starting with 2018 and till 2021. Despite the ongoing pandemic in the years of 2020 and 2021, the European PPA activity witnessed a 43% Compound Annual Growth Rate (CAGR) between years 2018 and 2021. As seen in Figure 4-1, 2019 was a turning point for the European PPA market with a total signed capacity of 9.05 GW realized by 106 deals. However, in year 2020, the market went through a shock, where the signed capacity decreased by around 3 GW compared to the precedent year. With the COVID-19 pandemic, electricity prices witnessed strong decrease to significant low levels. As a result, the appetite on the PPA market declined as corporates and utilities became concerned about locking themselves into fixed prices, with the fear that the downward trend of market prices continues. In 2021, the market restored its original growing trend with a total of 11.47 GW contracted through 144 deals. Another significant market characteristic that can be seen in Figure 4-1 is that corporate players continue to dominate the European PPA market, contracting the majority of the signed deals through the different years.

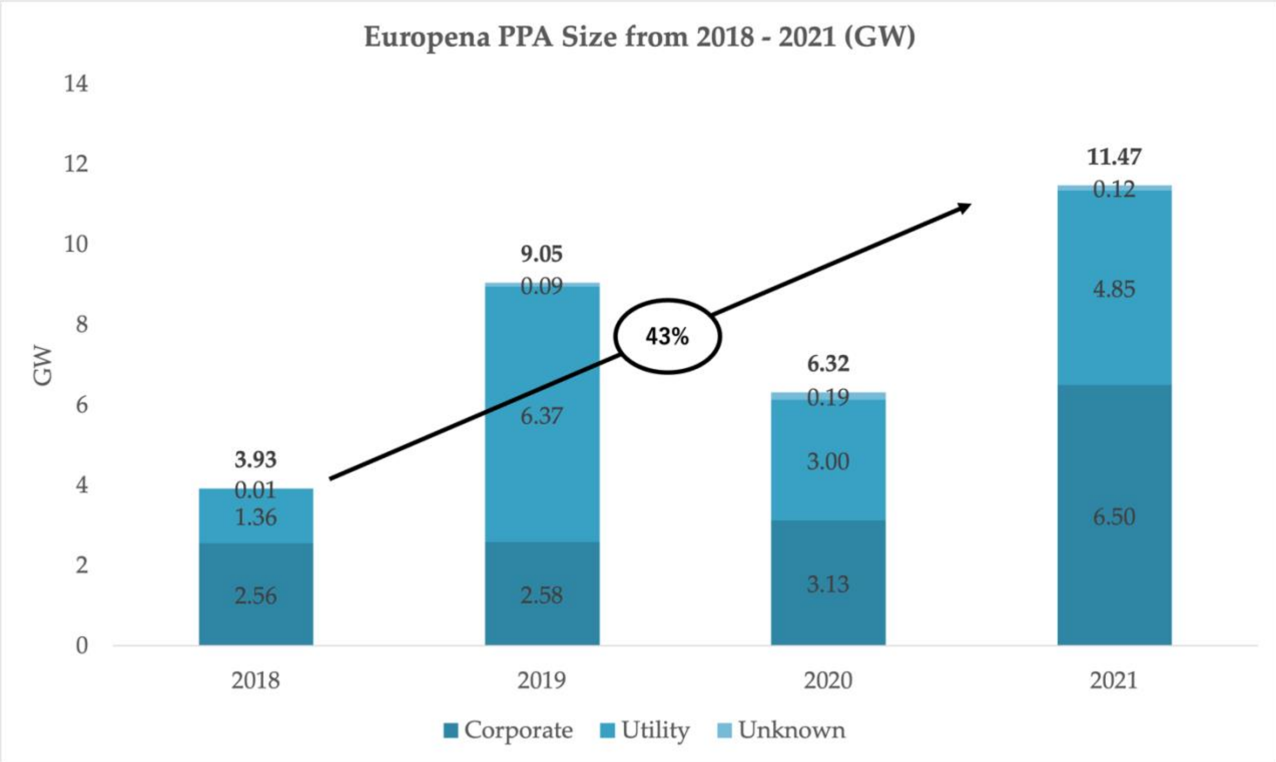

Figure 4-1: European PPA Market Size, 2018 - 2021 (GW)

Other than examining the overall PPA market size in Europe, it is rather significant to identify the dominating countries at the European level. Examining the map in Figure 4-2, we can quantify the size of the PPA market in each European country, starting from 2018 and up to 2021. The top five PPA countries in Europe, are: Spain (10.13 GW), Sweden (4.03 GW), Great Britain (3.17 GW), the Netherlands (2.33 GW) and lastly, Germany with 2.32 GW of contracted capacity. In fact, the mentioned five countries have dominated the top five positions in the past years on a yearly basis. This is especially true for Spain which covers around 1/3 of the total contracted PPA capacity in Europe in the examined period. Next to the Nordic countries, Spain has established itself as a mature PPA market due to several reasons. The abundance of resources in Iberia, especially solar, has been a major force in the rise of renewable energy projects in the country. In fact, more than 78% of the signed PPAs in the country are solar PPAs. Solar photovoltaic is very competitive in Spain and allows low PPA prices due to the low technology cost. As for other countries in the top 5, some of the reasons for their large PPA markets include the high renewable consumption of data centers in them, such as Sweden and the Netherlands, and the decrease in the governmental subsidies which is the case in Germany and Great Britain. Apart from the top countries, the map in Figure 4-2 shows that PPAs are gaining momentum in almost all European countries, despite the level of maturity of the markets as an increasing number of countries is encouraging investments in renewable energy to decarbonize its energy mix.

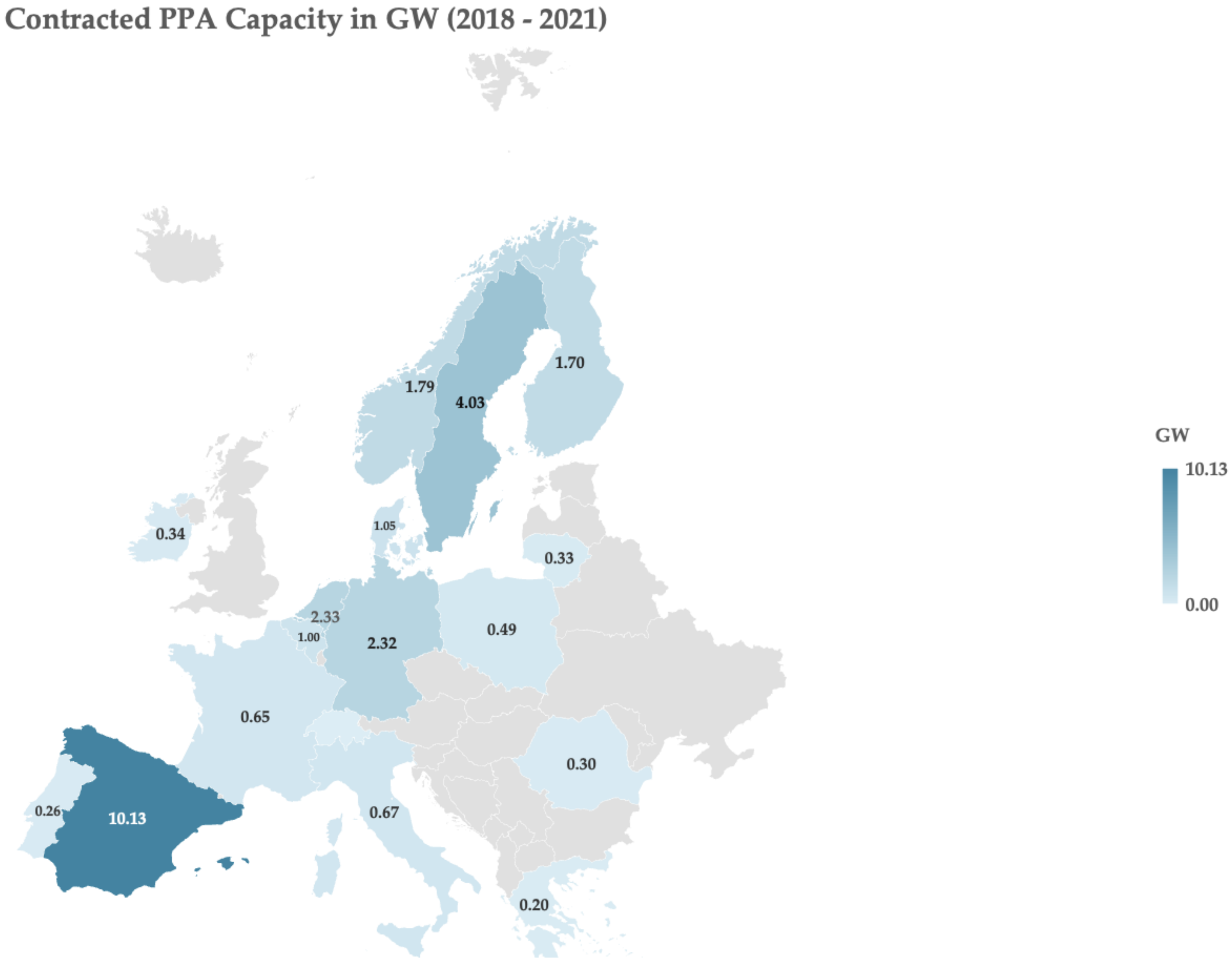

Figure 4-2: Contracted PPA Capacity in Europe, 2018-2021

In terms of the analysis based on the technology of the signed PPA, Figure 4-3 shows the division of PPAs by technology according to the contracted capacity. Over the past four years, an almost fair distribution of PPAs is observed by the most dominant technologies: onshore wind, offshore wind and solar photovoltaics. The two technologies dominating the European PPA markets are solar and onshore wind. Two possible reasons for this phenomenon are the relatively low costs for the

beforementioned technologies along with the decreased governmental support given to them.
As for offshore wind, to date, it consists only around 20% of the European PPA market.

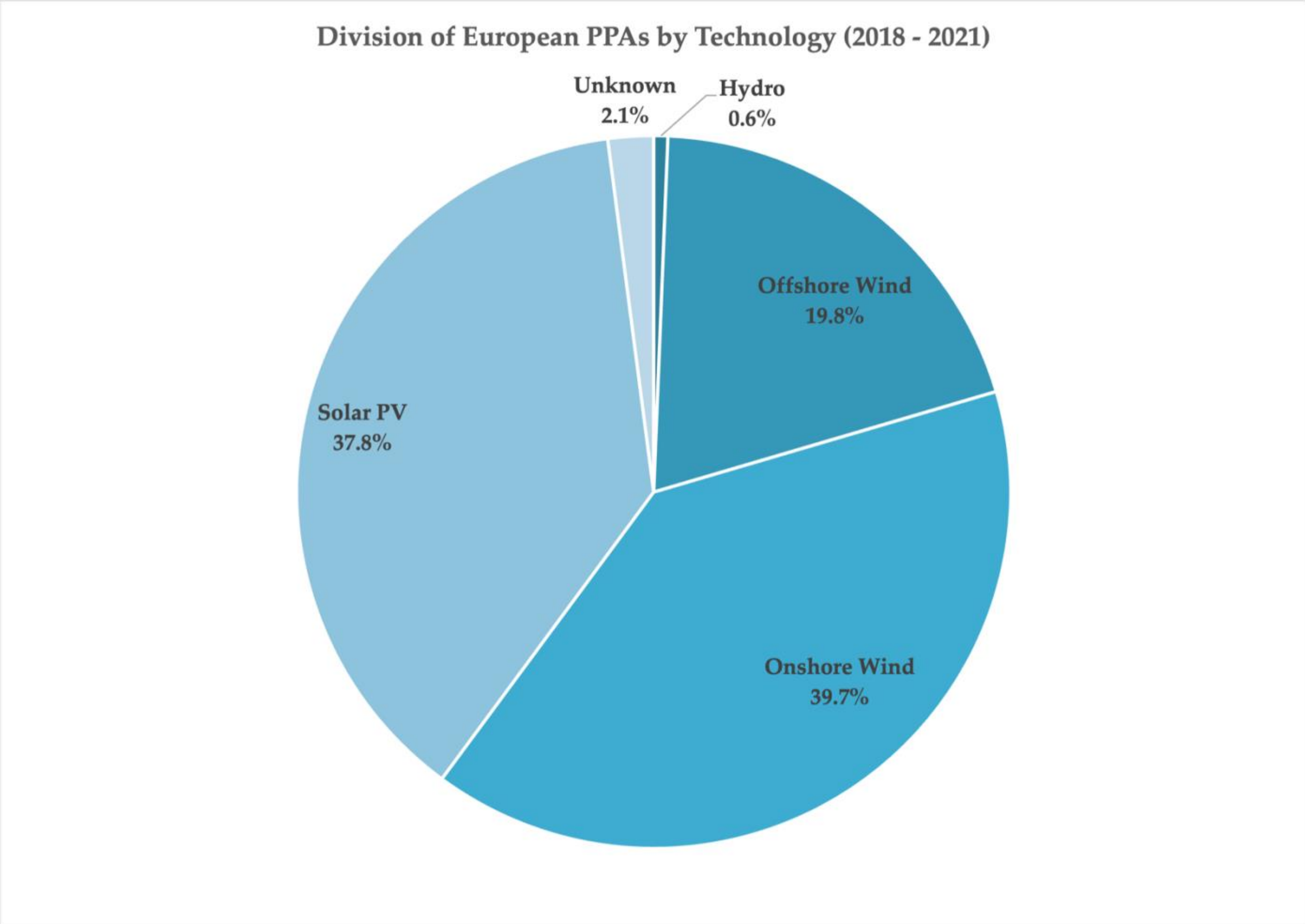

Figure 4-3: Evolution of PPA Technologies in Europe, 2018 - 2021

However future market perspectives expect that the share of offshore PPAs will continuously rise in upcoming years. A reason for the delayed emergence of offshore PPAs is the persistent subsidies to this technology in various European countries to encourage investments towards this amid higher relative costs compared to other renewable technologies.
For the sake of this research, an additional analysis was done to Pexapark's generic PPAs database. In additional to the previous division of PPAs according to the offtaker type: corporate or utility PPAs, a further taxonomy was developed to examine the division of PPAs by the type of corporate buyers. The development of this taxonomy along with its usefulness in forecasting the future supply of PPAs will be further

examined and explained in Section 10.1 where PPA supply forecasting is demonstrated.

Pexapark, and other advisory firms, have tried to make certain predictions on the evolution of the European PPA markets. However, in most cases, such forecasts tend to be more qualitative rather than focusing on quantifying the contracted capacity or deals. In its recent European PPA Market Outlook, Pexapark states that it forecasts a growing uncertainty regarding the evolution of renewables' business models. However, despite evolving challenges, investors' appetite in investing in green energy will on the rise in the future. Specifically, three general trends are expected to be seen on the European PPA market. First, the widely spread PPA model where a PPA is signed for ten years on a pay-as-produced basis is expected to change. As already seen on several markets, offtakers' appetite to long-term PPAs is decreasing driven by the high market volatility. Secondly, new players are emerging in the different countries through the form of investment funds. Such players are housing skills that would allow them play in the different roles of the renewables value chain, starting from origination of PPAs up to managing energy risks. This type of players will be able to accept shorter term PPAs, and therefore, the only possible constraint to the diffusion of short term PPAs would be the financing requirements. Lastly, more "mega-energy buyers" will appear on the European markets and will help in the further expansion of PPAs. Mega-buyers belong to energy-intensive industries, such as data centers and chemicals. As those industries require high amount of energy, they will exhibit a high appetite for large offshore wind parks and will allow the potential of this technology to unfold in future years (Pedretti and Kanellakopoulou, 2022).

The abovementioned three factors, coupled with data from the past years, hint to a bright future for the European PPA market.

5. Literature Review: State of the Art

When examining available literature, the topic of PPAs is relatively new compared to other energy-related topics. Therefore, in the screening of the literature to have a clear view of the status quo of forecasting methodologies developed, various energy topics were looked at such as forecasting the liquidity of PPA markets, forecasting the diffusion of renewable energy technologies, and forecasting renewable energy consumption…. To ensure an inclusive view of the available studies, two different types of publications were contemplated:

- Academic Publications: Academic publications refer to academic papers that are published as part of academic journals or scholarly press such as Elsevier. Published articles are written by academics and researchers in the fields. The electronic databases which were utilized to have an inclusive search for such papers are mainly Google Scholar, Scopus, and ScienceDirect.
- Professional Publications: Professional publications refer to consulting reports which are usually addressed to professionals in a certain industry and may contain the viewpoint of the publishing consulting company. Such reports may also be pitched to specific audience, such as clients of the advisory firm, making them not fully accessible to the public.

After a thorough examination of the literature, it was evident that most studies related to PPAs fall in the second category, professional publications, mainly due to the recent emergence of this topic and the limited number of researchers who are focusing their studies on it. In the first step of the literature review, the keywords used in the search of publications were mainly the following: "PPA forecasting", "forecasting the PPA market size", "PPA markets in Europe", "forecasting PPA markets in Europe", "future liquidity of PPA markets", "forecasting PPA demand", and "forecasting PPA supply". The results found were either directly linked to PPA forecasting or to renewable energy expansion forecasting. In the IEA's 2021 Renewables report, the focus is to forecast renewable energy diffusion in various regions worldwide up to 2026 (Bahar, 2021). For all regions, forecasts of the expansion of renewable energy technologies are based on scenario building, where main and accelerated scenarios are built according to the possible changes in regional policies in favor of renewable technologies. At the European level, the forecast was done for wind and solar PV technologies. Several factors were taken into consideration to build the scenarios including historical data on technology expansion, the 2030 National Energy and Climate Plans (NECPs), and the pace at which new policies will be implemented which might affect permitting challenges and governmental support. The detailed forecasting methodology is not explained in the report, but the report aims to build scenarios for future expansion based on historical observations and forecasts of possible future trends that might affect each market considered. A more focused study was published by Columbia University in March 2021 which aims at sizing the corporate PPA demand in the United States over the next 10 years (Kobus et al., 2021). The report forecasts the PPA consumption of the commercial and industrial sector in the United States based on three scenarios: base, upside, and downside. Starting from the total energy demand of the commercial and industrial sectors, the three cases are developed according to the evolution of the regulations in favor of virtual PPAs, the economic competitiveness of PPAs compared to wholesale electricity prices, the investment-grade of companies willing to enter PPAs, and their willingness to pay a premium for the renewable electricity. Although this study was done for the United States' PPA market, there is a significant absence of a similar academic study for the European PPA market evolution. For instance, the European power analytics provider, Aurora provides PPA market forecast reports across various European markets for its clients. However, such reports are part of a paid subscription on a market basis for each client. Similarly, Aurora is highly active in organizing Webinars where some insights about future evolution of PPA markets in Europe are given; however, only final predictions are displayed in such events without the explanation of the methodologies followed to reach forecasted numbers. An example of such webinars was held in November 2021 under the name "PPAs-What industrial offtakers need to know" (von Bülow, 2021). The presentation shows the results of PPA demand and supply forecasts for the year 2030 for major European markets such as the Nordics, Germany, and Spain to conclude whether they will be oversupplied or undersupplied. The presentation does not explain the methodology followed to do the forecast as it is considered a teaser for the company's paid services. In the presentation, demand forecasting was done by segmenting corporate PPA demand into four categories: green image seekers, green giants, intermediates, and price hedgers. The categories were created based on a two-by-two matrix showcasing the energy intensity versus the stakeholder pressure. As for the supply forecasting, the presentation considers four sources for projects which might sign a PPA: unsubsidized buildout, lifetime extension of assets, assets already under PPAs and route to markets. As for the category of academic publications, researching the abovementioned keywords leads to results related to forecasting the electricity production from PPAs (O'Neill and Chernyakhovskiy, 2016), forecasting the financial implications of PPAs (Das and Malakar, 2021) (Simaremare et al., 2020), and understanding critical success factors for PPAs (Miller et al., 2017) (Acharya, 2021). The abstracts of the academic papers found were examined, and the papers were classified to be out of scope for this research since the study in this report aims to do a sizing exercise for the European PPA markets.

Hence, to have a better understanding of the forecasting methods used in the energy industry, another set of keywords was used to enlarge the scope of the literature review. The new keywords used in the search include: "energy consumption forecasting", "renewable energy consumption forecasting", "forecasting electricity consumption", "forecasting renewable energy production". With the new set of keywords, an increased number of academic publications were found on electronic databases. The topic of electricity consumption forecasting is a well-established field of study that has gained researchers' interest through time. This has helped in identifying several forecasting methods that could be used as in inspiration to build a forecasting methodology for PPA markets. In their 2019 published journal article, Wei et al. reviewed conventional and artificial intelligence-based (AI-based) methods used in forecasting energy consumption and compared the models based on forecasting horizon, applied fields and results' accuracy (Wei et al., 2019). The conventional models that were reviewed include time series models, regression models and gray models. As for the AI-based methods, the main models examined were artificial neural networks (ANN), support vector regression (SVR), and random forest. To compare the performance of the different observed models, performance indicators were used, which included: mean squared error (R^2), mean absolute error (MAE), mean absolute percentage error (MAPE), and root mean-square deviation (RMSE). The analysis of the performance indicators proved that conventional models perform better in long-term energy forecasting on a yearly basis, while AI-based models were mostly used for short-term electricity forecasting, for example daily basis forecasting. Moreover, 68% of observed studies use conventional models to predict yearly energy consumption with non-linear and linear-regression models achieving the lowest MAPE. To forecast the renewable energy production in Poland till 2025, Brodny et al. utilized the method of neural networks (Brodny et al., 2020). According to their analysis, this method is suitable to predict the most accurate results since it can map complex relationships between input and output data, along with causal relationships which have not been sufficiently proven to build mathematical correlations. The study uses historical production data for various energy sources from 1990 till 2018 to predict renewable energy sources (RES) production from 2020 till 2025. Besides predicting the diffusion of renewable energy, the approach of artificial neural networks has been increasingly used to predict electricity consumption as well. In their paper, Leite Coelho da Silva et al. used artificial neural networks to predict the industrial electricity consumption in Brazil (Leite Coelho da Silva et al., 2022). In the paper, several methods were used to predict electricity consumption, including dynamic linear model, neural network autoregression, and multilayer perceptron. To identify the model with the best predictive ability, historical data was divided into training and testing dataset which ranged from the year 1979 till 2021. The models were compared using the mean absolute percentage error and the best one was identified to be the multilayer perceptron model. Apart from AI-based methods, many other papers have investigated energy problems using more conventional models. Kaytez examined several conventional approaches to the modeling of electricity consumption in Turkey (Kaytez, 2020). The examined models were compared using three indicators: MSE, RMSE, and MAPE by dividing the historical data into training, testing, and validation datasets. The paper develops a hybrid approach using least-square support vector machine and the Auto-Regressive Iterative Moving Average (ARIMA) model. Kayetz compares the developed model to other conventional predicting models such as multiple linear regression approach and other approaches previously seen in literature, and the result is that the proposed model was more accurate to predict Turkey's electricity consumption. The data used to train the model formed 85% of the historical data, 11% was used for testing and 4% for model validation. Historical input data ranged from 2000-2018 and the forecasted time horizon was from 2019 till 2022. To build the model, six independent variables were considered to predict the electricity consumption, including: installed capacity, gross electricity generation, population in Turkey, export, import and net electricity consumption. The ARIMA model was also used by several researchers, mainly to predict the electricity consumption at national levels. Pappas et al. proposed the ARIMA model to forecast the Greek electricity consumption and compared it to other time series-based model (Pappas et al., 2008). In addition, Ediger and Akar proposed both ARIMA and the Seasonal Auto-Regressive Moving Average (SARIMA) to forecast electricity demand in Turkey (Ediger and Akar, 2007). Other than regression and time-series model, the gray model was also utilized to forecast medium- and long-term electricity consumption. The grey model is a more accurate alternative to regression and time-series models to solve the problem of forecasting with "poor data". In fact, studies have shown that the grey forecasting model has more stable solutions and higher accuracy of predictions with smaller data samples since, instead of relying on external factors to make predictions, the model solely builds on historical data provided (Song et al., 2020). Moreover, Wu. Et al. studied the effect of sample size on the accuracy of the grey system model by using it to predict the Chinese electricity consumption (Wu et al., 2013). By trying different sample sizes and comparing them, they concluded that the lowest MAPE was obtained by the model that was trained using the smallest dataset (4 datapoints) while all other models which were further trained performed worse in forecasting future energy values. However, a strong assumption behind the grey model is that the variable being studied performs in a quasi-exponential manner with time. This forms a limitation to using the grey model since if the studied variable does not vary exponentially, then overestimations would be done when forecasting future values. A detailed summary of the reviewed papers, along with their objective, forecasting model, and comments is listed in Appendix A.

6. Research Objective and Methodology

6.1 Research Objective

As highlighted in the above section, a clear literature gap exists regarding the analysis of PPA markets, whether at the European or global levels. Given the new emergence and diffusion of such agreements, it is relatively difficult to find public data on the size of the markets, the factors affecting market growth, and the forecasting of the future evolution of such markets. Specifically, although some consultancy companies have their own sizing models to predict the growth of European PPA markets, such models are kept away from the public due to the high competition among business players. As for the side of academia, researchers have focused their attention on the problem of optimizing PPAs to ensure that renewable energy production and procurement under a PPA is profitable for both, investors, and corporates. Through examining the literature, the absence of a systematic known method for forecasting the liquidity of PPA markets is evident. Hence, the research's aim is to develop a replicable methodology that forecasts the size of the PPA market in each European market. The PPA supply, and the corporate PPA demand will be forecasted to determine whether the market being examined will be in the scenario of oversupply or undersupply of PPAs. More specifically, the study aims at bridging the gap in literature by developing different scenarios for the PPA market evolution, with the focus being the German PPA market. However, the developed methodology is characterized by being easily replicable, and can be used to forecast the size of other European PPA markets by studying them as closely as the German one. The major objective of this study is to build scenarios to answer the following three questions:

RQ1: Considering the historical corporate purchasing of PPAs in a certain market, what is the future appetite for corporate PPAs in upcoming years?

RQ2: Considering the projected projects pipeline of renewable energy investments, along with other volumes that might add to the PPA supply, what is the probable volume of assets asking for PPAs in the upcoming years?

RQ3: Under each scenario, do the projected supply and the expected demand lead to a PPA market that is balanced in the future?

Answering the above-mentioned questions is of relevance to many players who are active in the PPA market. Performing the proposed analysis on various European countries helps in identifying the most promising PPA markets in the upcoming years, therefore, assisting investors in selecting the key markets for their projects and investments. In addition, this analysis helps in assessing whether the forecasted PPA liquidity ensures the needed financing for the planned renewable energy projects in each market which could therefore lead to taking decisions of either slowing down planned projects or finding alternative ways to help such projects in their financing. Lastly, one could say that the analysis performed helps, to a certain extent, in analyzing whether the sustainability targets set by governments are achievable or whether major reconsideration of targets and change of regulations is needed in upcoming years.

6.2 Research Methodology

To solve the problem at hand: "forecasting the PPA liquidity in Europe", there was the need to develop a methodology first basing on one specific market, which then could be generalized to other European countries. Due to the delimitations imposed by the Thesis work being developed at Pexapark, the focus of the method development was, as mentioned before, Germany. Secondly, the problem of forecasting the liquidity was further divided into two subproblems. On one hand, there was the need to forecast the volumes of renewable energy projects in Germany which would be requiring PPAs in the upcoming years. On the second hand, there was the need to find the demand of the PPAs in Germany. Since PPA deals signed by utilities are generally not disclosed of for competition reasons, the focus of the forecast was corporate demand of PPAs in the future.

Regarding the forecast of PPA supply, three methods were initially tried: linear regression with the identification of the independent variables influencing the PPA supply volumes, neural networks by using the historical supply of PPAs to forecast upcoming values, and lastly, scenario building. Due to the lack of abundant historical dataset, the most accurate results are obtained using scenario building since it takes into account also possible market dynamics that could occur in the future without much reliance on historical volumes to do predictions. Moreover, linear regression models remain the second best option if one wishes to get an estimate of the future PPA size without performing specific market research and going in-depth in the understanding of specific market dynamics.

As for the corporate demand of PPAs, scenario building was also used to forecast the corporate purchasing of PPAs. To do this, historical purchasing of corporate players was analyzed to identify the major sectors in the German market buying PPAs. This was an inspiration from the work done by Aurora to forecast the volumes of the PPA markets, discussed in the above section. Then to build the different purchasing scenarios, the behavior the identified sectors was compared to that of the companies in the RE100 initiative and forecasts of the evolution of the behavior were done.

At the last step, the comparison of the scenarios of both demand and supply was performed to identify whether the German PPA market will be oversupplied, undersupplied, or in equilibrium in the future years.

Although in most of the following parts of the report mainly focus on the German market and its characteristics, in Section 12.4we highlight the main considerations that should be taken if one wishes to apply the proposed methodology of forecasting PPA market liquidity to other European markets. The aim is to facilitate the replicability of the methodology proposed and to summarize the major characteristics of the PPA markets in countries other than Germany.

7. Theoretical Considerations

This section of the report aims to give a brief understanding of the theoretical background behind the mathematical and forecasting methods that will be used in the upcoming parts of the report to forecast the supply and demand of PPAs. In addition, an explanation of the performance metrics used to measure the prediction accuracy of the models are explained below. To build an appropriate model to forecast the PPA market size in upcoming years, the goal was to start from simple algorithms and test their predictive abilities, and then move into more complex methodologies according to the need. The three main theories that will come across the reader are: linear regression, neural networks, and scenario-building. As seen, the start was with a linear model which is a relatively simple algorithm, but due to the relatively low performance of such algorithm in predicting complex interactions in the PPA markets, higher level algorithms and methodologies were proposed: starting from neural networks and up to scenario building with expert input to tune the model.
In this research, both linear regression and neural network analysis were performed using Orange Visual Programming, known as Orange. Orange is part of the Anaconda toolkit which uses Python and R programming languages. Orange is a data mining tool that has a user-friendly interface allowing the user to perform complex data analysis without having to write rigorous codes, but instead by using widgets that can be moved around in a workflow.

7.1 Linear Regression

Regression models have been widely used in literature for solving scientific questions with two main goals: either explanation or prediction. Regression models have been used to explain how a certain dependent variable is affected by a set of explanatory independent variables given to the model. In the problem at hand, the linear regression model is used to make prediction where a set of variables, predictors, are given to a linear model with the aim of forecasting the future behavior of the independent variable, supplied PPA volume. Simple linear regression (LR) refers to the type of model where the predictor is only one independent variable. However, as often

forecasted values are affected by several independent variables, multiple linear regression is used. Multiple linear regression overcomes the challenges created by a simple linear regression. Moreover, performing multiple analyses to study how each variable separately influences the predicted variable does not give an indication of how the combined predictors will interact affecting the predicted value. In addition, by using simple linear regression, we fail to obtain the unbiased effect of each variable on the forecast. Therefore, using multiple linear regression overcomes the before-mentioned limitations by considering the combined effect of all identified predictors on the forecasted variable. Then, using the suggested performance metrics, it is possible to quantify how close the forecasted values compare to the actual values.
If we assume that there are k explanatory variables, X_1, …, X_k that were identified based on n instances of the predicted variable (i=1, …, n), then the multiple linear regression would look as follows:

$$Y_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \cdots + \beta_p X_{ki} + e_i$$

Equation 7-1: Multiple Linear Regression Model

In Equation 7-1, e_i is the component reflecting randomness which represents the variation of the Y around its mean value. The β's are the regression coefficients, and they reflect the relationship between each corresponding independent variable and Y. For example, β_1 represents the change in the average value of Y with regards to one unit of change in the independent variables, X_1 while keeping all other variables constant. As for β_0, it is the slope of the above function, meaning that it represents the value of Y when all the independent variables (X's) are equal to zero.(Fitzmaurice, 2016).
In Orange, to build a linear regression algorithm, the input is the input dataset, which in some cases, is fed to the model with along with a preprocessor to preprocess the input data. Preprocessing can be used, mostly with large data sets, to clean the raw data; for example, by deleting instances with unknown output variable and estimating some missing values for independent variables based on the mean. As for the outputs of the linear regression widget, they consist of the learner which is the learning model that is obtained by the historical data points, along with the trained model, and the coefficients β of each independent variable.

7.2 Artificial Neural Networks

An artificial neural network (ANN) is the modelling of human brain function which has been used in various areas of science and engineering. Just like the brain functions, an ANN receives multiple signals and simplifies them by finding patterns in the input

given. The result would be the use of several input patterns to give one output (Kriegeskorte and Golan, 2019). In fact, ANN facilitate the modelling of multidimensional input data sets since they are able adapt from the changing behavior of input data to learn and generalize the observed changes. One of the main reasons for the popularity of such ANN in recent years is their ability to solve complex problems which are rather difficult to solve using conventional mathematical algorithms. An artificial neural network has three main elements in its configuration, known as layers: input layer, hidden layer, and output layer (Brodny et al., 2020).
One of the popular neural network models that is highly used in forecasting is the Multi-layer perceptron (MLP) network. MLP is a supervised learning algorithm that, starting from a given a set of features, it learns a non-linear approximation to calculate the target. Unlike conventional regression models, a MLP network can have multiple non-linear layers between the input variables and the output, known as hidden layers.

As seen in Figure 7-1, the input layers consists of a set of neurons, X_1, X_2 … X_i, which represent the features that will be used to build the model. The signals from each input in the input layer are sent to each of the hidden neurons in the above shown hidden layer. Each neuron that exists in the hidden layer does two transformations on the

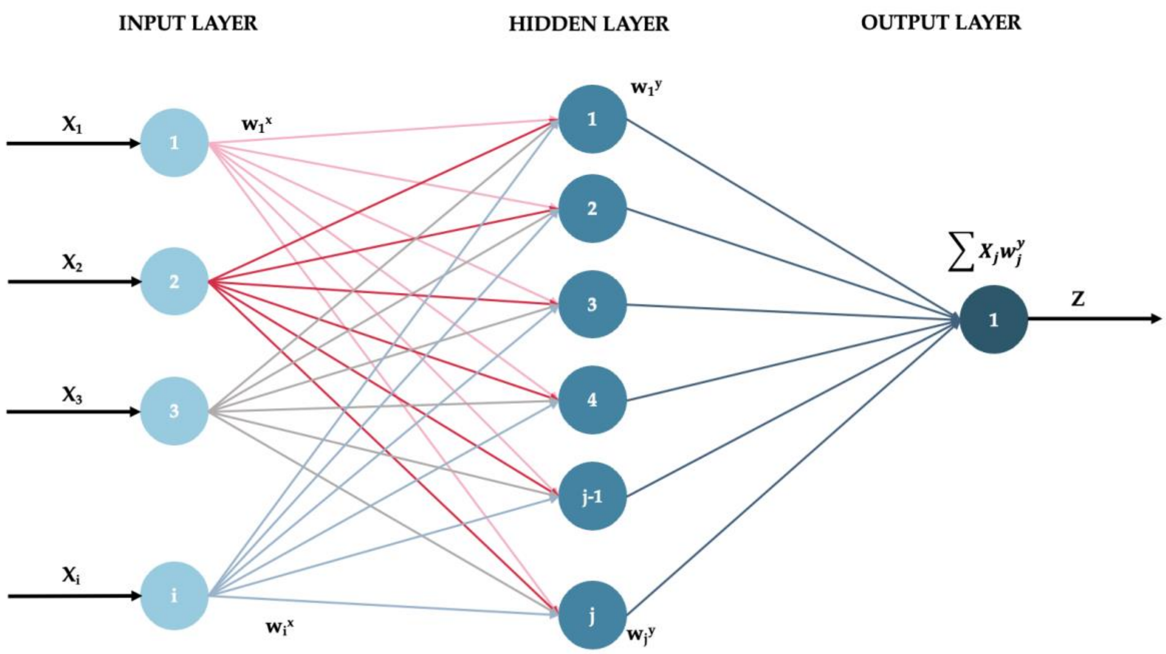

Figure 7-1: Elements of an MLP network with one layer

input given to it: firstly, a weight is given to each input feature and then, a non-linear activation function is applied. Therefore, a weighted summation is performed on the

inputs of a neuron followed by non-linear activation function in the last hidden layer. The output of the last hidden layer is sent to the output layer which gives the final result and output value, Z ("1.17. Neural network models (supervised)," n.d.).
In Orange, the activation functions that could be used in the hidden layer are Identity, logistic sigmoid function, hyperbolic tan function and rectified linear unit function. The regularization term (alpha), also known as L2 penalty term, is the regularization term used in Orange to avoid having a neural network that is overfitting the data. To stay in the acceptable range of data fitting, alpha is naturally kept between 0 and 0.1. In fact, the lower the alpha term the better, since alpha forced the weight parameters to be as small as possible which decreases the complexity of the neural network and avoids overfitting. The input needed to build a neural network are the input dataset along with a preprocessor to clean the raw data and the outputs consists of the MLP learner and the trained model.

7.3 Scenario-Building Technique

Scenario-building is a long-established technique widely used in the attempt of systematically performing future studies. In thinking about the future, there are several types of studies that can be performed, which differ on the answer that is sought after by the researcher. This leads to the rising of several scenario typologies. In their paper, Börjeson et al. identify three various types of scenario typologies: predictive, explorative, and normative (Börjeson et al., 2006). Predictive scenarios respond to the question "What will happen" where the most likely future scenario to occur is studied along with its possible variations using "What-if" analysis. On the other hand, explorative scenarios answer to the question "What can happen "and this type of scenario-building is often used to make predictions in highly unstable conditions, where the parameters that might affect the future of the target being studied are not precisely known to the researcher. As for the last scenario-type, normative, it tries to answer the question "How can a specific target be reached?". As the question suggests, such scenarios start with the current situation and focus on what changes to the current situation need to be done to be able to reach set objectives.
In this research, the predictive scenario is used in the attempt of predicting the future of PPA markets. The purpose of predictive scenarios is to foresee how the future will be in order to take appropriate measures in the present to adapt to its evolution. Such scenarios are useful for various players in the economy: investors, financial institutions, and governmental bodies. For instance, they help investors and financial institutions see identify possible challenges and opportunities in the future. As for governmental bodies, predictive scenarios help in early identifying possible problems in the future that might be avoided by taking appropriate regulatory changes and

decisions. In building predictive scenarios, historical data play a pivotal role in observing the behavior of the factors governing the evolution of the scenario. There are two angles to build predictive scenarios: forecasts and what-if scenarios. While forecasts examine the most probable development in the future, what-if scenarios examine the future development while considering some major changes in the variables affecting it. In the predictive forecast scenario-building approach, the reference scenario represents the most likely development in the future. Along with the reference results, other results are also examined, which are technically defined as "high" and "low" accompany it. The forecast is built based on several external variables which might be economic, regulatory, organizational, and even environmental. This type of predictive forecasting is best suitable in the short to medium term, when the explanatory variables are not expected to greatly vary with time. In this research, a predictive forecast scenario-building approach was adopted where the predicted scenario represents the most likely development of the PPA market (Börjeson et al., 2006).

7.4 Model Evaluation Metrics

In developing regression-based models, whether conventional or using artificial intelligence, one of the most critical tasks is selecting appropriate evaluation metrics to compare different models studied. Evaluation metrics, also known as loss functions, measure the ability of the chosen model and variables in keeping the predicted values as close as possible to actual values, therefore, minimizing the error function. In this research, the performance metrics that were used to assess the different models tested are the coefficient of determination (R^2), Mean Absolute Error (MAE), Mean Square Error (MSE), and the Root Mean Square Error (RMSE).

Before explaining individual evaluation metrics, it is useful to present some mathematical background to clearly identify some of the common parameters present in the different metrics explained below. First, we need to fix the following two variables:

- $X_{i:}$ representing the predicted i^{th} value
- $Y_{i:}$ representing the actual i^{th} value that is present in the dataset studied

The model being built has the aim of predicting an X value for the corresponding Y value in the actual dataset. Therefore, it becomes possible to define the mean of the actual values in Equation 7-2 and the mean total sum of squares in Equation 7-3 as follows, where m represents the total sample size:

$$\bar{Y} = \frac{1}{m}\sum_{i=1}^{m} Y_i$$

Equation 7-2: Mean of Actual Values

$$MST = \frac{1}{m}\sum_{i=1}^{m}(Y_i - \bar{Y})^2$$

Equation 7-3: Mean Total Sum of Squares

Coefficient of Determination (R^2)

The coefficient of determination (R^2) represents the portion of the variation in the dependent variable (predicted variable) that is explained by the set of independent variables used to build the model. R^2 is often used to assess the predictability of the developed models and how well the predicted values are replicable by the model. The coefficient of determination is usually between the range of 0 and 1, and an increase in R^2 reflects an increasing predictability of the proposed model. In some rare cases, R^2 reaches a negative value, and this occurs in two cases: either when the intercept of the regression model is not fixed, or when the mean value of the actual values performs better in predicting than the model being tested. R^2 is calculated as in Equation 7-4:

$$R^2 = 1 - \frac{\sum_{i=1}^{m}(X_i - Y_i)^2}{\sum_{i=1}^{m}(\bar{Y} - Y_i)^2}$$

Equation 7-4: Coefficient of Determination

In this research, the values of the coefficient of determination is used to determine the strength of the different models generated with regards to forecasting the PPA market size. The below scale was used:

Coefficient of Determination Range	Relationship Type
$R^2 < 0.3$	Very Weak Correlation
$0.3 \leq R^2 < 0.5$	Weak Correlation
$0.5 \leq R^2 < 0.7$	Moderate Correlation
$R^2 > 0.7$	Strong Correlation

Table 7-1: Coefficient of Determination Range

Mean Square Error (MSE)

The mean square error (MSE) is used to estimate the average of the squares of the errors which decreases when the errors of the model approach zero. MSE is always a positive number that is used to detect the outliers attributing higher weights to the wrong predictions due to its squaring. In simple words, MSE reflects the distance between the plotted model, which could be a line, to the actual values. The model performs best when MSE is equal to zero meaning all predicted values are the same as the actual values while with the increase of MSE, the model worsens in predicting the dependent variable. To calculate MSE, the difference between the predicted and actual values is squared and it is divided by the total number of observations as seen in Equation 7-5:

$$MSE = \frac{1}{m}\sum_{i=1}^{m}(X_i - Y_i)^2$$

Equation 7-5: Mean Square Error

Examining the equations of MSE and R^2, Equation 7-6 becomes evident:

$$R^2 = 1 - \frac{MSE}{MST}$$

Equation 7-6: Relationship between R^2 and MSE

Since MST is constant for the dataset being studied, then we can say that R^2 and MSE are inversely proportional. Therefore, ordering the tested models using either of the two performance metrics would lead to the same final result.

Root Mean Square Error (RMSE)

The root mean square error is the square root of the MSE. The RMSE reflects the faultiness of a model in predicting the dependent variable considered. Like MSE, as the error in the model predictions increases, RMSE also increases. Thus, ordering a model using MSE and RMSE will lead to the same result. RMSE is defined as in Equation 7-7:

$$RMSE = \sqrt{\frac{1}{m}\sum_{i=1}^{m}(X_i - Y_i)^2}$$

Equation 7-7: Root mean square error

Mean Absolute Error (MAE)

The mean absolute error (MAE) is used to measure how close the predictions are to the actual values in the given dataset. Differently than MSE, MAE does not have high penalization for outliers in the training and testing datasets. Moreover, MAE is the arithmetic average of the difference between the actual and predicted values. MAE is simpler than MSE and RMSE which give a greater weight for errors by squaring differences between actual and predicted values. A high MAE reflects a bad performing model while as MAE decreases, the model has a higher predictability. MAE is calculated as in Equation 7-8 (Chicco et al., 2021):

$$MAE = \frac{1}{m}\sum_{i=1}^{m}|X_i - Y_i|$$

Equation 7-8: Mean Absolute Error

According to Chico et. al., although all of the above explained metrics reflect the performance of prediction models, the coefficient of determination remains the most accurate metrics. By just examining MSE, MAE, and RMSE, it is difficult to know how the model truly performs since such metrics range from 0 to infinity, therefore by just looking at their value, we cannot precisely know how good or bad the model performs. In addition, these metrics tend to measure the performance of the model relative to the given dataset which, in some cases might fail to generalize to other datasets. Therefore, R^2 remains a more accurate metrics since its value ranges between 0 and 1 where a positive value of R^2 could also be interpreted as the measurement of correctness of the model. Hence, R^2 is considered to be the most robust and accurate measure to assess the quality of a built model (Chicco et al., 2021).

7.5 Data Normalization

In machine learning, feature scaling is an important step for preprocessing the input data as it improves the performance of the models built. Specifically, linear regression and neural networks are classified as gradient descent-based algorithms which use the gradient descent to optimize the model. Such models require the data to be scaled to ensure that the gradient descent decreases smoothly towards the minima. One of the common feature scaling techniques is data normalization. In data normalization, rescaling of each feature is done such that each becomes a variable between 0 and 1.

The process of data normalization is done as in Equation 7-9:

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}}$$

Equation 7-9: Data Normalization

In Equation 7-9, X_{min} and X_{mx} represent the minimum and maximum values of the feature being normalized, X represents the original non-normalized value, and X′ would be the respective normalized value between 0 and 1 (Bhandari, 2020). By standardizing the data, each feature will have a mean of 0 and a standard deviation of 1. The goal of normalization is to bring all features to a common scale (between 0 and 1) since algorithms tend to be biased towards features of higher values in the case where features are not normalized. Data preprocessing through normalization was performed in excel before training and testing linear and neural network models.

8. Factors Affecting PPA Diffusion

To build a linear regression model, the first step is to identify the independent variables that mostly influence the evolution of the PPA market supply. To first identify the factors influencing PPA market size, a study of literature was done. While some factors were clearly visible by analyzing past published research, others were added due to the insights gained during the internship at Pexapark. Part of the internship included participating in client calls which included PPA negotiations; hence, the factors considered during the negotiation of single PPAs were considered in this analysis as we assume that variables that affect the closing of one deal would also affect the PPA market size in general. In the following subsections, an enumeration of the identified independent factors to forecast the supply of PPAs are enumerated.

8.1 Levelized Cost of Electricity (LCOE)

In their paper, Miller et al. highlight the importance of analyzing the LCOE value and its components during the negotiation of a PPA (Miller et al., 2017). PPAs form a central guarantee for financial institutions to give loans to renewable energy projects. Since PPAs define the long-term revenues of a certain project, negotiation of PPA terms is highly dependent on knowing the LCOE as this will affect the payback time of the project, and its profitability. As a rule, for a PPA to be feasible, the LCOE levels should be lower than the PPA prices seen on the market. Therefore, one can say that the same factors affecting LCOE levels also affect the PPA pricing. The LCOE a metric to express the cost of the generated electricity which is obtained by dividing the total project costs by the present value of the electricity produced. According to the National Renewable Energy Laboratory, the standard equation to calculate LCOE is given by Equation 8-1:

$$LCOE = \frac{(CapEx \times FCR) + OpEx}{\left({}^{AEP_{net}}/_{1000}\right)}$$

Equation 8-1: Standard LCOE Equation

Where:

- LCOE: levelized cost of electricity (€/MWh);
- FCR: fixed charge rate (%);
- CapEx: Capital Expenditure (€/kW);
- OpEx: Operational Expenditures (€/kW/year);
- AEP_{net}: net annual energy production (MWh/MW/year)

The capital and operating expenditures allow to capture the cost voices of the renewable energy projects, and the fixed charge rate is the amount of revenue required to cover the CapEx carried through the project's lifetime. As the for the net annual energy production, it is the average production of the plant per year (Stehly and Duffy, 2022). A comprehensive understanding of LCOE values and factors affecting them is crucial in the development of a PPA market in a certain country as it equips buyers and sellers with the needed information to proceed in their PPA negotiations.

8.2 Wholesale Electricity Prices

Wholesale electricity prices affect the evolution of PPA markets as their fluctuations shape the behavior of both, buyers, and sellers on the market. Though rising electricity prices have posed negative effects on European power markets, they have proven to positively influence investments in renewable energy projects, along with PPAs. Through the past year, European electricity prices were rising due to increasing gas prices coupled with Russia's invasion of Ukraine. Although this has negatively affected end consumers of electricity, it has worked in the advantage of renewable energy sellers. As electricity prices rise in the wholesale markets despite the type of energy generated, renewable producers start gaining extra margins as they do not need to purchase any fuel for their plants (Bahar, 2021). If renewable energy sources benefit from subsidy schemes, such as two-way contract for difference subsidies, such increase in electricity prices often does not lead to higher revenues since generators need to pay back the extra revenue generated. However, merchant energy producers could benefit economically from increasing prices on the market. Those merchant producers often seek to close PPAs to ensure stable revenues for their assets through time and obtain the needed financing (Ferris, 2022). Moreover, with the expectation of high forward pricing, power producers are encouraged to negotiate PPAs with floating price structures. In this way, they have the possibility to benefit from rising market prices while still having the benefit of securing financing. On the side of big corporate players, they are becoming increasingly interested in signing PPAs with various pricing structures to hedge themselves against the fluctuating wholesale energy prices. Some of the recently observed structures include cap-and-floor as well as fixed pricing with indexation mechanisms. This is especially true for energy intensive industries which use PPAs to manage their energy costs which form a big portion of the cost of goods sold (Dominy and Zubair, 2020). Therefore, amid rising power prices, PPAs appear to be a suitable solution for corporates which can obtain lower PPA prices for high tenor PPAs and for producers which hedge themselves against short-term market fluctuations. However, the positive relationship between wholesale energy prices and PPA prices is not certainly proved. With continuously fluctuating power market prices, high uncertainty in PPA negotiations arise making both buyers and sellers reluctant in locking themselves in fixed priced agreements for upcoming years.

8.3 Capacity Factor

Weather conditions in a certain market could be considered an indirect variable shaping its PPA market. As weather conditions can act either in favor or in contrast to the electricity generation from a certain technology, they indirectly also affect the technology of the signed PPAs in the market. In fact, technologies with favorable weather conditions will be the ones that attract most investments when it comes to renewable projects, and therefore will dominate the PPA market of the country. In most cases, the effect of weather conditions on the production of a renewable energy technology is quantified using the capacity factor. Capacity factor could be defined as the actual electricity production of a power plant as a percentage of the maximum designed electricity output in a certain period of time (Neill and Hashemi, 2018). Moreover, the capacity factor could be calculated as in Equation 8-2 (Bajpai and Tekumalla, 2021) :

$$Capacity\ Factor = \frac{Actual\ Energy\ (\frac{kWh}{year})}{Full\ Rated\ Power\ of\ plant\ (kW) \times\ 8760\ (\frac{hours}{year})}$$

Equation 8-2: Capacity Factor

Moreover, the capacity factor of solar, wind and hydro renewable energy plants is influenced by the location of the plant which determines the weather conditions. For instance, if wind turbines are placed in locations with low wind, then they will be subjected to idle non-producing hours for elongated times during the year. Similarly, placing solar panels in locations with relatively low solar potential decreases the power output from them. Since the weather conditions, and consequently the capacity factor, affect the net electrical production of power plants, they will also affect the economics of the project such as the LCOE and the pay-back time. For instance, fixing all other variables in the LCOE, a power plant producing less electric output during its lifetime will have a higher LCOE compared to a plant placed in a better location with higher electricity produced during its lifetime. Therefore, the weather conditions are considered a pivotal aspect to consider when deciding to invest in a certain market as they determine the most suitable technology to invest in. As a result, in often cases, the most common renewable energy technology in a certain country will also dominate most of the PPA deals signed. So, one can say that the weather conditions are one of the independent variables to be considered to forecast the evolution of the PPA market.

8.4 Governmental Support

Historically, the bankability of renewable energy projects has been largely dependent on the governmental support. However, with the continuous decrease in the LCOE of various renewable energy technologies, many governments have started scaling down their renewable subsidy schemes. This has shifted the attention of renewable investors to PPAs which ensure stable revenues with time and therefore facilitate the financing of the project (Christophers, 2022). Moreover, PPAs and governmental subsidies provide de-risking for a renewable investment and guarantee its profitability. Specifically, the past years have proved that investors tend to be attracted to corporate PPAs, and less to utility PPAs. This has emerged due to two main reasons: utilities offer lower prices for their PPAs compared to corporates since they are not the end-consumer of the purchased energy, and utilities often sign PPAs with lower contract term compared to corporates. In addition, corporates mostly offer a fixed price PPA, which decreases the risk related to profit on the investor’s side, and corporates sign pay-as-produced PPAs which decreases the production profile risk as well. A noticeable trend across European countries is that markets with decreasing or ending subsidy schemes are witnessing higher PPA contracted volumes since investors need to look for alternative revenue streams (Hall, 2020). For instance, in markets where auctions for contract-for-differences auctions are held, investors would firstly aim at winning in the auction since signing a purchasing contract with the government represents an offtaker with almost null default risk. This allows the decrease in the capital costs of the planned project compared to a PPA with a corporate offtaker who has a relatively higher default risk. Therefore, one of the factors affecting the size of the PPA market in a country is the amount of governmental support given, where the two variables are inversely proportional through time.

8.5 Country-Specific Renewable Energy Targets

The most straightforward factor affecting the size of a PPA market is the yearly renewable energy projects newbuild which is defined by the country-specific targets. It is evident that countries with higher decarbonization goals witness a higher capacity of yearly renewable newbuild compared to countries with relatively lower targets. This increase in renewable capacity undoubtedly leads to higher number and capacity of signed PPA deals on the condition that market dynamics permit the closing of deals. For instance, in markets with persistent high governmental support, despite the increased investments in renewable energy projects, the PPA market is still at its infancy. For this reason, the newbuild, along with the governmental support and other factors should be considered to properly quantify and forecast the evolution of a PPA market.

9. PPA Supply Forecasting

To forecast the supply of PPAs, three methodologies have been tested to identify the one that performs best with least errors in prediction. Firstly, linear regression was tested, with several trials, each having its own model input and assumptions. As linear regression appeared to be a non-optimal solution to solving the problem at hand, a more complex method, artificial neural network, was tested. Afterwards, it became evident that with the current available data, the optimal methodology to forecast PPA markets is through scenario building with the use of experts' knowledge. Each of the mentioned methodologies is rigorously explained in the subsections below.

9.1 Linear Regression

To build an appropriate linear regression (LR) model, several questions were raised: is it more accurate to build a model that forecasts the size of the PPA market based on technology, country, or region? Therefore, several modifications were performed on the built model to identify the most suitable configuration and assumptions. Furthermore, the relationship between the dependent variable, PPA volume supply, and the independent variables was studied while varying the time lags between the change in a variable and the impact implied on the PPA volumes. As mentioned earlier, linear regression models were built and analyzed using Orange Visual Programming. Several linear regression models were tested including the following: model based on one technology for all European markets, model based on all technologies per market and technology-specific models at the European level. Each is explained below, with its corresponding assumptions, results, and performance metrics.

In building the linear regression models, five independent variables were considered to reflect the factors that affect the diffusion of PPAs in a certain market; the variables are listed below:

- Wholesale Electricity Price in €/MWh;
- LCOE in €cents/kWh;
- Yearly subsides awarded volumes in GW;
- Yearly Newbuilt Assets in GW;
- Capacity Factor in percentage points (%).

For the volumes of newly built assets and awarded subsides, a time lag was considered between the change in the variable and its effect on the PPA supply volumes. As for the other independent variables, no time difference was considered with respect to the PPA volumes.

A time difference of 1 year was considered between subsidies awarded and the PPA volumes, where the subsidies awarded in year t-1 will influence the PPA volumes in year t. This is a fair assumption since usually, an investor tries to participate in an auction to be given governmental support, then in the case of failing to receive a subsidy, he/she will start searching for an offtaker to sign a PPA. In most of the cases, the negotiation of a PPA takes between 6-12 months, so taking a time lag of 1 year between the two variables is a considered to be a fair assumption. The time lag between the volumes of newly built assets and the PPA volumes is technology dependent. Moreover, a PPA is signed in the development phase of a renewable project where financing is obtained, and afterwards, the construction phase starts. Since each technology takes a different number of years to be constructed, the time lag between construction and financing phase differs among technologies. For example, an offshore wind project usually takes more time to be constructed than a solar project

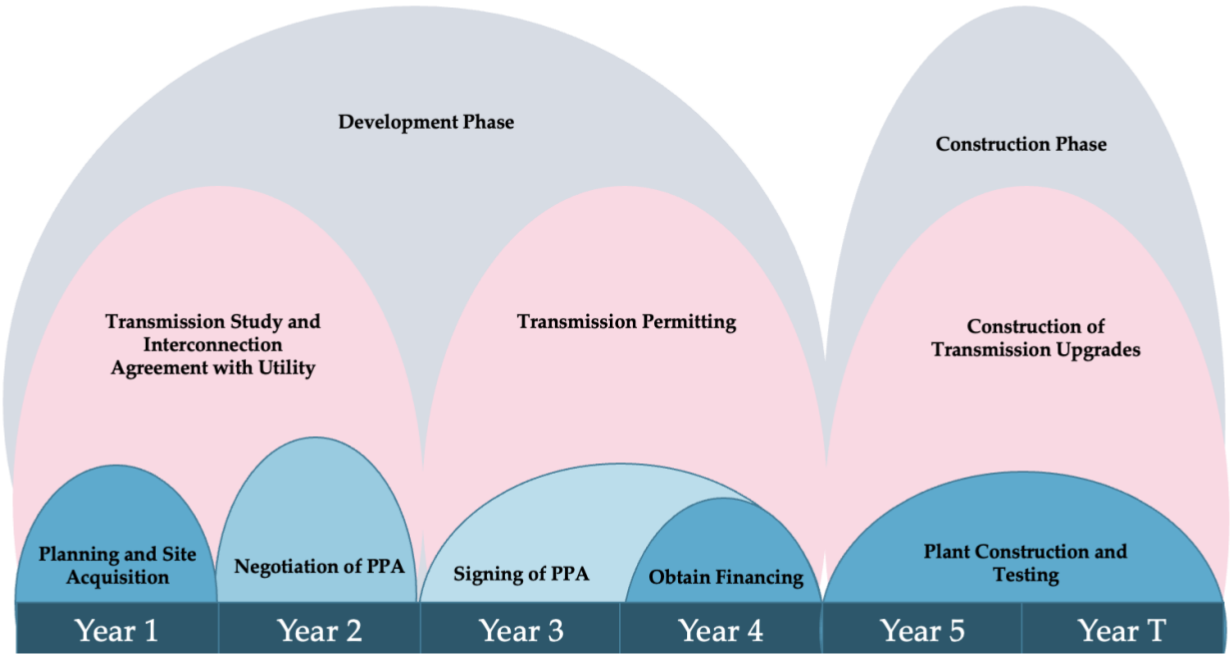

Figure 9-1: Development Timeline for Utility-Scale Renewable Project

due to its remote location and complexity of transportation and building material on the site.

Figure 9-1 better illustrates the timeframe related to a renewable energy project. In year 1 in the below timeline, the investor usually applies for a subsidy scheme. If the result turns out to be negative, then the negotiation of a PPA starts which ends in the signing

of a PPA within 1 year. With the signing of the PPA and obtaining the required financing, the development phase ends, and the construction phase starts whose duration depends on the technology of the project being developed. For utility scale solar projects, the approximate time needed between development and end of construction phase is 1 to 2 years ("Development Timeline for Utility-Scale Solar Power Plant," n.d.). As for onshore projects, the development phase usually extends from 1 to 2 years ("Wind Project Development & EPC — Descriptive Information," n.d.). Lastly, offshore projects remain the technology with the highest time needed in the construction phase which takes around 2 to 4 years (Ebenhoch et al., 2015).
Therefore, the general framework to build a linear regression model in Orange is the shown in Figure 9-2, and explained below:

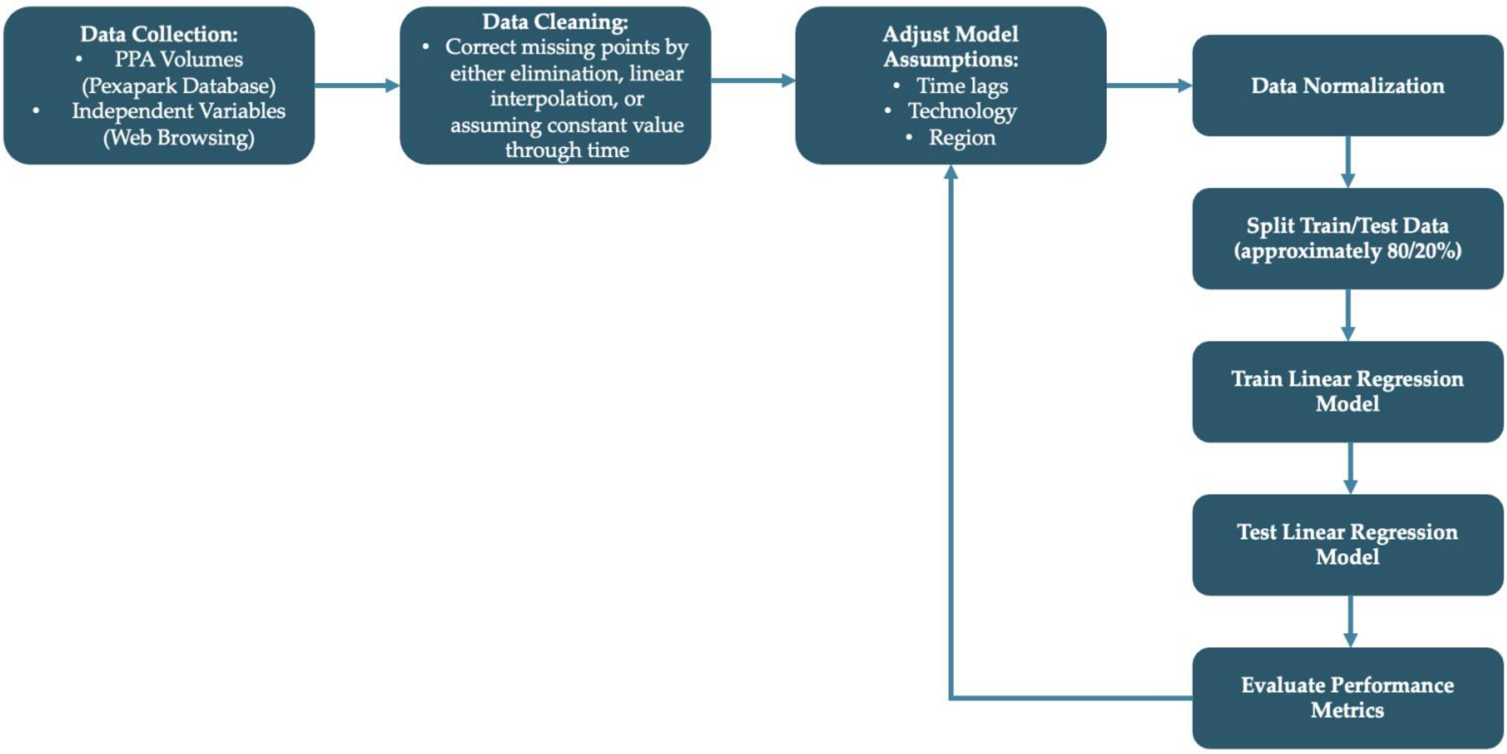

Figure 9-2: Linear Regression Model-Building Framework

Step 1: The first step consists in collecting the data for the five independent variables being considered by searching public available data either published by renewable energy news outlets such as PV Magazine, Renewables Now, and Montel, or published by governmental institutions or research bodies.

Step 2: Data Cleaning was done to account for missing values in some variables. In this regard, the years with the missing data points were eliminated from the dataset, or the missing data point was deduced by linear interpolation or by assuming that the feature remains constant between two years. The decision between the three proposed solution was case dependent. For example, if in a certain year, many features were not publicly found, then the year was eliminated. However, in the cases where just 1 feature out of the 5 was missing, one of the two other propositions was used to clean the data.

Step 3: The model assumptions were taken which consist in defining the time lags considered for the 2 two variables: subsidies, and newbuild volumes, defining the technology for which the model is built, and the region (country-specific or European level).

Step 4: Data Normalization was performed in Microsoft Excel before feeding the datasets to Orange

Step 5: The normalized data was split between training and testing datasets, and in most cases 80% of the complete dataset was used for training, and the remaining 20% for testing the trained model.

Step 6: The training dataset is fed to Orange to train a Linear Regression Model.

Step 7: The trained model in Orange is fed with the testing dataset to see the accuracy of the predictions made.

Step 8: The results of testing the Linear Regression Model are examined using the model evaluation metrics proposed in Section 7.4. If the obtained results are not satisfactory, then the model assumptions are re-adjusted and steps 3 till 8 are repeated till a model with acceptable performance metrics is obtained.

The different models tested are enumerated in the below subsections.

9.1.1 Technology-Specific Models

The first trial in building linear regression models was done by creating a technology-specific model that predicts could be commonly used for various European countries. The initial aim was to create three of the above-described model: for solar, onshore, and offshore PPA volumes separately. Data for solar and offshore were relatively easier to find compared to onshore wind, and with less cleaning needed. However, for

onshore wind, the prevalent problem was the absence of data regarding onshore wind LCOE in European countries and specific onshore yearly newbuild for each country. Hence, a technology-specific model that combines all European countries was possible to build for only solar and offshore. The built models for solar and offshore wind are done using datapoints from countries with relatively highest PPA volumes in each technology considered. The models are developed on a European level to obtain a bigger dataset compared to building the model to be market specific. In fact, using the above five independent variables to build a technology and market specific model would not be possible at this date since the data related to PPA volumes in Europe dates back only to 2018. Hence, the number of independent variables is greater than the datapoints available, 4 years, which makes it impossible to build an appropriate linear regression. Therefore, the building of the technology-specific models utilizes data from several countries; however, the models could be used to predict PPA supply volumes in specific markets.
Below, the various models' assumptions, along with the predictions obtained during testing phase, and the performance evaluation metrics are explained. The raw data to perform the linear regression is found in the Appendices Section.

9.1.1.1 Solar-Specific Model

The first step in building a solar-specific linear regression model was to collect the data relating to both, independent and dependent variables. The tables showing the raw data used to build a solar-specific model are found in Appendix B, specifically in the Solar Raw Data section. After data cleaning was performed, model assumptions were made, normalization of data and then training and testing the built model to examine if the assumptions taken lead to acceptable results. For solar energy, independent variables whose time lag has been adjusted were: wholesale electricity prices, subsidy volumes, and solar newbuild volumes. Several models were tried by varying the time lag to till the identification of acceptable results were reached. To build a solar-specific linear regression model, datasets from the following countries were used: Germany, Great Britain, Spain, Italy, France, and Portugal. Those countries were chosen as they represent the biggest solar PPAs markets at the European level, based on Pexapark's database of historical PPAs. The various models built are based on trial and error where the various assumptions were changed in each trial as a way to identify the model with the best performance metrics, therefore, the model that predicts the supply of PPAs with minimal error.

TRIAL 1

The first solar-specific model was built by considering the assumptions in Table 9-1:

Variable	Time Lag
PPAs Signed	Year t
LCOE	Year t
Capacity Factor	Year t
Wholesale Electricity Price	Year t-1
Renewable Newbuild	Year t+2
Subsidies	Year t-1

Table 9-1: Solar-Specific LR Trial 1 Assumptions

The main assumptions taken in this model are that the electricity price on the wholesale market and the subsidies given by the government have a delayed effect on the PPA market. For instance, if the asset does not win in the auction system to receive governmental support, it starts PPA negotiations which take 1 year before the signing of the PPA. In addition, it was assumed that solar projects take two years to be built after the PPA is actually signed. After taking the above assumptions, the Solar Raw Data of Appendix B was normalized, divided into training and testing data, and fed to Orange to perform model training and testing. The entire dataset consisted in 14 data points, out of which 11 points were used for model training and 3 were used for testing. The non-normalized and normalized datasets are found in Solar Trial 1 section of Appendix B.

The results of this trial are seen in Table 9-2:

Linear Regression	MSE	RMSE	MAE	R2
	0.04	0.2	0.178	-76

Table 9-2: Solar-Specific LR Trial 1 Performance Metrics

The results of the first trial show that the created model fails to properly predict the evolution of PPA supply. R^2 is a negative number which shows that the created model does not follow the trend of the data. Therefore, the predictions made by this model were very far from the actual PPA values and will not be discussed.

TRIAL 2

Therefore, some changes were made to the assumptions to test whether the model performance will improve. Specifically, changes were done to the assumptions of subsidy volumes and wholesale electricity price. Although in trial 1, there was the attempt to study these parameters with a timelag with reference to the PPA volume, in Trial 2, we assumed that they have instant effect on the PPA market with no time difference between their evolution and influence. The non-normalized and non-normalized datasets were formed of 17 datapoints, out of which three were used for model testing. The tables of data is seen in Solar Trial 2 section of Appendix B.
The model of trial 2 was built by considering the assumptions in Table 9-3:

Variable	Time Lag
PPAs Signed	Year t
LCOE	Year t
Capacity Factor	Year t
Wholesale Electricity Price	Year t
Renewable Newbuild	Year t+2
Subsidies	Year t

Table 9-3: Solar-Specific LR Trial 2 Assumptions

The only factor considered with a time lag is the solar newbuild capacity, where a period of two years was considered with respect to the signing of the PPA. The results given by the performance evaluation metrics were the following:

Linear Regression	MSE	RMSE	MAE	R2
	0.019	0.139	0.130	-56

Table 9-4: Solar-Specific LR Trial 2 Performance Metrics

As seen in Table 9-4, although the performance improved compared to Trial 1, the results are still unacceptable since the coefficient of determination is still a negative value.

TRIAL 3

As a third step, the model was modified by changing the assumptions as seen in Table 9-5:

Variable	Time Lag
PPAs Signed	Year t

LCOE	Year t
Capacity Factor	Year t
Wholesale Electricity Price	Year t
Renewable Newbuild	Year t+1
Subsidies	Year t-1

Table 9-5: Solar-Specific LR Trial 3 Assumptions

Unlike the two previous trials, in this trial the assumption was made that between the signing of a PPA and the end of construction phase, only one year is needed for the asset to become commercial. In addition, it was assumed, similary to trial 1, that between the failure to obtain governmental support and the signing of a PPA, one year of negotiation of terms is needed. In this case, only 14 data points were available to analyze which are shown in their non-normalized and normalized form in Solar Trial 3 section of Appendix B. As for the performance evaluation metrics, they are displayed in Table 9-6:

Linear Regression	**MSE**	**RMSE**	**MAE**	**R2**
	0.127	0.357	0.316	-1.219

Table 9-6: Solar-Specific LR Trial 3 Performance Metrics

Compared to the two previous models tested, this model showed a significant improvement in performance where the coefficient of determination increased by more than 50 points. However, the performance of the model is still considered to be unacceptable since the coefficient of determination persists to be negative. Hence, the assumptions need to be changed again.

TRIAL 4

In the last trial regarding linear regression model building, the assumption of having one year time lag between subsidies and PPA volumes was kept, while the delay between signing of a PPA and end of construction was considered to be 2 years. The assumptions are better seen in Table 9-7:

Variable	Time Lag
PPAs Signed	Year t
LCOE	Year t
Capacity Factor	Year t
Wholesale Electricity Price	Year t
Renewable Newbuild	Year t+2

Subsidies	Year t-1

Table 9-7: Solar-Specific LR Trial 4 Assumptions

The assumptions taken in this model are the most probable ones to prevail for a solar renewable investment, as seen during the internship period. A solar project applies to a subsidy, then if it fails in obtaining support, PPA negotiations start, and take up to one year till the PPA signing. Upon PPA signing, the construction of the wind farm initiates which usually takes up to two years for the farm to be fully commissioned. The above assumptions yielded in 15 datapoints, which were divided into training and testing data. The datasets used are seen in Solar Trial 4 of Appendix B. As for the performance evaluation metrics, they are displayed in Table 9-8:

Linear Regression	MSE	RMSE	MAE	R2
	0.141	0.375	0.272	0.290

Table 9-8: Solar-Specific LR Trial 4 Performance Metrics

Therefore, the results of testing this model are satisfactory. The created model succeeds in modelling the trend in the solar PPA market with a coefficient of determination of around 0.3. This value shows a weak positive relationship that is linear between the independent factors and the supply of solar PPA volumes (Ratner, 2009). In addition, the MAE is 0.272. Since the MAE shows how big the error is, then to know whether an MAE of 0.272 is an acceptable value, we should bring it back to the non-normalized value. Therefore, doing the inverse of normalization of the MAE which reflects the PPA volumes, it is around 0.87 GW. Therefore, on average, the model build misses in forecasting by around 800 MW, which is an acceptable value given the size of the PPA markets (in the range of 1-10 GW per year in Europe).
Thus, both, in terms of coefficient of determination and MAE, the model in trial 4 is acceptable. The results of the model's prediction compared to the actual PPA values are seen in Table 9-9 and Table 9-10.

Model Forecasts	Actual Values
0.3716	1
0.205	0.0412
0.0457	0.0709

Table 9-9: Normalized Solar-Specific LR Trial 4 Results

Model Forecasts (GW)	Actual Values (GW)

1.192	3.207
0.657	0.132
0.147	0.228

Table 9-10: Non-normalized Solar-Specific LR Trial 4 Results

Eventhough the performance evaluation metrics show an acceptable result, by examining the difference between the actual and predicted values we see that the model's predictions could be up to 2 GW greater than the actual values. Moreover, in most of the cases, the model tends to overestimate the size of the PPA supply.
In addition, the coefficients obtained by the linear regression were examined, and they are shown in Table 9-11. The coefficients obtained for the wholesale electricity price, capacity factor, subsidy volumes and the solar newbuild are coherent to what was seen in literature. For example, the model correctly identifies the negative relationship between the volume of subsidies given and the PPA market volumes. However, the model fails in identifying the inversely proportional relationship between the LCOE and the PPA market volumes.

Intercept	-0.428
Wholesale Electricity Price	-0.127
LCOE	0.370
Capacity Factor	0.683
Solar Subsidy Volume	-0.103
Solar Newbuild Volume	0.390

Table 9-11: Solar-Specific LR Trial 4 Coefficients

For all the reasons mentioned above, the conclusion of this trial is that even if it behaves better compared to other trials that try to forecast the solar PPA volume supply, the model can still be improved. Therefore, the search for a more optimal model continues.

9.1.1.2 Offshore-Specific Model

Similar to the work done to build a solar-specific linear regression model, the first step in building an offshore-specific model is to collect the data of the independent variables and the offshore PPA supply volumes. The tables showing the raw data used to build an offshore-specific model are found in Appendix C, specifically in the Offshore Raw Data Section. Afterwards, data cleaning was cleaning, and assumptions related to time lag between variables and the outcome were changed to be able to

identify the most accurate model. Like the case of solar energy, the main assumption that was changed is related to newbuild volumes.
Following the trials done in the search of a solar-specific model, the best results were obtained when the assumptions made regarding subsidies indicate a time lag of 1 year relating subsidy volumes to PPA volumes on the market. Hence, this assumption was fixed when searching for the best model to forecast the supply of offshore PPAs. The markets upon which the offshore specific-models were built are the biggest offshore wind markets in Europe according to Pexapark's PPA database: Great Britain, the Netherlands, Belgium, and Germany.

TRIAL 1

The first offshore-specific model was built by considering the assumptions in Table 9-12:

Variable	Time Lag
PPAs Signed	Year t
LCOE	Year t
Capacity Factor	Year t
Wholesale Electricity Price	Year t
Renewable Newbuild	Year t+3
Subsidies	Year t-1

Table 9-12: Offshore-Specific LR Trial 1 Assumptions

Other than the one-year delayed effect that subsidies have on the PPA market volumes, the main assumption in this trial was that the construction phase of an offshore project takes around 3 years. This indicates a three-year time lag between the signing of an offshore PPA and the commissioning of an offshore project. After taking those two assumptions, the Offshore Raw Data was adjusted to match the assumptions and 16 data points were obtained, out of which 3 were used for model testing. The normalized and non-normalized data for this trial can be seen in Offshore Wind Trial 1 section of Appendix C.
The resulting performance measurement metrics are seen in:

Linear Regression	MSE	RMSE	MAE	R2
	1.099	1.048	0.917	-59.896

Table 9-13: Offshore-Specific LR Trial 1 Performance Metrics

This model fails to predict the evolution of offshore PPA supply. The coefficient of determination is a large negative number, showing a contradictory trend between the model and the actual data. In addition, the error values are all nearly one which shows high forecasting error from the side of the model. Thus, another model with other assumptions were tried.

TRIAL 2

In the second trial to build a model that predicts the offshore PPA supply, we took the assumption of four-year time lag between the signing of an offshore PPA and the commissioning of the farm. The number of years were increased compared to trial 1 since offshore wind farms need a considerable amount of time for their building due to the remoteness of the area, the need to build offshore substations, and cables to connect the farm to the mainland grid. In this trial, the obtained dataset was made of 17 datapoints, and is shown in Offshore Wind Trial 2 section of Appendix C. The assumptions are better shown in Table 9-14:

Variable	Time Lag
PPAs Signed	Year t
LCOE	Year t
Capacity Factor	Year t
Wholesale Electricity Price	Year t
Renewable Newbuild	Year t+4
Subsidies	Year t-1

Table 9-14: Offshore-Specific LR Trial 2 Assumptions

The results obtained in this model showed improvement compared to the previous trial. The performance measurement metrics are displayed in Table 9-15:

Linear Regression	MSE	RMSE	MAE	R2
	0.011	0.104	0.090	0.486

Table 9-15: Offshore-Specific LR Trial 2 Performance Metrics

In fact, this model has shown the best predicting results so far, even when compared to solar-specific linear regression models. The coefficient of determination is around 50%, which shows that 50% of the variance in the PPA supply is predicted by the independent variables considered. Therefore, the variables and assumptions used to build the model show a weak towards moderate relationship with respect to the PPA market size. In addition, MAE is only 0.09 which shows that the error in predicting is only around 120 MW. This is highly acceptable since a 100 MW of over or underestimation refers to around a misprediction related to one PPA since PPAs are usually in the range of hundreds of megawatts.

TRIAL 3

The third trial relating to offshore-specific linear regression model involved the varying again of the delay between the signing of the PPA and the completion of the plant building. In this case, the time lag was taken for 2 years between the offshore PPA signing and the completion of building the asset. After fixing the raw data to take into account this new assumption, 20 data points were obtained, and normalized and the dataset can be examined in Offshore Wind Trial 3 section of Appendix C. The assumptions taken are shown in Table 9-16:

Variable	Time Lag
PPAs Signed	Year t
LCOE	Year t
Capacity Factor	Year t
Wholesale Electricity Price	Year t
Renewable Newbuild	Year t+2
Subsidies	Year t-1

Table 9-16: Offshore-Specific LR Trial 3 Assumptions

Also in this case, three points were used for data testing and the performance of the model is displayed in Table 9-17:

Linear Regression	MSE	RMSE	MAE	R2
	0.007	0.085	0.064	0.505

Table 9-17: Offshore-Specific LR Trial 3 Performance Metrics

As seen above, by adjusting the assumptions, the overall model performance improvement was observed in all the performance measurement metrics. The coefficient of determination shows a moderate relationship between the independent variables and the offshore PPA volume supply. Moreover, MAE, RMSE and MSE show very weak errors in the model predictions. When the MAE of 0.064 is brough back to its non-normalized value, we obtain a value of 85 MW which indicates that the model misses in its predictions on average with 85MW, a negligible value compared to actual PPA supply volumes per year.

The results of the model's prediction compared to the actual PPA values are seen in Table 9-18 and Table 9-19:

Model Forecasts	Actual Values
0.3495	0.3538
0.1560	0.1047
0.2305	0.0935

Table 9-18: Normalized Offshore-Specific LR Trial 3 Results

Model Forecasts (GW)	Actual Values (GW)
0.467	0.473
0.209	0.140
0.308	0.125

Table 9-19: Non-normalized Offshore-Specific LR Trial 3 Results

Examining the normalized and non-normalized predictions done by the model, we see that in 2 out of the 3 testing datapoints the model perfectly performs in the prediction of the PPA supply volume with error lower than a hundred megawatts.

To further examine the proposed model, the coefficients of the linear regression model were examined to double check whether they are in line with the studied relationship of each independent variable with the PPA supply volumes.

Intercept	-0.049
Wholesale Electricity Price	0.093
LCOE	-0.525
Capacity Factor	0.798
Solar Subsidy Volume	-0.083
Solar Newbuild Volume	0.213

Table 9-20: Offshore-Specific LR Trial 3 Coefficients

The obtained relationships are all in line with the observed ones during the literature review phase. However, the only possible concern is regarding the wholesale electricity price which shows in this model a positive relationship with the supply of PPAs. Therefore, the model concludes that an increase in the wholesale electricity prices would lead to higher contracted PPA volumes, which is not in line with what was observed during research.

9.1.1.3 Onshore-Specific Model

After finding acceptable models to forecast solar and offshore PPA volumes, there was also the need to develop a similar model to forecast onshore PPA supply. However, while trying to do so, an obstacle was faced. The publicly available data relating to onshore wind markets at the European level turned out to be insufficient to form a decent dataset to build a model on. The raw data that was obtained could be found in in Appendix D, specifically in the Onshore Wind Raw Data Section. The two main problems were the lack of data pertaining to the onshore wind subsidies and onshore wind LCOEs in European markets. In fact, the markets that the model was supposed to build on are: Sweden, Spain, Norway, Finland, the Netherlands, and Great Britain. For all of the mentioned countries, the lack of public data on their onshore wind markets was visible. Therefore, a model for onshore wind supply forecasting could not be created. However, in the future, with the increased transparency in data, a model can certainly be drawn in a similar way to the other technologies.

9.1.1.4 Takeaways of Technology-Specific Models

By developing technology-specific models, the models obtained showed weak positive to moderate relationship between the selected independent variables and the actual PPA supply volumes for each renewable technology. Moreover, there was a big limitation regarding the forecast of onshore wind PPA supply volumes. Therefore, depending on the created models to forecast future PPA supply would result in incomplete results. The results showed that building technology-specific models is actually feasible, with acceptable results; however, this approach would lead to more accuracy and more complete results once more data is publicly available to allow the building of a model unique for each technology with the highest predicting capability possible. For the above-mentioned reasons, we tried to search for more accurate models by shifting the perspective to creating a unique model to forecast all of the technologies simultaneously.

9.1.2 Technology-Neutral Models

Since the approach of forecasting each technology separately failed now, there was the need to try to build a model that is technology neutral. This model would be built by using the datasets of all the technologies combined. So, the model was based on the

raw data relating to offshore, onshore, and solar technologies found in Appendices B, C and D. Even if the model was built this way, it could be eventually used to predict technology-specific volumes by inputting independent variables relating to one technology.
In this regard, the technology-neutral model was firstly built for one market only, Germany, and then there was the trial to build a unique model that could be used across all European markets.

9.1.2.1 German Technology-Neutral Model

In building a technology-neutral model, the first step was to try to build a German specific model that combines all technologies: solar, offshore wind, and onshore wind. For all three technologies, the following assumptions were taken:

Variable	**Time Lag**
PPAs Signed	Year t
LCOE	Year t
Capacity Factor	Year t
Wholesale Electricity Price	Year t
Renewable Newbuild	Year t+2
Subsidies	Year t-1

Table 9-21: German Technology-Neutral LR Assumptions

The above assumptions were made since for both solar, and offshore technologies, the technology-specific models performed best when the time lag between newbuild and PPA volumes was two years, and the time lag between the subsidy volumes and PPAs was one year. Due to the above assumptions, the obtained dataset was formed of 12 datapoints, seen as normalized and non-normalized values in German Technology-Neutral Data of Appendix E.
The performance of the model obtained is seen in Table 9-22:

Linear Regression	**MSE**	**RMSE**	**MAE**	**R2**
	0.010	0.100	0.095	0.161

Table 9-22: German Technology-Neutral LR Performance Metrics

Eventhough the MAE appears to be acceptable; the coefficient of determination reflects a very weak correlation between the independent and dependent variables. This means that the independent variables considered failed to fully explain the variation in the PPA supply volumes. However, the model appears to be a good one with an MAE value reflecting only around 60MW distance between the predicted values and the actual values of the PPA supply.

Looking at the actual versus the predicted PPA supply volumes, we see the following in Table 9-23 and Table 9-24:

Model Forecasts	Actual Values
0.2746	0.3657
0.0412	0.1013
0.3351	0.2010

Table 9-23: Normalized German Technology-Neutral LR Results

Model Forecasts (GW)	Actual Values (GW)
0.171	0.228
0.026	0.063
0.208	0.125

Table 9-24: Non-normalized German Technology-Neutral LR Results

In all three test points, the predicted PPA supply volumes miss the actual volumes by an amount lower than 100 MW, which indicates a good performance of the model.in fact, even looking at the model coefficients, we see that, unlike all other models that were tested, the technology-specific model succeeds in capturing the correct relationship between the independent variables and the PPA supply volumes. The coefficients are seen in Table 9-25:

Intercept	-0.156
Wholesale Electricity Price	-0.161
LCOE	-1.269
Capacity Factor	1.886
Solar Subsidy Volume	-0.440
Solar Newbuild Volume	1.078

Table 9-25: German Technology-Neutral LR Coefficients

From the coefficients, we see that the highest correlations exist between the LCOE, capacity factor and the PPA supply volumes in Germany. Therefore, technologies with low LCOE and high capacity factor are the ones mostly prevailing in the German market.

The low coefficient of determination can be further improved by adding more predictors, independent variables, to the models which contribute to the explanation of the variation in PPA supply. Due to the limited size of the dataset at the moment, it is not possible to increase the number of predictors. Hence, this is an improvement that can be done in future work.

9.1.2.2 European Technology-Neutral Model

The last trial in building a linear model to predict PPA supply revolved around using the raw data collected for all European markets to build a common model that could be re-applied for various countries. Obtaining such model would increase the robustness and repetitiveness of the created linear regression model, as well as increase its utility. The first step was to put together the raw data relating to the three considered technologies for the countries that were studied in previous sections. The assumptions that were taken in building this model were the same as in Table 9-21 where the time lag between subsidies and PPA volumes is 1 year, and the time lag between the construction of a renewable project and the signing of a PPA is 2 years. The normalized and non-normalized datasets used to build, train, and test this model are listed in European Technology-Neutral Data of Appendix E. The dataset consisted of 26 datapoints, out of which 3 points were used for model testing. The performance of the model obtained is seen in Table 9-26:

Linear Regression	MSE	RMSE	MAE	R2
	0.009	0.097	0.096	0.543

Table 9-26: European Technology-Neutral LR Performance Metrics

The results show a significant improvement in the coefficient of determination compared to the previous models obtained, and specifically to the German Technology-neutral linear regression. In fact, this model shows a moderate correlation between the independent variables and the size of the PPA supply market. However, the average error which is reflected by the MAE is higher than the case of the German-Specific Model with an absolute value of around 300MW in predictions compared to actual supply volumes.

Examining the actual and predicted values by the model, we obtain the two below tables:

Model Forecasts	Actual Values
0.1864	0.0726
0.1324	0.0390
0.278	0.3579

Table 9-27: Normalized German Technology-Neutral LR Results

Model Forecasts (GW)	Actual Values (GW)
0.5979	0.2329
0.4246	0.125
0.891	1.1475

Table 9-28: Non-normalized German Technology-Neutral LR Results

The non-normalized predictions of the model appear to be not very accurate as the difference between predicted and actual PPA supply volumes could reach up to 0.5GW of error. The coefficients of the model are seen in Table 9-29:

Intercept	0.0465
Wholesale Electricity Price	0.0540
LCOE	-0.2802
Capacity Factor	0.3115
Solar Subsidy Volume	-0.1884
Solar Newbuild Volume	0.3256

Table 9-29: German Technology-Neutral LR Coefficients

All coefficients obtained are in line with the relationship observed during research of literature, except for the coefficient of the wholesale electricity price. In fact, there is no one clear relationship between electricity prices and the signing of PPAs, since sometimes an increase in electricity prices might positively influence the willingness of offtakers to sign PPAs to hedge themselves, thus increasing the volumes. In addition, this is the only model created with a positive intercept, which proves a better model compared to others, since even in normalized values, the PPA volumes should be measured using a positive scale to yield a positive non-normalized value.

The relatively high errors obtained in predicting could be explained by the inability of a linear model to properly map the relationships between the independent variables and PPA supply volume. This is true due to the complex interactions between the different parameters, and the lack of a big enough dataset to properly capture relationships. Therefore, neural network models were built to see if the capturing of relationships would be improved, and if an increased coefficient of determination and a decreased error are obtained.

9.2 Neural Networks

In building a neural network (NN) to do the predictions, the same trials that were done to build a linear regression model were performed. A noticeable trend was that the assumptions leading to the best-performing linear regression models have also led to the best-performing neural network model. Hence, in this section, only the most accurate neural network models obtained will be discussed in depth, while only mentioning the performance metrics obtained for the other eliminated models. Also, in the case of neural networks, the normalized datasets were used to train and test the various models. For each trial in building a neural network, the number of neurons in the hidden layers as well as the regularization term (alpha) were varied to get the model with the highest coefficient of determination given the assumptions taken. In the report, for each trial, only the alpha and the number of neurons yielding the best performance in each case are listed. In all the neural network trials, the rectified linear unit function (ReLu) activation function for the hidden layer was used. The solver for weight optimization is stochastic gradient-based optimizer (Adam).

9.2.1 Technology-Specific Models

Just like in linear regression models, the first step in building neural network forecasting models was based on developing technology-specific models.

9.2.1.1 Solar-Specific Model

In the case of building a solar-specific neural network, the same trials performed in the linear regression section were used here. The data found in Appendix B were utilized in this section too. Also in the case of neural network, the best results achieved in terms of performance evaluation metrics were in trial 4, where the newbuild was considered with a time lag of two years and the subsidies with a time lag of 1 year. The main assumptions, regularization term, along with the number of neurons in the hidden layer leading to the best outcome in each trial are listed in Table 9-30:

Neural Network	Regularization Term (alpha)	Number of Neurons in Hidden Layer
Trial 1	0.0002	60
Trial 2	0.0002	100
Trial 3	0.0002	100
Trial 4	0.0009	10

Table 9-30: Solar-Specific NN Models Parameters

To be consistent with the section of linear regression models, the results of the other trials, 1 to 3, are listed below in Table 9-31 :

Neural Network	MSE	RMSE	MAE	R2
Trial 1	0.022	0.147	0.127	-40.489
Trial 2	0.013	0.116	0.113	-39.11
Trial 3	0.143	0.378	0.230	-1.491
Trial 4	0.092	0.303	0.275	0.537

Table 9-31: Solar-Specific Neural Network Performance Metrics

Trial 4 performs the best in terms of coefficient of determination. The neural network model in trial 4 even outperforms the parallel in linear regression which had a coefficient of determination of 0.290. The coefficient of determination obtained reflects a moderate correlation between the independent variables and the solar PPA volumes supplied.

Moreover, looking at the predictions done by the neural network model developed, the following results were obtained, which are shown in normalized and non-normalized forms:

Model Forecasts	Actual Values
0.5462	1
0.2444	0.0412
0.2378	0.0709

Table 9-32: Normalized Solar-Specific NN Trial 4 Results

Model Forecasts (GW)	Actual Values (GW)
1.752	3.207
0.784	0.132
0.763	0.228

Table 9-33: Non-normalized Solar-Specific NN Trial 4 Results

It is evident that despite having a coefficient of determination that shows a moderate relationship between the independent and dependent errors, the forecasts done by the neural network model in this case are far off from the actual PPA values. This is largely attributed to the non-negligible value of MAE which reflects that the model is giving predictions that are on average 800 MW different than the actual values. In fact, looking at the obtained results from the model testing, we see that in the first test point, the model underestimates the PPA volumes by around 1.75 GW which is a non-negligible wrong estimation. Hence, this model cannot be considered to be reliable despite having a high coefficient of determination.

9.2.1.2 Offshore-Specific Model

Also for the case of offshore specific model, the same three trials done in building a linear regression model were used. Hence, the normalized data found in Appendix **Error! Reference source not found.** was utilized to train and test the neural network model in the various trials. Similar to what was done for the Solar-Specific Model, trials 1 and 2 are only illustrated in terms of the performance metrics obtained, while trial 3, which leads to the most accurate predictions is further explained. Firstly, the model parameters are displayed in Table 9-34:

Neural Network	Regularization Term (alpha)	Number of Neurons in Hidden Layer
Trial 1	0.0002	100
Trial 2	0.0002	100
Trial 3	0.0002	100

Table 9-34: Offshore-Specific NN Models Parameters

For all the trials performed, the regularization term that yielded the best performance metrics is 0.0002 and the number of neurons in hidden layers is 100. The performance metrics obtained are shown in Table 9-35:

Neural Network	MSE	RMSE	MAE	R2
Trial 1	1.056	1.027	0.862	-57.481
Trial 2	0.019	0.137	0.095	0.107
Trial 3	0.008	0.091	0.065	0.426

Table 9-35: Offshore-Specific NN Performance Metrics

Similarly to the results of the linear regression model, trial 3, whose assumptions are a time lag of 2 years in terms of construction of the asset and time lag of 1 year with respect to subsidies, performed best. The coefficient of determination is 0.426 however, still showing a weak correlation between the independent variables and the PPA supply volumes. However, unlike the neural network developed in the case of solar-specific model, the MAE found for the offshore model is considerably lower reflecting an average error in the model's forecast of only around 10 MW, which is a very good result compared to the actual size of the PPA deals on the markets.

9.2.1.3 Onshore-Specific Model

The problem faced in linear regression model building also appears in neural networks. A model specific to onshore wind projects could not be built due to the lack of enough public data to allow the formation of a clean dataset that could produce an acceptable model to be trained and tested.

9.2.2 Technology-Neutral Models

The second step was to try to form a unique neural network model which is able to perform the prediction of the PPA supplied volumes for all technologies. The first trial was to build the mentioned model at the German level. Due to the bad quality performance of a German-specific technology neutral model, the search for a technology-neutral model formed at the European level was done. Also in these two cases, the datasets used for training and testing the models are the same as the ones used in linear regression which are listed in Appendix E.

9.2.2.1 German Technology-Neutral Model

The same assumptions that were used to build a German Technology-Neutral Linear Regression model displayed in Table 9-21were used here, and the dataset is shown in in German Technology-Neutral Data of Appendix E. The characteristics of the built model are displayed in Table 9-36:

Neural Network	Regularization Term (alpha)	Number of Neurons in Hidden Layer
	0.0002	100

Table 9-36: German Technology-Neutral NN Model Parameters

The performance of the neural network model obtained is seen in Table 9-37:

Neural Network	MSE	RMSE	MAE	R2
	0.028	0.166	0.159	-1.332

Table 9-37: German Technology-Neutral NN Performance Metrics

The created model shows a negative coefficient of determination and an MAE of 0.159 reflecting around 500 MW of average error in the predictions of this neural network model. Hence, this model is not reliable due to the two mentioned reasons. The results of the model in terms of predictions compared to actual values will not be further discussed due to the high error in forecasting.

9.2.2.2 European Technology-Neutral Model

The last trial in building a forecasting neural network model is to build a model that is unique for all technologies across all European markets. The dataset used to build this model are in European Technology-Neutral Data of Appendix E, and the assumptions taken are a two-year time lag for the renewable newbuild installations to be completed and a one-year time lag between the effect of subsidy volumes on the size of the PPA supply volumes.

The characteristics of the built model are displayed in Table 9-38:

Neural Network	Regularization Term (alpha)	Number of Neurons in Hidden Layer
	0.0002	100

Table 9-38: European Technology-Neutral NN Model Parameters

The performance of the neural network model obtained is seen in Table 9-39:

Neural Network	MSE	RMSE	MAE	R2
	0.007	0.086	0.081	0.638

Table 9-39: European Technology-Neutral NN Performance Metrics

The obtained performance evaluation metrics reflect a high accuracy of the model built. The coefficient of determination is in the range of high moderate to strong correlation between the independent variables and the supply of PPA volumes. In addition, the MAE of 0.081 reflects an average error of 260 MW in the obtained forecasts compared to the actual PPA supply values. The forecasts compared to the actual values in normalized and non-normalized forms are shown in Table 9-40 and Table 9-41:

Model Forecasts	Actual Values
0.1934	0.0726
0.2870	0.3579

Table 9-40: Normalized European Technology-Neutral NN Results

Model Forecasts (GW)	Actual Values (GW)
0.620	0.239
0.920	1.1475

Table 9-41: Non-normalized European Technology-Neutral NN Results

By examining the model forecasts compared to the actual values, we realize that even if this model outperforms all other models developed, its forecasts still have high range of error compared to the real supplied PPA volumes. In fact, test point 1 shows an error of around 400 MW, which is a non-negligible error in forecasting PPA volumes. Hence, even if this model performs better in terms of performance measurement metrics compared to all other models, whether linear regression models or neural network models, it is not a satisfactory model to be utilized to forecast European PPA markets.

9.3 Discussion of Linear Regression and Neural Network Models

From the several trials done to build a suitable linear regression or neural network model that is capable of forecasting the future size of the PPA markets, the obtained results were not satisfactory. Although the models reveal a clear correlation between the independent variables used and the PPA volumes, the models fail in capturing a clear trend that allows accurate future forecasts. A possible reason for this lack of model accuracy could be insufficient size of datasets used due to the infancy of European PPA markets. This is especially applicable to neural network models, whose performance significantly increases when the dataset size increases. In fact, this appears to be true for both neural networks, and linear regression models which show the most accurate forecasting results when building a European technology-neutral forecasting model. This model was trained and tested using the largest dataset formed of 28 datapoints when compared to all other trials, whether technology-specific or technology-neutral models. Hence, the performance of such models can be further improved when more data is made public or created through time regarding the European PPA markets. For the time being, using such models could be beneficial to obtain quick estimates of the future size of the PPA market: whether an estimate of the diffusion of a certain technology in a market or the overall PPA market size of a country. The independent variables could be plugged in in the model and estimates would be given, without the need of any expert knowledge or intervention.

However, the aim of this research is to develop a more accurate model to forecast the PPA market size precisely helping investors in taking future decisions and steering the regulations done by governmental bodies. Thus, the search for a higher precision model continued, this time while developing an extensive model for forecasting that requires expert intervention using scenario-building techniques.

10. Scenario-Building Technique

In the section of PPA Supply Forecasting, several linear regression and neural network models were built to forecast the PPA supply across European countries. However, such models were characterized by low level of accuracy. Although they are able to give a rough estimate regarding the PPA market size given a set of independent variables, they fail to capture market specifics and give accurate numbers which are needed to study markets closely. Moreover, such models could be further improved in the future by increasing the size of the datasets in both stages of training and testing the models. Indeed, the model that showed the highest accuracy is the technology-neutral model which was trained based on a pan-European dataset relating to PPA volumes.

Hence, to get a more accurate estimation of future PPA supply, in each European market should be studied separately to identify specific market characteristics, factors that affect the PPA diffusion and possible future scenarios for its evolutions. In this research, a general model that requires expert's knowledge was developed to forecast both, the expected PPA supply and the expected demand for PPA volumes. This method could be applied to each European market separately, after studying the individual market dynamics. The scenario-building technique, for both supply and demand forecasting, consists in developing a reference scenario, which is the most probable scenario to occur according to historical data, along with high and low scenarios.

In the following subsections, the explanation of the general methodology to be used is done along with the study of the German market dynamics and the factors to be considered to apply the proposed model to estimate the supply and demand of PPA volumes in the German market in upcoming years.

10.1 PPA Supply Forecasting Methodology

In this section, the general methodology to forecast the PPA supply volumes in a European market is proposed. To forecast the future PPA supply, a reference scenario is built, whose assumptions are heavily based on historical trends and dynamics seen in the market under steady. The method is based on the knowledge that on a market, renewable assets work towards getting governmental support to secure stable revenues with time. If they fail in doing so, they start their search for an offtaker to sign a PPA to be able to get the needed financing from banks; however, not all renewable assets succeed in finding an appropriate energy buyer. Hence, in all markets, the renewable assets are divided to three portions: part benefiting from subsidy schemes, another portion signing a PPA on the market, and the latter part stays merchant on the electricity market. Below, the steps to forecast the supply of PPAs are listed:

Step 1: Gather the publicly available data on the market. Precisely, the future renewable goals of the country along with the announced future subsidy volumes are needed. Such information is usually found in Governmental publications, as part of the country's commitment to combat climate change and shift to renewable energy. The data collected should have the same timespan as the number of years

Step 2: Perform a background check on the market for which the forecast is to be done. Make a study of its subsidy scheme awarding mechanism, the current and expected events taking place in the market that might either affect the electricity market in general, or the PPA market specifically. This step will help in making proper approximations and assumptions during the forecast. For example, important aspects to consider are possible undersubscription in renewable auctions seen in the past, regulatory barriers to the diffusion of a certain renewable technology, or possible additions to the PPA market, for example through assets that are losing their subsidy schemes.

Step 3: For each factor that might affect the PPA supply volumes, find a reference value, high and low values to help in building the scenarios. For example, if the market suffers from undersubscription to renewable auctions, study the results of the historical auctions to get the average percentage of undersubscription, along with the maximum undersubscription rate and minimum one to be able to build the three scenarios. Do the same step for each parameter that affects the market size. This way three scenarios are built.

Step 4: Since accurate historical data relating to European PPA markets date back to 2018, collect the renewable newbuild along with the subsidy and the PPA volumes for the market studied for the period dating from 2018 to 2021. For each historical year and for each built scenario, compare the merchant renewable volumes to actual PPA volumes to get the percentage of merchant volumes signing a PPA each year where:

$$\begin{aligned} &Merchant\ Renewable\ Volume_t\ (GW) \\ &\qquad = Renewable\ Newbuild_{t+2} - Corrected\ Subsidy\ Volume_{t-1} \end{aligned}$$

Equation 10-1: Merchant Renewable Volume

Similar to what was done in building linear regression and neural network models, a difference of two years is considered between building of the renewable asset and the signing of a PPA, and a difference of one year between a renewable auction and the PPA signing. The corrected subsidies refer to the announced subsidies that are corrected based on market trends (e.g. undersubscription to auctions) which lead to the building of the three scenarios: reference, high, and low.

Step 5: For the reference scenario, divide the actual PPA volume of each year by its corresponding merchant volumes. For each of the past years, a unique percentage of merchant assets signing a PPA will be obtained, referred to as X. Identify the average X value, the minimum and the maximum.

Step 6: Using the yearly historical PPA volumes, use the X value identified in Step 5 to get the predicted PPA volume by the model. Use the average X for the reference scenario, the maximum X for the high scenario and the minimum X for the low scenario. Compare the predicted values to the historical actual data by calculating an evaluation metrics that computes error, for example, RMSE.

Step 7: Repeat steps 5 and 6 for the high and low scenarios.

Step 8: Compare the three calculated RME values to identify the best set of maximum, minimum, and average X value (percentage of merchant assets signing a PPA).

Step 9: Using the future renewable newbuild and subsidy volumes identified in Step 1, calculate the PPA supply volumes in future years as follows:

$$PPA\ Supply\ Volume_t(GW) = Merchant\ Renewable\ Volumes_t\ \times \mathrm{X}$$

Equation 10-2: PPA Supply Volume

In Equation 10-2, X refers to the percentage of merchant assets signing a PPA. In the above equation, botaverageh, the merchant renewable volumes and the value of X vary depending on the scenario being studied.
Till now, the calculated PPA volumes are in gigawatts.

Step 9: If there are other sources of volumes that are adding to the PPA volume, consider them at this step. For example, consider renewable assets that are losing their subsidies and searching for a PPA on the market.

Step 10: To be able to compare the PPA supply volumes to the PPA demand, the PPA volumes are converted to a unit of energy (GWh or TWh). To do so, use public data to get the average production hour of each the technologies to convert its annual PPA volumes to TWh.

Step 11: Use the historical database of the country's PPA to get the average tenor of the PPAs on the market.

Step 12: Use the historical signed deals with their tenors, along with the forecasted PPA volumes with the average tenor to get the yearly PPA supply in TWh/GWh for the upcoming years. For the historical deals, only the corporate deals are considered in this calculation to be able to properly match the forecasted demand and supply.

The scheme below summarizes the steps to be followed to forecast the size of the PPA supply volumes in a market:

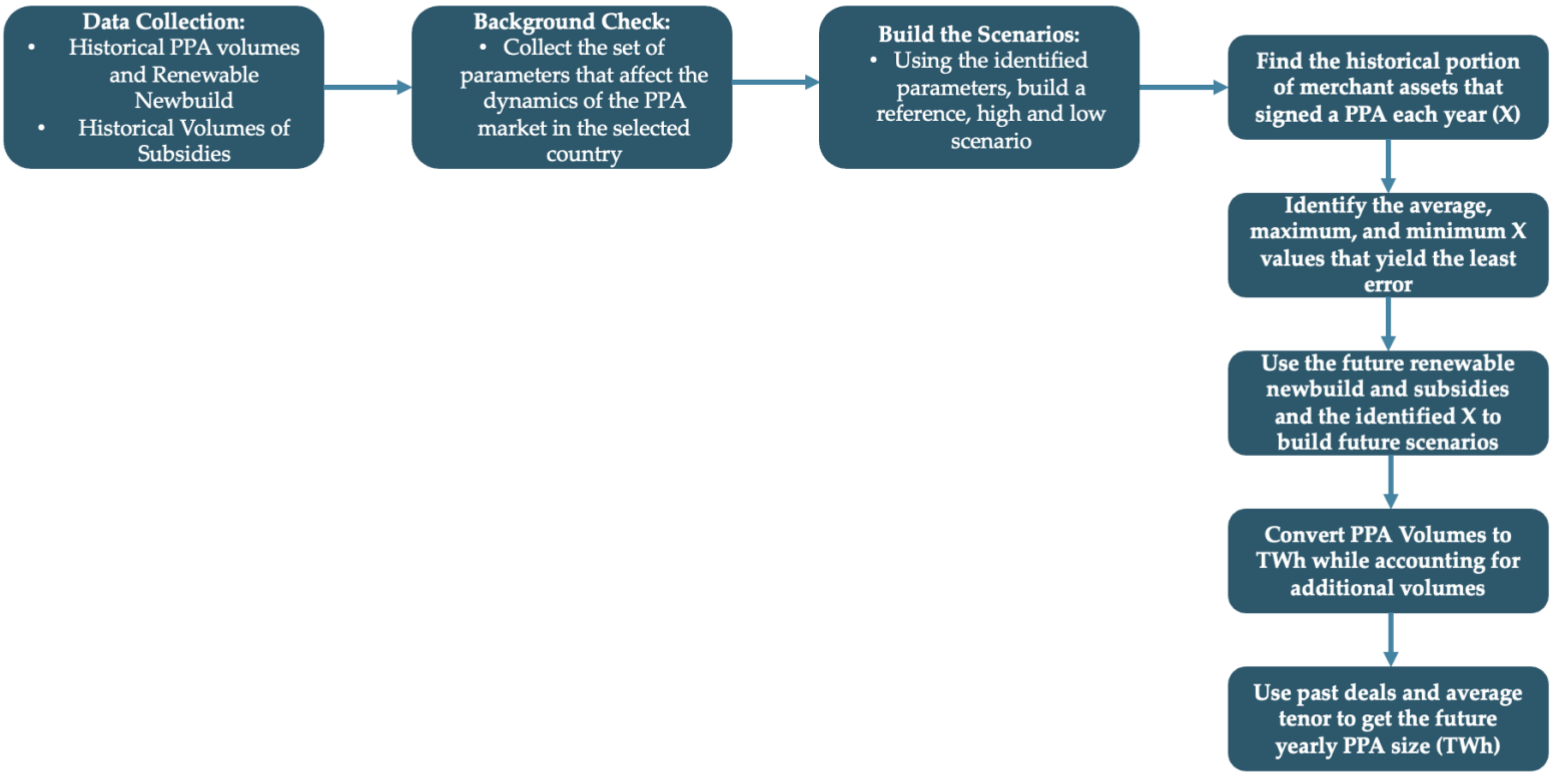

Figure 10-1: Scenario PPA Supply Forecasting Method

10.2 PPA Demand Forecasting Methodology

After the supply forecasting methodology has been explained, having an estimate of the PPA volume demand in upcoming years is beneficial to compare yearly demand and supply in the selected market. In forecasting the demand, the focus was on forecasting the demand of PPA volumes by corporate players in the market studied. The PPA volumes requested by utilities are not studied since most utility players tend to sign PPAs without publicly announcing them. This happens due to the nature of work of utilities which compete with one another to secure lowest energy prices for elongated periods of time. On the other hand, corporate players are proud to disclose of their deals as they highlight their commitment to sustainability and fighting climate change. Several methods have been tried to forecast the demand of corporates ranging from forecasting the demand of individual corporate companies in a market to finding overall corporate demand; however, the forecast based on industry-level analysis appears to be the most feasible given the public data available and the most repetitive to be applied in all European countries. Below, the steps to forecast the corporate demand of PPAs are listed:

Step 1: Start from the list of RE100 companies ("Growing renewable power," n.d.) and classify each company in the RE100 to its respective industry according to the Global Industry Classification Standard (GICS) (*Global Industry Classification Standard Methodology*, 2020). The list of RE100 companies were divided according to sector, and according to industry group, and the complete list divided to sectors is in Appendix F.

Step 2: For each industry identified in the RE100, identify a function that mimics the behavior of the companies in the industry in terms of renewable energy goals. To do so, prepare a list of the individual company goals in the industry and do fitting to get one curve that would represent the average industry goal. The fitting is done using a Sigmoid Function to make sure the result is a fitted curve that is always increasing and never exceeding 1 (100% renewable energy goal).
RE100 is a global initiative that joins together all corporates with the goal of reaching 100% energy consumption from renewable energy.

NOTE: Sigmoid Function
The Sigmoid Function is a mathematical function that has an S-shape curve. The logistic Sigmoid Function was used in mapping RE100 RE goals as it gives a value ranging from 0 to 1. The logistic Sigmoid Function is defined as in

$$S\,(x) = \frac{1}{1 + e^{-x}}$$

Equation 10-3: Logistic Sigmoid Function

In the analysis, three constants were used in the above equation to do the appropriate fitting for each industry; hence, the equation was modified as follows:

$$Y_{fit} = \frac{1}{1 + Ae^{-Bt+C}}$$

Equation 10-4: Modified Logistic Sigmoid Function

Y_{fit} refers to the ideal RE goal for a given industry in each year. A,B and C are constants that differ from one industry to another, and t refers to the year. To build the Logistic Sigmoid Function, the years were indexed according to the first year of data available. For example, if year 2014 represents the first data for the industry, then it refers to year 1, and all years follow.

Step 3: Starting from the list of the publicly announced corporate deals in the market studied, classify the corporate players into their respective industries in a similar way that was done for the RE100 companies (using the GICS).

Step 4: For the studied market, identify the main industries that have been active in the PPA market and for each of the top industries, find the last available data regarding its annual electricity consumption in the respective market. The method assumes that this electricity consumption would be stable in the forecasting years.

Step 5: For each of the top industries, and for each upcoming year, use the function identified in Step 2 to get the annual demand of renewables. This value is corrected by subtracting from it the natural flow of renewables that the company receives through the renewables in the grid mix of the country to get the actual PPA demand. The following equation is used to predict the Ideal PPA Demand in year t of industry i:

$$Ideal\ PPA\ Demand_{t,i} = \left(\frac{\beta_{t,i} - \alpha_{t,i}}{1 - \alpha_{t,i}}\right) \times Y_{t,i}$$

Equation 10-5: Ideal PPA Demand for Industry i

Where in the above equation:

- Ideal PPA Demand$_{t,i}$: The PPA demand requested by industry i, in year t, if the industry in the studied market perfectly behaves as companies in the RE100 who are in the same industry. This is measured in a unit of energy, TWh.
- $\beta_{t,i}$: RE Goal$_{t,i}$: The renewable energy goal for industry i, in year t, which is obtained from the Sigmoid Functions fitting which is a percentage. This goal reflects the average goal of the industry according to RE100 companies' behavior.
- $\alpha_{t,i:}$ RE from grid$_{t,i}$: The percentage of renewable energy in the grid mix of the studied market.
- $Y_{t,i}$: Electricity Demand$_{t,i}$: The electricity demand of the industry in energy unit (TWh), which was identified in Step 4 and considered constant through time.

NOTE: Derivation of Equation 10-5**:**

Equation 10-5 was derived using a system of 2 equation and 2 unknowns:

1. $Y_{t,i} = Ideal\ PPA\ Demand_{t,i} + Electricity\ from\ Grid_{t,i}$
2. $Ideal\ PPA\ Demand_{t,i} = Total\ RE\ Demand_{t,i} - Renewable\ Electricity\ from\ Grid_{t,i} = (\beta_{t,i} \times Y_{t,i}) - (\alpha_{t,i} \times Electricity\ from\ Grid_{t,i})$

By re-arranging equation 2 to get the $Electricity\ from\ Grid_{t,i}$, and replace it in Equation 1, Equation 10-5 is obtaine.

Step 6: By using the β value from the RE100 companies, the high case scenario is obtained where all companies in the industry of the market are behaving in a similar manner to the RE100 signees. Therefore, there is the need to develop a correction factor to take into consideration that: not all companies in the industry of the market are in the RE100 companies, and even the RE100 companies do not always behave in a consistent way with the announced goals.

For the year with the last available historical data for the industry analyzed, the correction factor (CF) is calculated which compares the volume of the publicly announced deals in a given year to the ideal PPA volumes that should have been signed to achieve the RE100 goal achieved through fitting. The formula of the correction factor is the following:

$$Correction\ Factor_{t,i} \quad = \ Publicly\ Announced\ Deals\ _{t,i} \ /Ideal\ PPA\ Volumes\ _{t,i}$$

Equation 10-6: Correction Factor Equation

In the above equation, the publicly announced deals and the ideal PPA volumes are in MW, therefore, the correction factor is a unitless number. Starting from the correction factor calculated for the industry, the reference, high and low scenarios are created as follows:

- High Scenario: CF is 1 in all years. The industry behaves in the exact way as announced by RE100 companies, reaching its yearly announced goals.
- Reference Scenario: CF gradually increases in a linear way. The start point is the CF obtained from the last available year with publicly announced deals. This CF will gradually increase until it reaches one, meaning the industry gradually improves its performance till it reaches the ideal one.
- Low Scenario: CF is constant through the years and is equal to the last calculated CF. The industry does not improve its performance.

Step 7: For each of the following years in which the forecast is to be done, calculate the demand for PPAs in corrected in unit of energy, TWh, as follows:

$$Corrected\ PPA\ Demand_{t,i} = \ Ideal\ PPA\ Demand_{t,i} \ \times \ Correction\ Factor_{t,i}$$

Equation 10-7: Corrected PPA Demand Industry i

This is done for each year in the forecast since in each year, the Ideal PPA Demand as well as the Correction factor changes.

Step 8: Repeat steps 5 till 7 for each of the top industries identified in the studied market.

Step 8: For each year in the forecast calculate the total corrected PPA demand in the market for all the industries combined using a unit of energy, TWh. This reflects the total corporate PPA demand in the market for each year. It will be compared to the supply volumes and is calculated as follows:

$$Corrected\ PPA\ Demand_{t} = \sum_{i=0}^{i} Corrected\ PPA\ Demand_{t,i}$$

Equation 10-8: Total Corrected PPA. Demand for Year t

The scheme below summarizes the steps to be followed to forecast the size of the PPA demand volumes in a market:

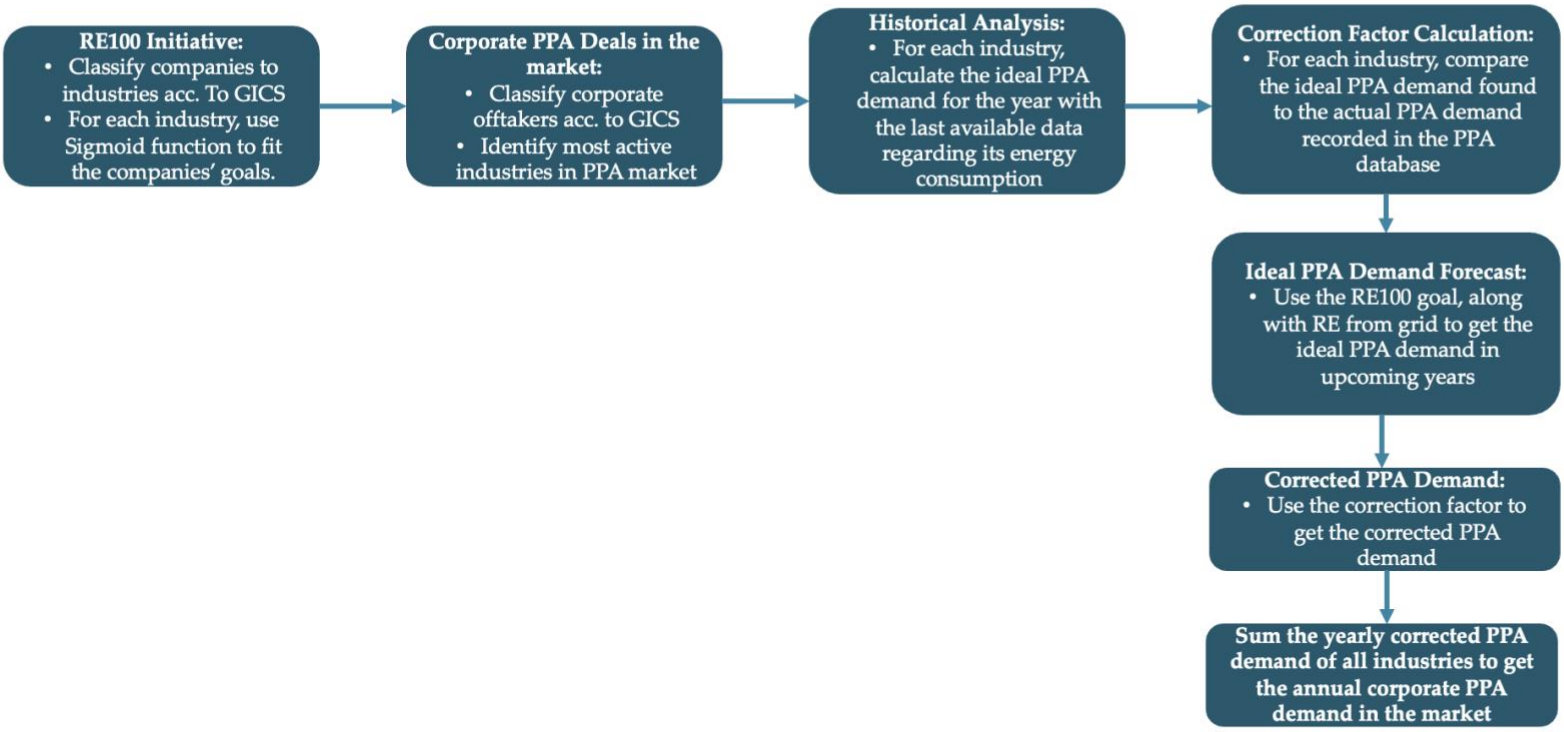

Figure 10-2: Scenario PPA Demand Forecasting Method

After using the above two methods to forecast the supply and corporate demand of PPAs in a certain market for upcoming years, the different scenarios of each are compared on a yearly basis. The comparison of the supply to the demand will allow to draw conclusions on the maturity of the market, along with the adjustments that need to be made either from developers' side or buyers' side or even regulators' side to ensure a balance between supply and demand.

In the Section 11 below, the assumptions and considerations that should be applied to Germany to perform the scenario-building technique for both supply and demand forecasting are described in detail.

11. Application of Scenario-Building Technique to Germany

As mentioned earlier, the scenario-building technique was specifically applied to the German market, as the results of the PPA forecasting were demanded to be published by the German Energy Agency (DENA).
This section of the report aims at better explaining the proposed methodology by demonstrating its application to the German market.
Before applying the proposed forecasting methodology to Germany, the study of the German renewable energy market, and specifically, PPA market was performed, and the resulting characteristics and considerations are shown in the below subsections.

11.1 Research for Supply Forecasting

As mentioned in the Section 10.1, there are several considerations to be taken to apply the scenario-based supply forecasting for a certain market. The research that should be done around the market of analysis should be mainly centered around the following topics:

- Research on the historical renewable newbuild in the country along with the future goals for renewable expansion, and the average load hours of each technology in the market;
- Research on the historical renewable subsidy schemes along with the future announced subsidy volumes;
- Research on the historical PPA deals, along with their tenors.

Hence, the application of the proposed model for supply forecasting was focused on the above three topics, and its results are enumerated in this section.
In January 2022, the German minister of Economic Affairs and Climate Action presented the country's climate action status. The presentation, which was coupled by a brief report, highlighted the status of the country in terms of climate targets and the expansion of renewable energy in the grid. This report was extremely helpful in building the supply analysis for Germany as it included data about historical and future renewable newbuild volumes, percentage of renewable energy in the grid mix, and the volumes of the subsidies.

GERMAN RENEWABLE NEWBUILD

The German government has strict goals for its energy sector to be met by 2030 as it realizes that the energy sector is responsible for the largest shares of emissions in the country. Despite having 220 million tons of CO_2 equivalent emitted in 2020 by the energy sector, Germany aims of having only 108 million tons of CO_2 equivalent in the year of 2030. While in the past emissions decreased by an average of 15 million tons of CO_2 equivalent per year, between 2022 and 2030, they need to fall by 36 to 41 million tonnes per year. In fact, Germany aims to become a greenhouse-gas neutral economy by 2045, at latest. This indicates that the energy sector must more than half its emissions compared to today.

To meet such target, the German government realizes the importance of basing its energy sector renewable energy which would increase decentralization and decrease the country's need to import fossil fuels from other markets. In addition to investing in renewable energy, the German government highlights the need of investments in energy efficiency projects along with the increased electrification of its sectors.

The key to achieving the climate protection goals is to replace the coal and nuclear power plants that are reaching their end life by renewable energy installations. In 2020, renewable energy accounted for 42% of the overall electricity consumption in the country. This is expected to increase to 80% by 2030. However, an obstacle faced by Germany is that the starting point to reach such an expansion is not very positive. To illustrate, year 2021 was the first year since 2000 where the share of renewable energy in the final electricity consumption fell, both in absolute and relative terms. The main reason for this decrease is the shy investments in renewable energy.

The historical, along with the future expansion goals of the different technologies are seen in Figure 11-1 and Figure 11-2. Furthermore, the individual expansion of offshore wind and onshore wind is further divided in Table G-1 of Appendix G. The graphs below show the yearly addition of capacity that was recorded in the past years, and the required yearly future addition to reach the German targets. Moreover, an expansion of 100GW of onshore wind, 200GW of solar photovoltaics, and 30GW of offshore wind is expected by 2030 (*Eröffnungsbilanz Klimaschutz*, 2022). Hence, the yearly additions displayed in the two graphs below will be the starting point of forecasting the supply of PPAs in the German market.

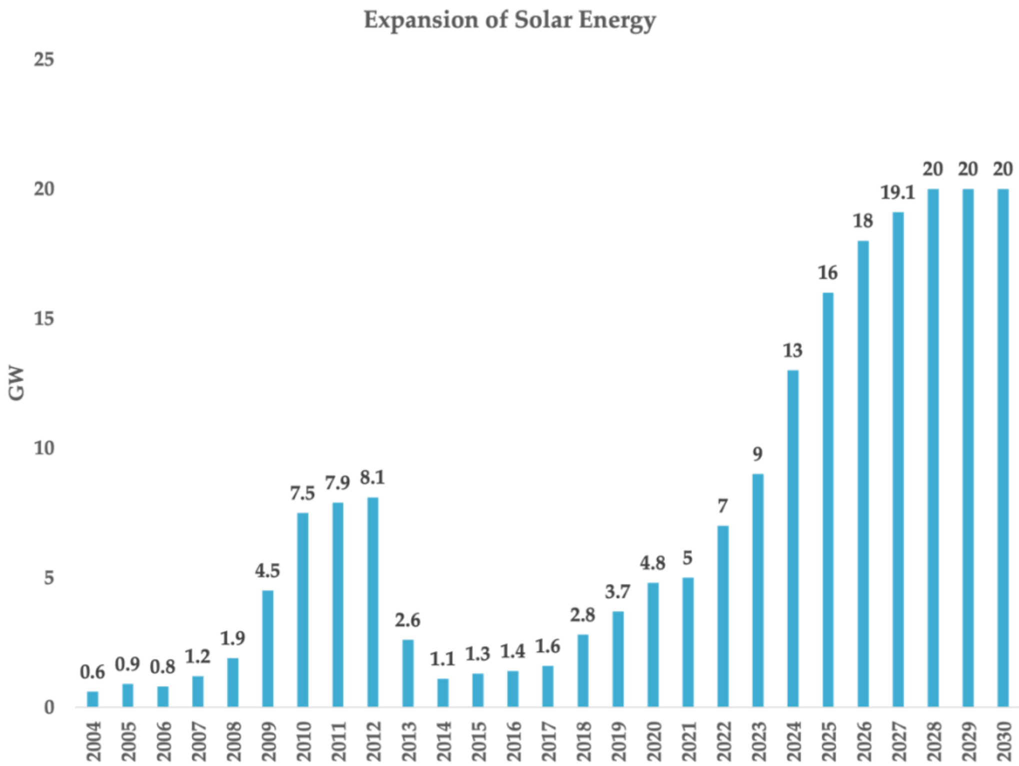

Figure 11-1: Addition of Solar Capacity in Germany

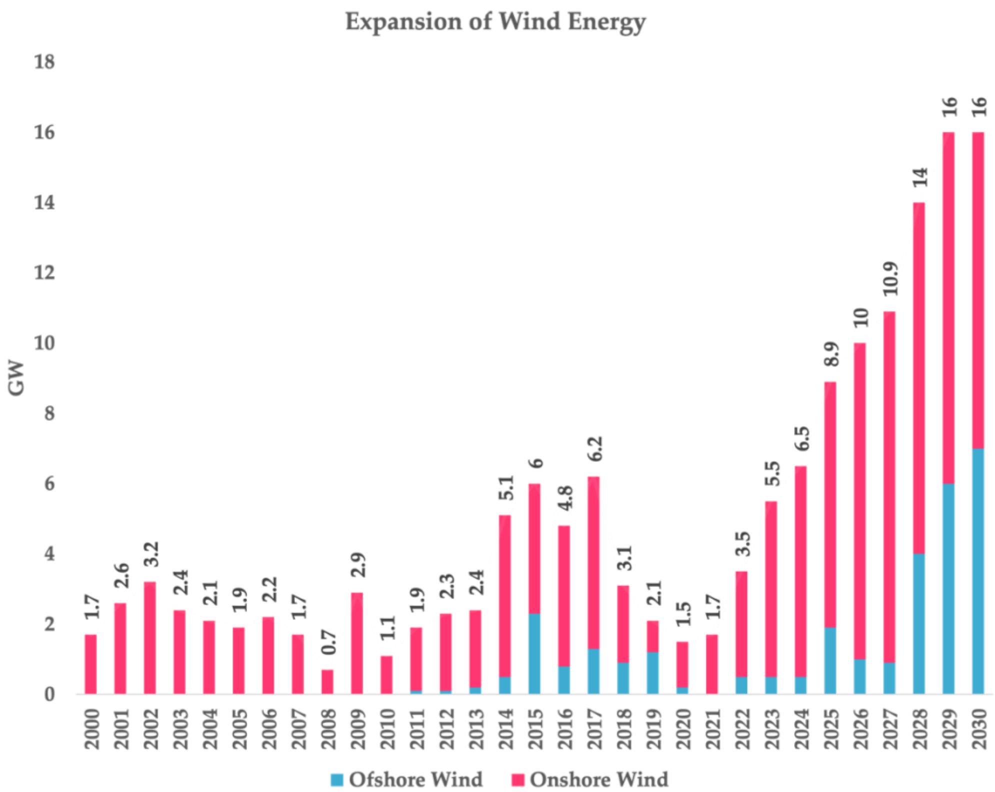

Figure 11-2: Addition of Wind Capacity in Germany

German Renewable Subsidy Schemes

Onshore Wind

Onshore wind newbuild is facing challenges in Germany. The difficulty in obtaining permits for the projects is leading to a decreased capacity of annual installed onshore wind plants. This has been mainly caused by the absence of unified regulations regarding species protection. The situation will stay the same unless the German government stipulates a common environmental standard.

The past onshore wind auctions have been persistently undersubscribed in the market. Therefore, for the future years, we expect that the advertised onshore subsidy volumes will not be all awarded to new plants. To take proper assumptions regarding the undersubscription phenomenon, the results from the past auctions have been examined and their summary is displayed in

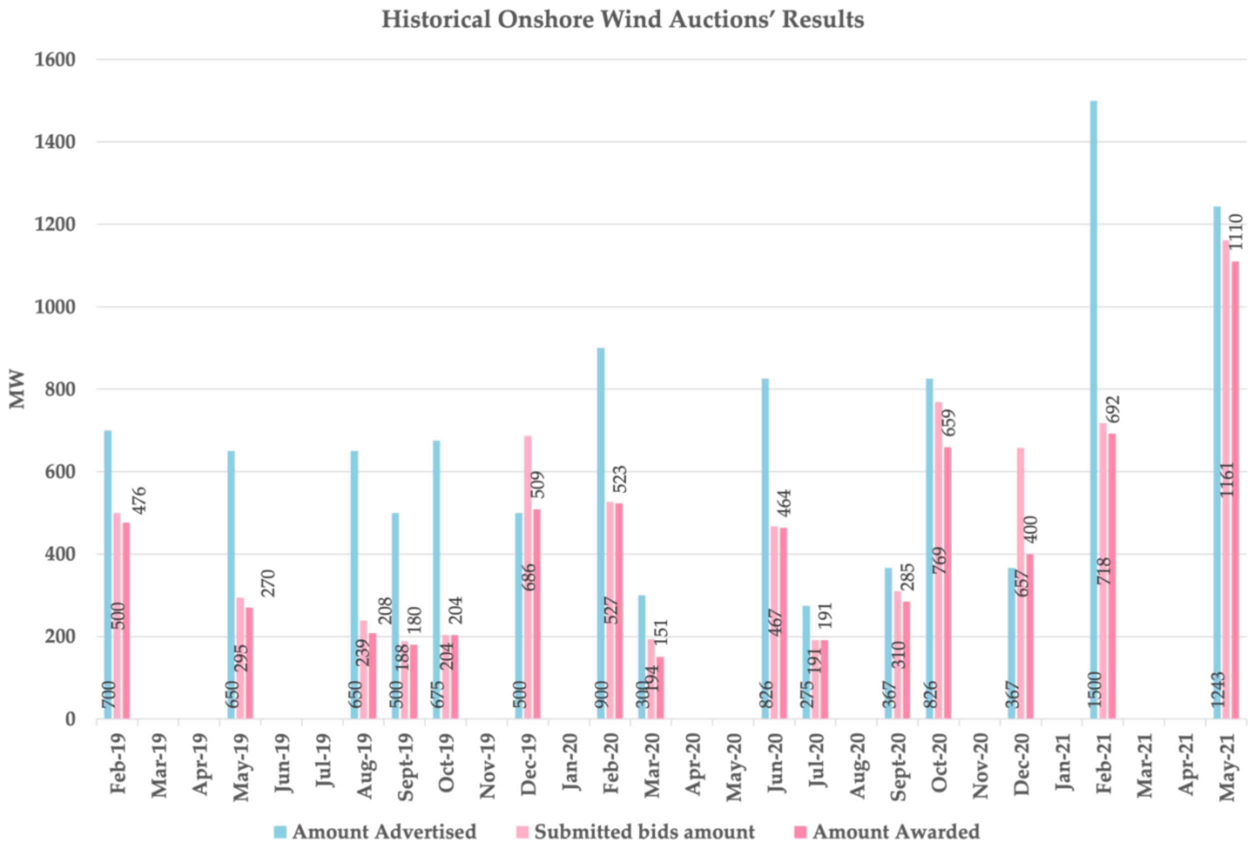

Figure 11-3: German Onshore Wind Auction Historical Results

All the auctions, except for the two taking place in December 2019 and 2020, are undersubscribed. In addition to that, we observe that not all bidding plants are awarded, since the awarded amounts are not equal to the submitted ones. This leads to the consideration that the auction amounts for onshore wind released by the Government for future rounds need to be adjusted to take into account this recurring phenomenon. Two scenarios emerge:

Scenario 1: Renewable newbuild is greater than the amount advertised
In this case, we need to consider the ratio between the amount awarded and the amount advertised which is the awarding rate relative to the amounts advertised and will be referred to as R_a. Indirectly, this also takes into consideration the undersubscription phenomenon of the auctions.

Scenario 2: Renewable newbuild is less than the amount advertised
This reflects the status quo in Germany which is facing delays in permitting and therefore reduction in newbuild of onshore wind farms. This is the main reason behind the undersubscription to onshore wind auctions. In this case, it is important to consider the ratio between the awarded bids to the submitted bids which is the awarding rate relative to the submitted ones which will be referred to as R_s. In this case, we take the assumption that all onshore newbuild will try to submit bids in the auctions.
Therefore, we need range values for two ratios that are included in the assumptions:

$$R_a = Awarded\ Bids \Big/ Amount\ Advertised$$

Equation 11-1: R_a Factor

$$R_s = Awarded\ Bids \Big/ Submitted\ Bids$$

Equation 11-2: R_s Factor

Both R_a and R_s are indirectly proportional to the supply volumes of PPAs. Therefore, the high scenario would be the one where those ratios are at their minimum observed values in the past recoded tenders and the low scenario would be when they are at their maximum since this refers to high volumes of subsidies which will lead to lower PPA volumes on the market. As for the reference case, it refers to when these variables are at their average values of the past. The data used to calculate the two parameters is found in Table G-2 of Appendix G.

The obtained values for each of the two parameters in three scenarios is found in the table below:

Onshore Wind Subsidies		
	Ra	Rs
High Case	30%	61%
Reference Case	63%	90%
Low Case	100%	100%

Table 11-1: Values of R_a and R_s

Offshore Wind

The past offshore wind auctions in Germany have been characterized as "zero-bid" auctions. Since 2018, zero cent bids were winning which means that offshore wind operators are capable of operating on the market without receiving any state support (Koch and Neumann, 2021). This case also prevailed in the most recent offshore wind auction, taking place in September 2021. The German offshore wind market is a "central model" where grid access is only guaranteed to awarded plants during auctions. This implies that even if the auctions remain at zero-bid level, which is the case, developers need to win in the auctions to be able to execute their projects.

For this assumption, we consider that till 2025, the commissioned assets will have the feed-in-tariff obtained from the Renewable Energy Sources Act (EEG). So, starting 2026, the amount of offshore wind subsidies becomes zero for newly built offshore wind installations.

Thus, even if the government has stated the capacity of future offshore auctions, this refers to the capacity that will be awarded as permits and grid connections, and we believe that zero-bids will continue to prevail on the market. For the purpose of our calculation, the supply in the PPA market will not be affected by such volumes, therefore, the future capacities (MW) of offshore auctions will be considered always to be zero beyond 22025.

Solar Photovoltaics

By examining the results of past solar tenders in Germany, we see that no correction factor is needed for this tender type since in all of the past solar tenders, the amounts that were advertised by the government were actually awarded("Bundesnetzagentur

- Solar Freifläche," 2022). Solar tenders witness the phenomenon of oversubscription, therefore we assume that this will continue also in the future.
In the case where the newbuild is less than the advertised amount, then we assume that all of the newbuild will get subsidies.

The future amount of subsidies to be awarded by the German government are given in Table 11-2 (Appunn, 2020):

Annual German RE Tender Volumes							
	2022	2023	2024	2025	2026	2027	2028
Onshore Wind (GW)	4.00	3.00	3.10	3.20	4.00	4.80	5.80
Offshore Wind (GW)	0.91	0.90	2.90	3.50	0.00	0.00	0.00
Solar PV (GW)	6.00	2.00	2.00	2.05	1.95	1.95	1.95
Innovation Tenders (GW)	0.60	0.60	0.65	0.70	0.75	0.80	0.85

Table 11-2: Future RE Tender Volumes in Germany

German pioneer installations

The German energy transition has been led by the feed-in tariffs introduced by the EEG in the year 2000. Under this scheme, renewable energy assets were guaranteed secure cash flows for a period of 20 years. Starting the end of 2021, such plants will gradually start losing this privilege due to the end of the 20-year defined period; hence, the operators need to find alternative ways to generate stable revenues. Even though these plants will still have grid priority, meaning that the grid operators need to give them preference into feeding to the network over conventional plants, some of their owners may decide to dismantle their assets. However, if the assets have not reached the end of their lifetime, owners have several possibilities to continue operation: repowering, direct marketing, PPAs, or community solutions (Appunn and Wehrmann, 2019).

Out of the 3,500MW of offshore wind losing their subsidy at the beginning of 2021, around 70% continued operation without applying to any support from the government and only 3% was dismantled (Appunn, 2021).
From the 70% continuing operation without subsidies, a portion will refer to repowering and direct marketing by selling the produced electricity directly on the electricity market while another portion will refer to a PPA to secure stable future revenues.
The wind turbines that were commissioned at the beginning of the EEG subsidy are mostly with low hub heights and low power class compared to the state of art technology. DENA Market Monitor 2030 results show that project developers estimate the share of capacities that could be repowered account for 20-50% of the post-EEG wind assets (Fischer and Ebner, 2019). For the remaining portion, PPAs can contribute to their continued operation. Experts surveyed by DENA assume that a high proportion of the wind sites cannot be repowered and will therefore refer to PPAs. Therefore, generalizing the scenario occurring in 2021 to future years, the following scheme is obtained:

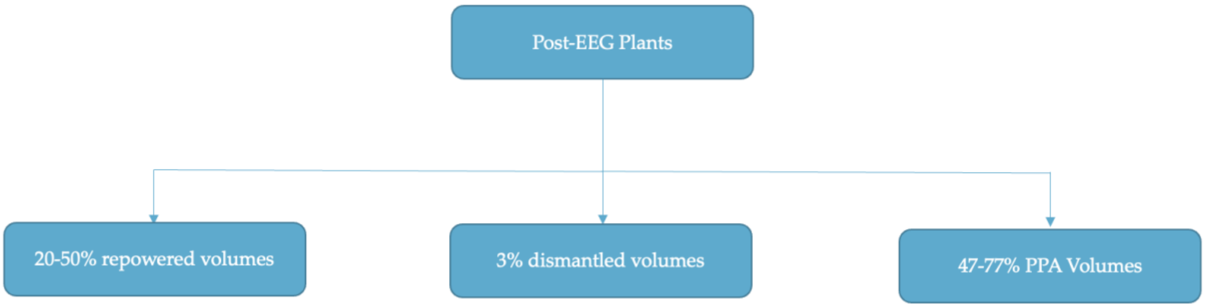

Figure 11-4: Post-EEG Plants

Hence, in the model, the dismantling percentage of post-EEG plants is considered to be constant at 3% per year in the upcoming years. To develop scenarios for post-EEG wind plants, the sensitivity is developed based on the percentage that will be signing a PPA. The low scenario emerges when 47% of the yearly assets dropping from EEG sign a PPA and the high scenario is when 77% sign one. The reference case is considering the average of the proposed range by DENA which would be 62% of wind assets yearly signing a PPA. According to the post-EEG cases that were advised by Pexapark, the annual load hours of such assets is lower than that of newly built wind farms. This fact is mainly due to the relatively older wind turbine models used. Hence, the load hours of post-EEG wind assets would be considered 1550 hours/year.

As for the solar post-EEG plants, mostly small installations (up to 100kW) will be the first to lose their subsidies in early years. Such plants could use storage solutions to increase the self consumption or seek the help of direct marketing companies. The new German law will continue supporting such plants by providing them with remuneration up till 2027 which is the difference between the market value and the marketing costs.

The graph in Figure 11-5 shows the size of the yearly installed PV plants in Germany. This will be used to estimate the percentage of the solar assets losing their EEG that will need a PPA (Tepper, 2016). The factor determining the need for PPA is the size of the plant since most of the plants installed in the early phases of the EEG were for prosumers who would consume a portion of the produced electricity. Therefore, these plants are too small to need a PPA. We can see on the graph that with the years, as the EEG was changed in favor of bigger plants who consequently became eligible for specific tenders, the percentage of installation of larger plants started increasing. From the size of past PPAs signed on the market, we can say that plants that are in the outermost sections, 100-1000kWp and >1000kWp, are the ones that refer to obtaining PPAs after their EEG drop off.

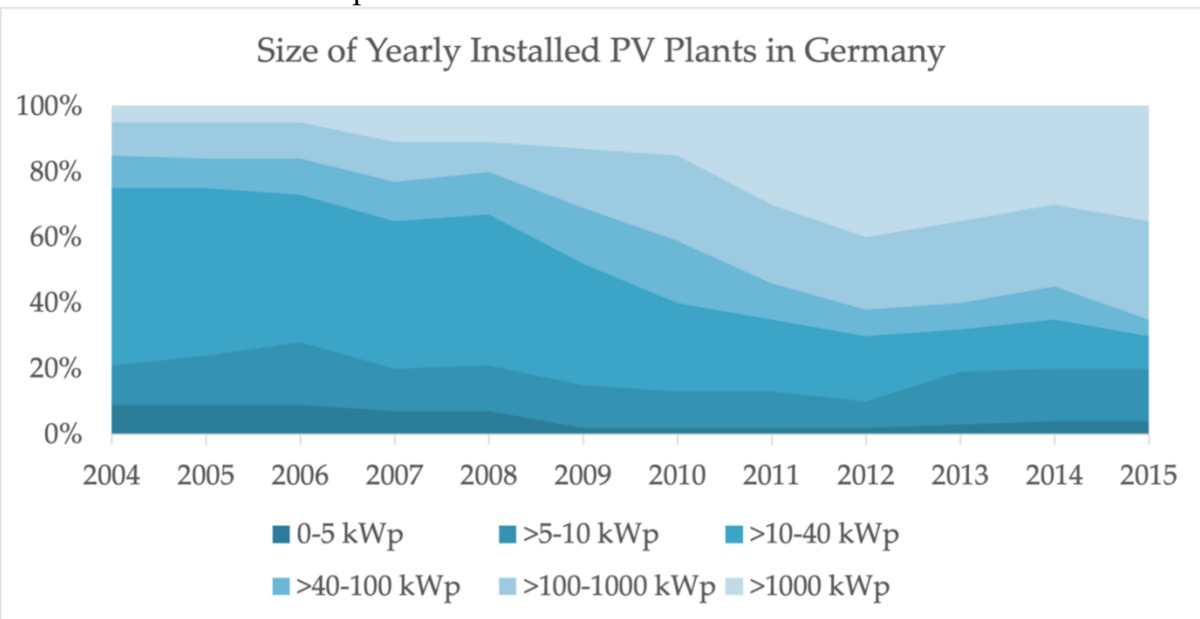

Figure 11-5: Post-EEG Solar Assets

To do a sensitivity on solar plants post-EEG, the high scenario is when all plants above 100kWp sign PPAs. The reference scenario is when half of plants above 100kWp sign PPAs and the low scenario is when only plants above 1000kWp seek PPAs. To get the various percentages, the average values from 2004 till 2006 were considered since those plants will be the ones losing their EEG by year 2026. This was done to avoid distortion caused by years beyond 2006 which witnessed a higher portion of plants with bigger size. For example, to get the percentage of post-EEG solar assets signing PPAs in the high case, the percentage of plants that are greater than 1000kWp was considered in each of the years from 2004 till 2006, and the average of those years was prevalent in future years. For solar post-EEG assets, the average load hours is assumed to be 800 hours/year.

The yearly capacity of assets losing their EEG subsidies is shown in Figure 11-6 (Appunn and Wehrmann, 2019) (Koptyug, 2022):

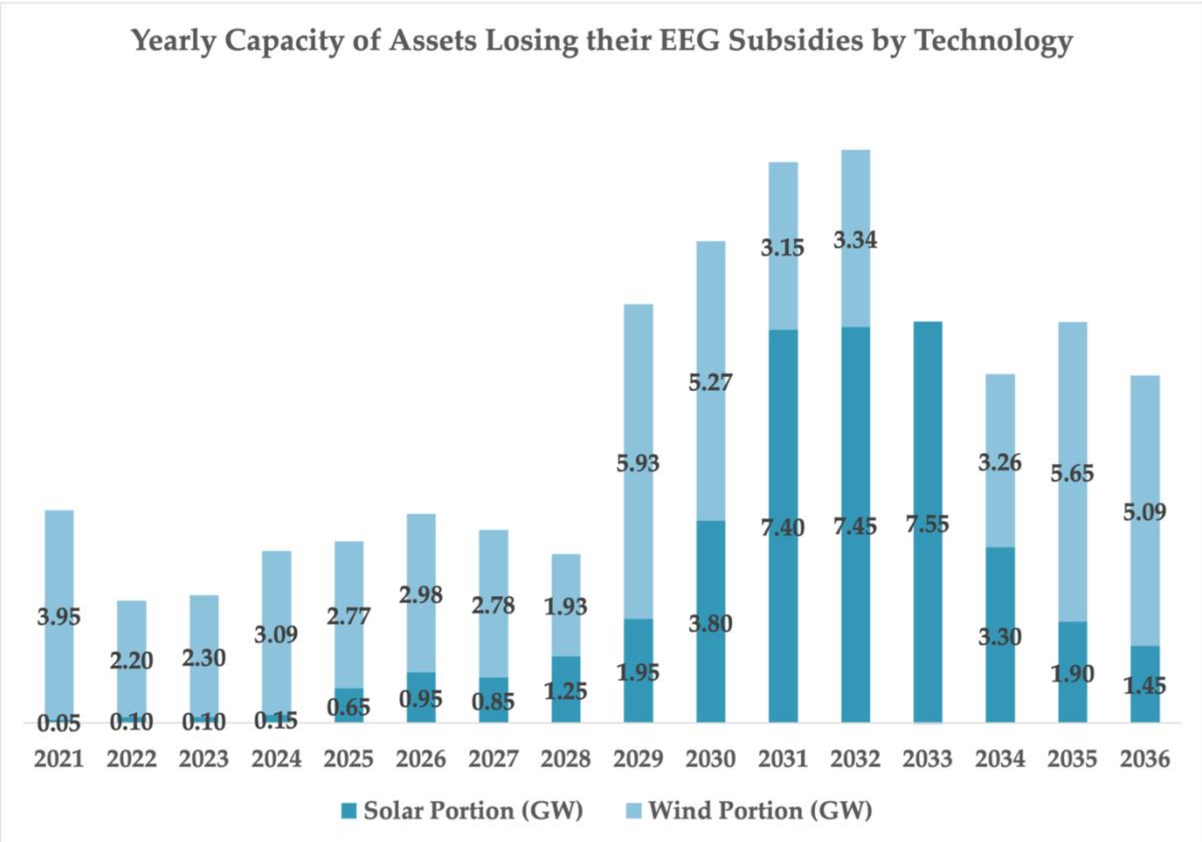

Figure 11-6: Yearly Capacity of post-EEG plants

The high and low scenario assumptions are applied to each technology to get the amount of PPAs. PV modules and wind farms have an average lifetime of 25-30 years (Kellenberg, 2021) (“Wind power,” n.d.). This should be considered when studying the second life of post-EEG plants. For all post-EEG assets, we assume that they operate on the market for around 5 years after losing their support. Therefore, in our analysis,

assets losing EEG will start to disconnect from the grid gradually starting year 2027, which is beyond the timeframe of forecasting.
Hence, the German Pioneer Installations form additional PPA volumes on the market, which do not come from renewable newbuild.

PPA DATABASE ANALYSIS

The last step in preparing for applying the scenario-building technique is to study the list of the past PPAs signed in the country in the years before. By examining the past deals, the average tenor of the PPAs is 10.14 years. This number is used to know approximately for how many years the future PPAs will be signed, and to be able to convert the deals from unit of power (MW) to a unit of energy (TWh) for the years following its signature. This allows the sizing of the market on a yearly basis.
In addition, with the help of the Quantitative Team at Pexapark, the average load hours of the different technologies in hours/year (h/year), in their different lifetime phases were identified and they are listed in Table 11-3:

	PV	Onshore Wind	Offshore Wind
Existing Assets Full Load Hours (h/year)	800	1550	3520
Newbuilt Assets Full Load Hours (h/year)	1000	2788	4500

Table 11-3: Average Load Hours of RE in Germany

In addition to the identified factors using the PPA database in Germany, the percentage of merchant assets signing a PPA should also be calculated. To do so, the data from 2018 to 2021 were used.
The model created for supply forecasting was built for the years mentioned, where starting from the renewable newbuild, the subsidies announced were corrected as suggested in this section and the high, low, and reference scenarios were obtained for the value of merchant volumes. Then, for each of the scenarios, the X value for each year was obtained by re-ordering Equation 10-2. Hence, for each scenario, a unique X value will be calculated for each historical year. The result is shown in Table 11-4.

Historical X Values				
	2018	2019	2020	2021
High Scenario	3%	7%	12%	7%
Reference Scenario	3%	8%	13%	7%
Low Scenario	3%	8%	15%	8%

Table 11-4: Historical X Values in Germany

To select the X values that lead to the most accurate results, back testing was used on the model. Considering each scenario, the highest, lowest and average X values were used and the obtained PPA volumes using the model were compared to the actual volumes on the market. For example, to test the results of the high scenario, X was taken as 12% in the high scenario, 3% in the low scenario and 5% in the reference scenario. Using the merchant renewable volumes calculated in an earlier step, the X values were plugged in the model to get the calculated PPA volumes. Then the calculated PPA volumes were compared to the actual recorded volumes using RMSE. The result was that the X values with lowest error were 12%, 5%, and 3%, which refer to the X values obtain in the high scenario. The RMSE obtained was 3 compared to an RMSE of 3.4 and 3.1 for the low and reference scenarios respectively. In addition, the coefficient of determination for the high scenario X values was 0.902. Hence, 12%, 5%, and 3% were used as X values to build the scenarios in forecasting.

11.2 Research for Demand Forecasting

Referring to Section 10.2, the starting point to forecast the future corporate demand of PPAs in a country is to analyze the historical deals and divide the players into their corresponding GICS industry group and sector. Hence, the following steps were done:

- Examine historical corporate PPA deals in Germany to classify the offtakers according to GICS
- For each of the top industries identified, use the respective RE100 industry to build the Sigmoid Function Describing the ideal yearly renewable energy goals
- Find the historical energy consumption of each top German industry and calculate its historical real renewable goal by using the PPA database.
- Compare the real yearly renewable goal to the ideal one obtained from RE100 to obtain the Correction Factor of each industry.

TOP OFFTAKER INDUSTRIES IN GERMANY

The list of past PPAs in Germany was examined and corporate offtakers were divided according to their relative industries according to the taxonomy proposed by the GICS. The top identified industries, along with some of the companies belonging to them, and their historical PPA purchasing are seen in Table 11-5:

Industry	Historical PPA Purchasing till 2021 (MW)	Company Examples
Transportation	554	Deutsche Bahn, MVV
Information Technology	400	Amazon, Google
Chemicals	349	Covestro, BASF
Automobiles and Components	130	Daimler, Mercedes Benz
Food and Staples Retailing	105	Nestlé, REWE Group
Wireless Telecommunication Services	60	Deutsche Telekom

Table 11-5: Top German PPA Offtaker Industries

Other industries active in the German PPA market are Metals and Mining and Professional Services. However, such industries were not considered in the forecasting of demand due to the absence of public data regarding their annual electricity consumption.

LOGISTIC SIGMOID FUNCTION

For each of the top industries identified in Table 11-5, the fitting using the Sigmoid Logistic Function was done based on the RE100 data. This allows to obtain a unique function that describes the behavior in terms of RE goals for each industry. In this section, the work done for the chemicals industry will be extensively described, to allow a deeper understanding of the methodology. As for the other industries, only the final results will be shown.

The RE100 companies belonging to the chemicals industry are Ajinomoto, AkzoNobel, Corbion, International Flavors and Fragrances, Koninklijke DSM, Sekisui Chemical Co, and TCI Co. As seen in Table G-3 in Appendix G, the chemicals companies in RE100 goals are listed in the table, and the years are indexed starting year 2015. Then for each year, the Y_{fit} is calculated using Equation 10-4: Modified Logistic Sigmoid Function, using the index of the year and the random constants (A,B and C) that are firstly chosen. Aftwerwards, the residual and residual squared are calculated for each data point. The final values of the constants are found by the Solver function in Excel by setting the objective to minimize the sum of residuals squared through changing the 3 constants values.

The final result would be an optimized Y_{fit} for each industry that fits the data with the least errors possible.

For example, the obtained function of the chemicals industry is plotted in Figure 11-7.

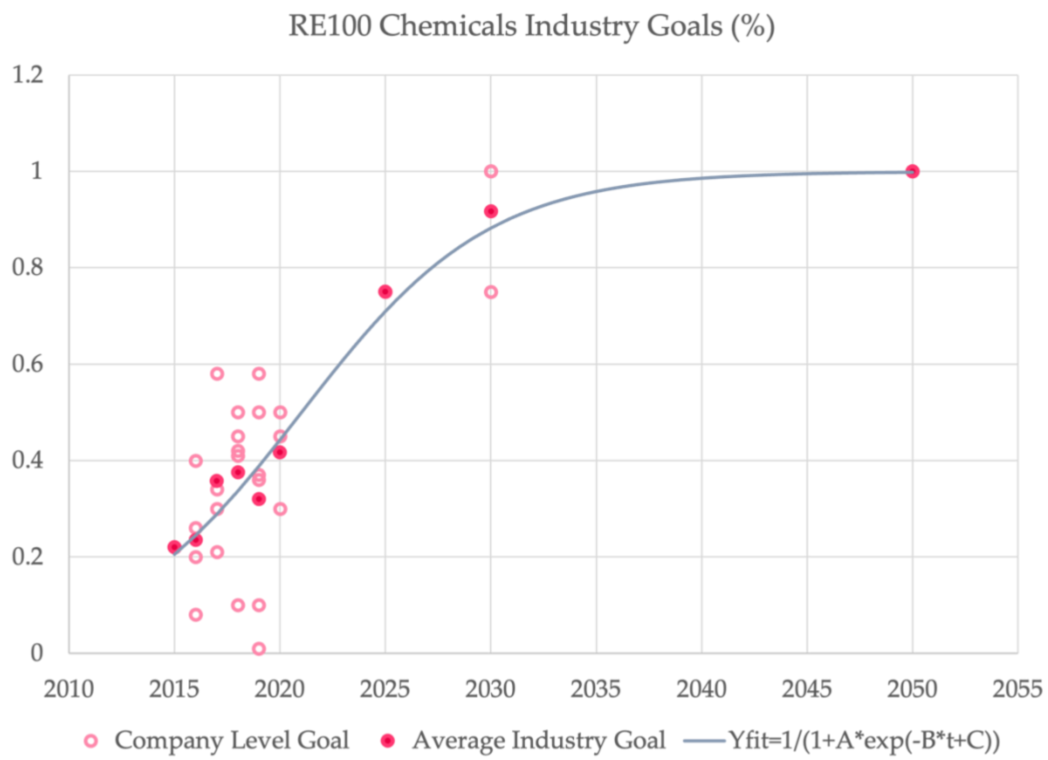

Figure 11-7: RE100 Chemicals Industry

We can see in the graph, the individual chemical companies' goals in the RE100, along with the yearly average industry goals, and the Y_{fit} line. The yearly Y_{fit} values reflect the RE goal that should be adopted by companies in the chemicals' industry to be behaving in the exact way as RE100 companies in the same industry.

The generated Y_{fit} functions of the other top industries were generated in the same method, and they are displayed in Figures 11-8 till 11-12.

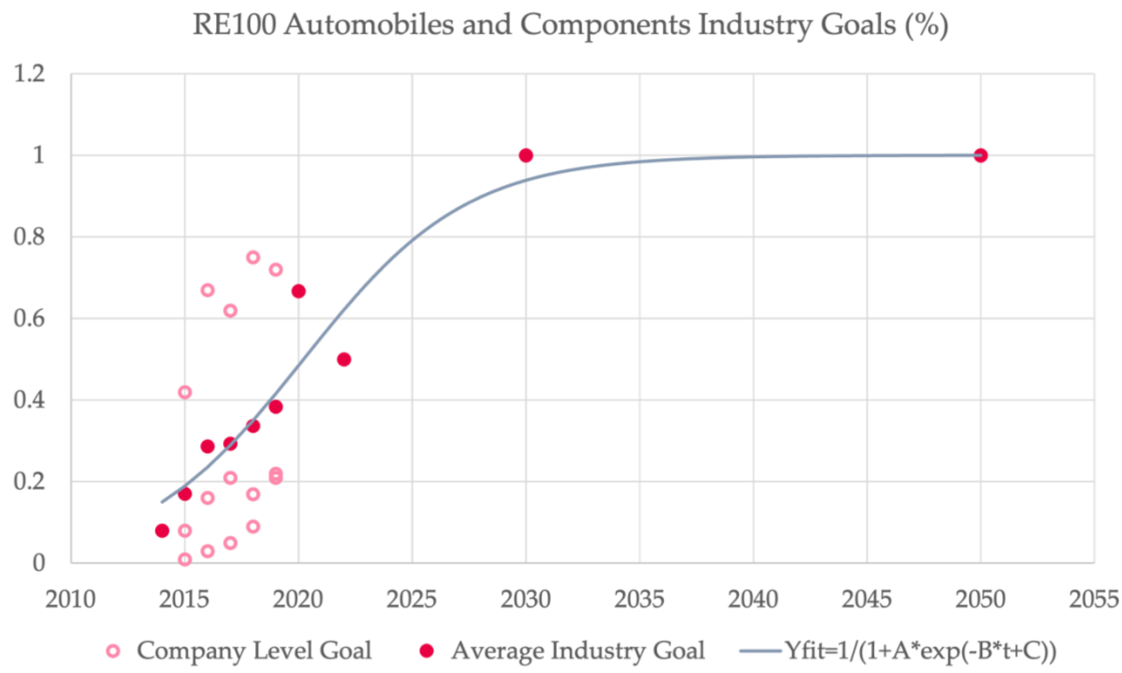

Figure 11-8: RE100 Automobiles and Components Industry

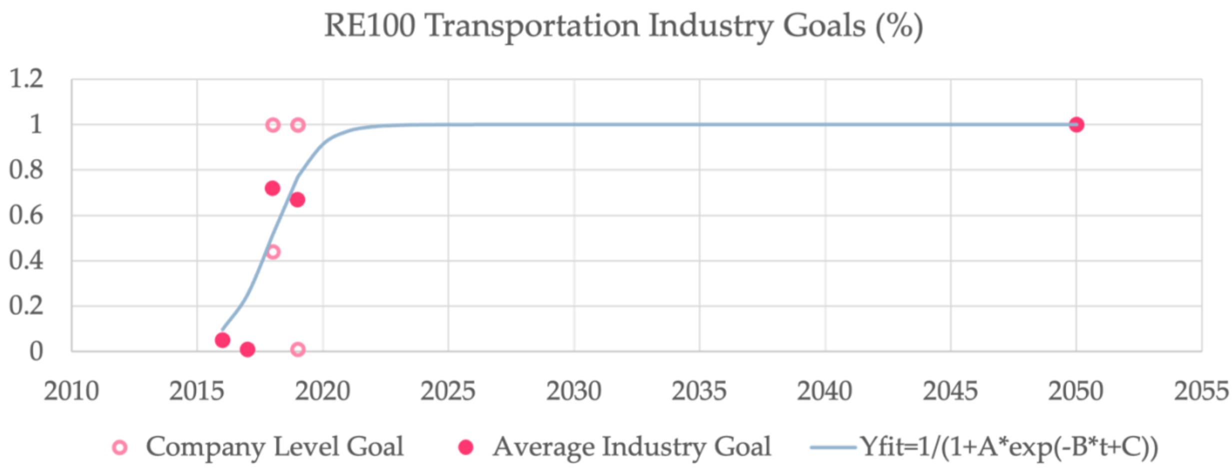

Figure 11-9: RE100 Transportation Industry

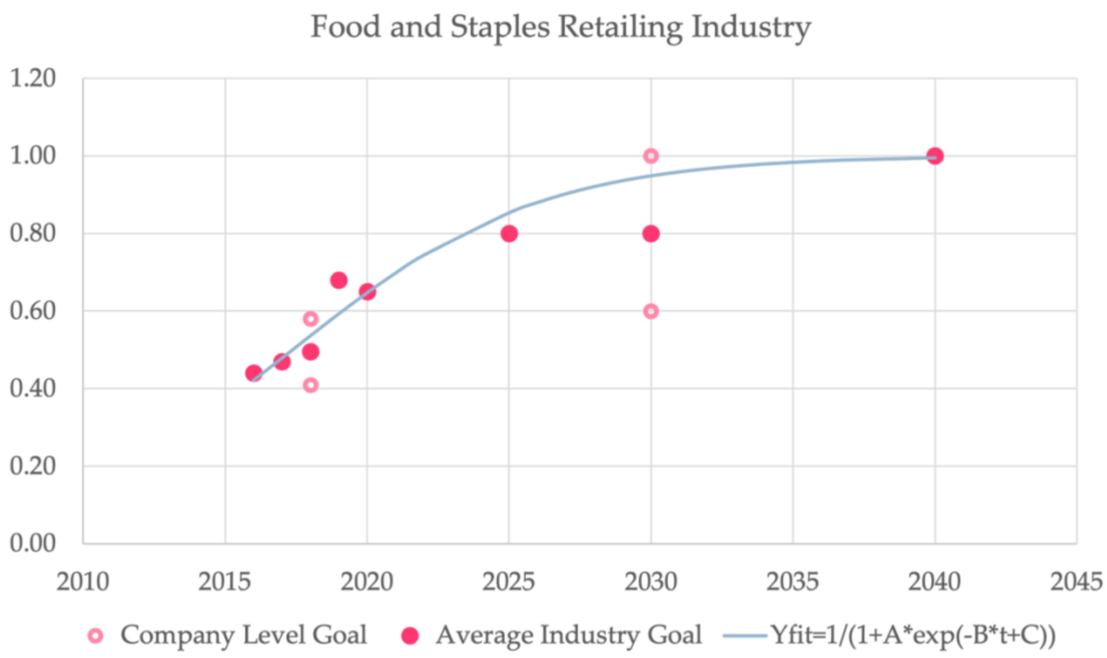

Figure 11-11: RE100 Food and Staples Industry

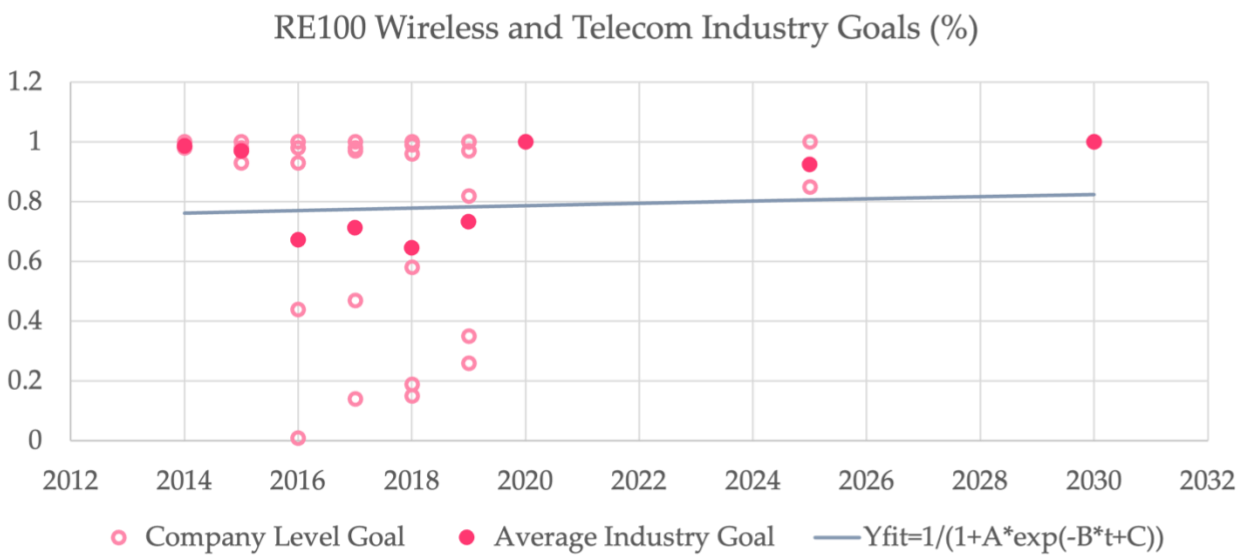

Figure 11-10: RE100 Wireless and Telecom Industry

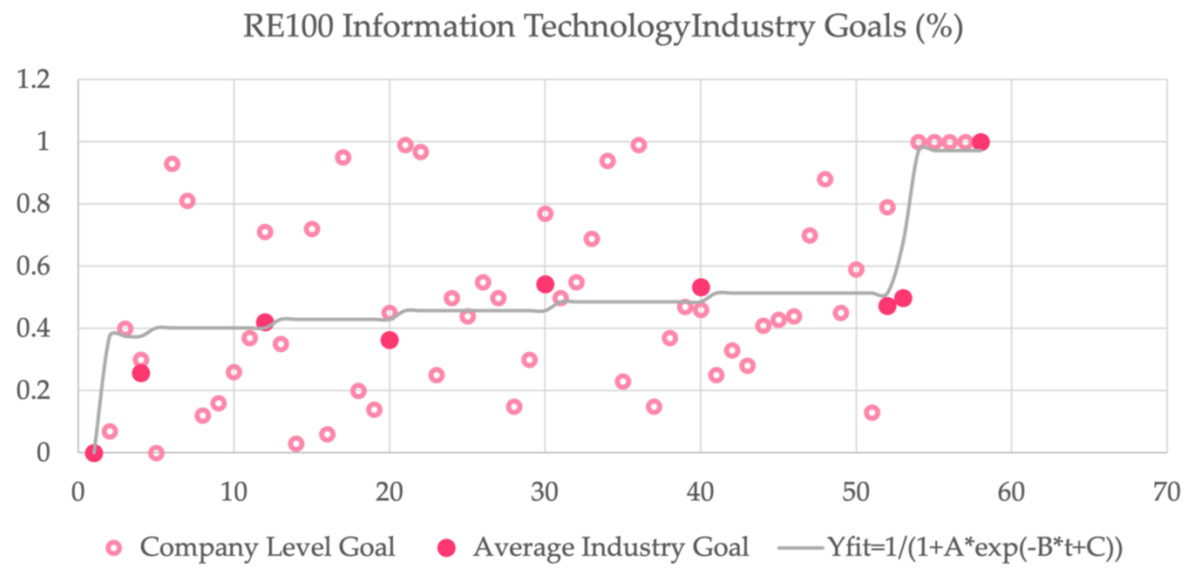

Figure 11-12: RE100 Information Technology Industry

It is evident that for some industries, a smoother curve is obtained, while for others the curve looks rather distorted with the absence of a clear trend. This is the case for Information Technology and Wireless and Telecommunications Industries. Two reasons lead to such fit lines: in the case of Wireless and Telecommunications, there is the absence of a large enough dataset which allows the smoothing of the curve, while for the Information Technology, there are a lot of companies belonging to this industry in the RE100 and each company has its own pace in decarbonization. Hence, the large discrepancies in the process of decarbonization of companies in the same industry lead to a non-smooth fitted curve.

Correction Factor

To complete the demand forecast analysis, a correction factor for each top German industry should be created which compares the green energy purchasing of the German industry to its respective RE100 industry RE goal. The process to calculate the CF for each industry is displayed in Table 11-6. The correction factor for each industry is the ratio of the publicly announced deals to the ideal PPA volumes that should have been purchased given the electricity consumption in the year studied. RE from the grid is obtained from the yearly data of the percentage of RE in the German electricity grid which is displayed in Figure 11-13. Also for the RE in grid mix, some datapoints were announced by the German government (*Eröffnungsbilanz Klimaschutz*, 2022) while others were fitted using the logistic sigmoid function.

Industry	Year (t)	Electricity Consumption (Y inTWh)	RE from grid (α)	RE100 Goal (ℬ)	ℬ - α	1- α	Ideal PPA Volumes (TWh)	Publicly Announced Deals (TWh)	Correction Factor
Wireless Telecommunication	2020	45.000	0.452	0.787	0.335	0.548	27.492	0.060	0.002
Automobiles and Components	2021	16.340	0.486	0.554	0.068	0.514	2.170	0.060	0.028
Food and Staples	2021	46.000	0.486	0.697	0.212	0.514	18.937	0.450	0.024
Transportation Infrastructure	2021	15.830	0.486	0.971	0.485	0.514	14.940	2.017	0.135
Chemicals	2019	51.560	0.418	0.388	-0.030	0.582	-2.694	0.450	1.000
Information Technology	**2020**	45.000	0.452	0.514	0.062	0.548	5.083	1.125	0.221

Table 11-6: CF Calculation Germany

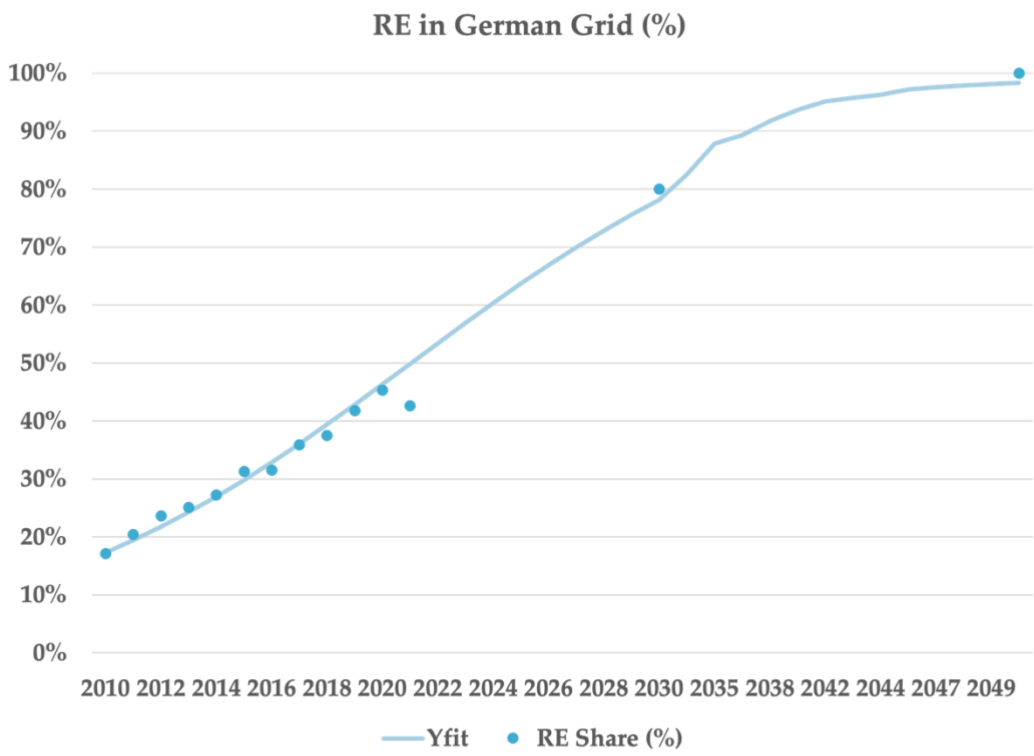

Figure 11-13: RE in German Grid Mix (%)

After the above calculations were done, the CF was adjusted for each industry to create the reference, high and low scenarios. As mentioned earlier, the low scenario is when the CF remains constant to its calculated value in Table 11-5 for each industry. The reference scenario is when for each industry, the CF for the 1st year of forecasting, year 2022, and then the CF increases linearly to become one in the last year of forecast, year 2027. A CF of 1 indicates that the German industry behaves in the same exact way as its respective RE100 industry. The high scenario, which is the least probable is that starting year 2022, the German industries will start behaving in the same way as RE100 companies, hence having a CF of 1 in all upcoming years.

11.3 Summary of Assumptions for German Market

The assumptions for the building of the scenarios on the side of demand and supply for Germany are listed below, along with the sensitivity value for each of the assumptions.

Assumptions for Supply Forecasting		
Onshore Wind Subsidies: Ra	High Scenario	30%
	Reference Scenario	63%
	Low Scenario	100%
Onshore Wind Subsidies: Rs	High Scenario	61%
	Reference Scenario	90%
	Low Scenario	100%
Merchant Assets Signing a PPA	High Scenario	12%
	Reference Scenario	5%
	Low Scenario	3%
Post-EEG Wind Assets Signing PPA	High Scenario	77%
	Reference Scenario	62%
	Low Scenario	47%
Post-EEG Solar Assets Signing PPA	High Scenario	47%
	Reference Scenario	16%
	Low Scenario	15%

Table 11-7: German Assumptions for Supply Forecasting

<table>
<tr><th colspan="3">Assumptions for Demand Forecasting</th></tr>
<tr><td rowspan="3">Correction Factor</td><td>High Scenario</td><td>1</td></tr>
<tr><td>Reference Scenario</td><td>CF of last year with available data increasing linearly to 1</td></tr>
<tr><td>Low Scenario</td><td>CF of last year with available data</td></tr>
</table>

Table 11-8: German Assumptions for Demand Forecasting

12. Scenario-Building Results' Discussion

In this section, the results of the scenario-building method of forecasting are illustrated and discussed. Firstly, the separate results of each demand and supply are seen with some conclusions; then, the comparison of the forecasted demand and supply is done to draw out the conclusions and insights regarding the future of the German PPA market.

12.1 German PPA Supply Forecasting

In forecasting the supply of PPAs in Germany, three scenarios emerged: high, reference, and low scenarios. Each of the scenarios has its own assumptions and considerations, therefore leading to differences in market size. The results of all the supply scenarios in terms of yearly additions in GW are presented in Table G-4 of Appendix G.

HIGH SUPPLY SCENARIO

The high supply scenario results in the highest yearly PPA supply volumes compared to the other two scenarios. It is not very far-fetched in Germany given the dynamics that were recently observed in its PPA market. The main challenges that need to be overcome to make the high supply scenario feasible are the local opposition against onshore wind projects, and the dismantling of post-EEG renewable assets. The results of the high supply scenario are displayed in

Figure 12-1. The graph shows the yearly accumulated supply from previous years, along with the yearly additional supply and the accumulated supply (in bold) which is the sum of the previous two values. In this scenario, by the end of 2022 the PPA market is expected to almost double in terms of the TWh sold on the market. To reach this size, the market should grow by around 4-6 GW of contracted capacity per year between years 2022 and 2027. This will result in a market volume of around 30 GW by 2027. This figure reflects a 10 times fold increase compared to end of 2021 values when the size of the German PPA market was around 2.5 GW. Although the results of this scenario appear to be rather high when compared to current market values, the German government could take several decisions to help achieve a growth trend similar to this one. The number of permits applications have witnessed a further decrease in the first quarter of 2022. However, an energy policy reform package has been suggested and will be debated in the German government to ensure the presence of enough permits and land for the further roll out of renewables, specifically onshore wind. The effect of this reform will start appearing in 2023, which might be a good signal for achieving the high supply scenario. Another action to be taken by the German regulators is to work on reducing the restrictive planning and the difficulty in obtaining licensing for post-EEG plants that wish to do repowering. This way, post-EEG plant operators can repower their old assets and search for potential buyers to sign a PPA with.

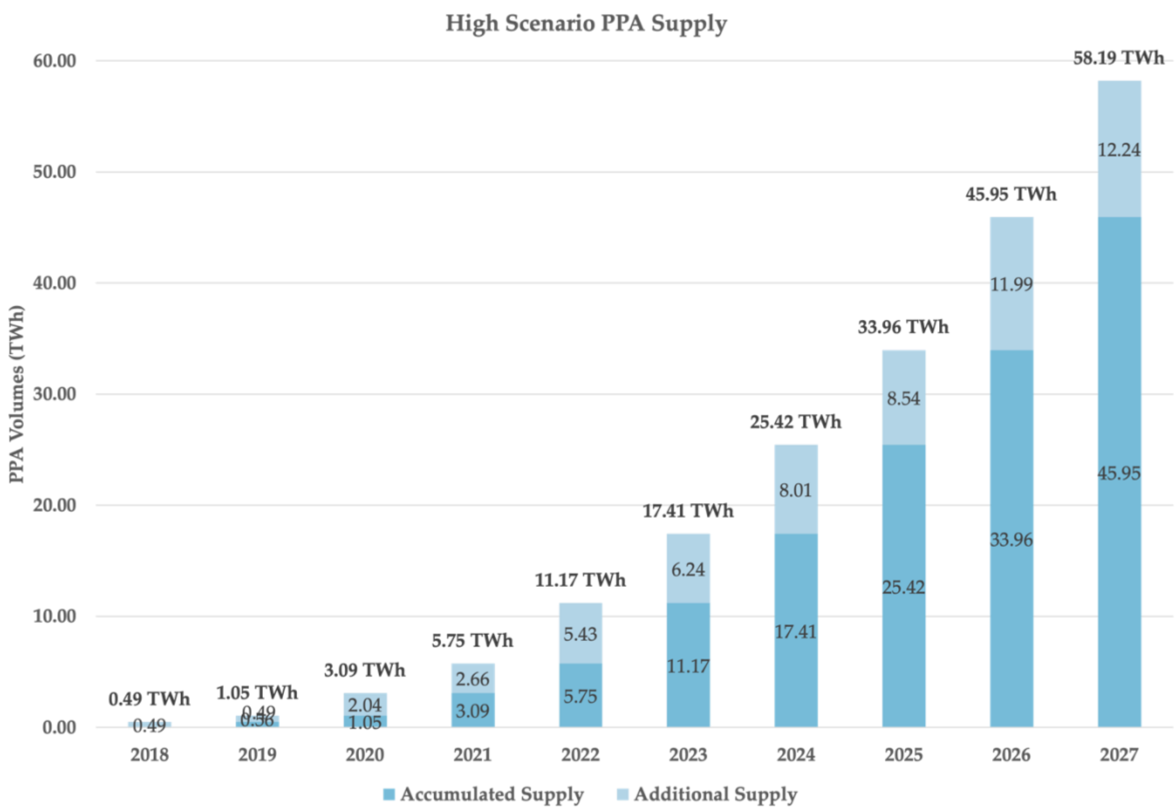

Figure 12-1: High Scenario PPA Supply Results

REFERENCE SUPPLY SCENARIO

Similar to what is observed in the high supply scenario, the volumes of contracted PPAs yearly additions tend to increase going towards the last years of the forecasts.

This observed trend emerges from the fact that the planned newbuild additions are increasing through time. In this scenario, the yearly PPA additions are in the range of 2-3GW leading to a PPA market size in 2027 of 17 GW. Compared to 2021 figures, this represents a 6-fold increase in the PPA contracted capacity. The reference scenario will evolve if the German government does not do any reforms to facilitate the onshore wind permitting process and, in the case, where less than half of the post-EEG wind farms will seek a PPA. Moreover, in this case, around half of the solar assets in the range of MW will sign a PPA rather than be merchant on the market. We can say that the reference scenario would prevail without any governmental interventions, however, to allow its prevalence market players should be aware of the potentialities that signing a PPA would bring to their assets. Hence, this scenario emerges only with proper awareness of the project developers of the PPA market dynamics, and the opportunities presented by it.

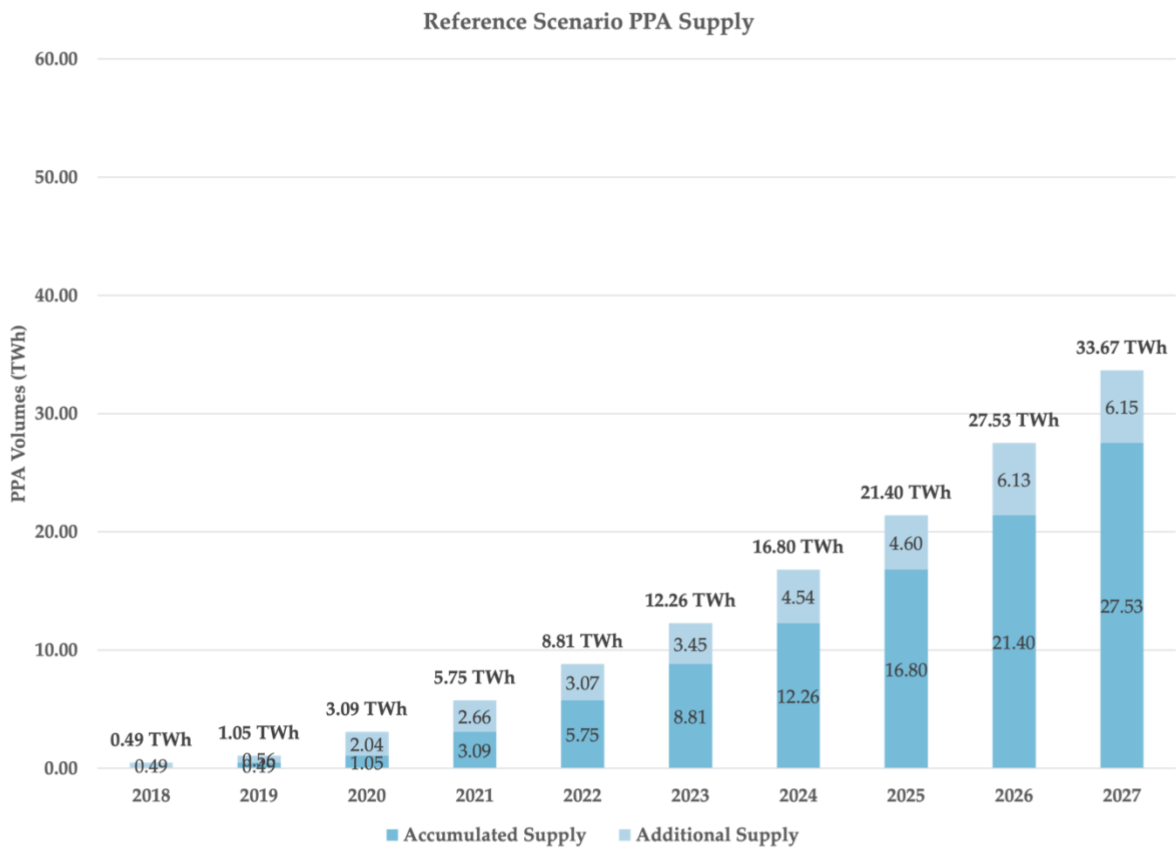

Figure 12-2: Reference Scenario PPA Supply Results

Low supply scenario

The low supply scenario is the worst scenario in terms of the evolution of the German PPA market. This case is characterized by both, the absence of the developers' awareness regarding the benefits of a PPA, and the absence of any governmental decisions and reforms to help the renewables and PPA markets in their further growth. In this case, the yearly growth in the PPA volumes in TWh is similar to what was seen in the previous years with around 2-3 TWh yearly growth. Only the years 2026 and 2027 represent a significant growth which is driven by the increased volumes of renewable newbuild. This scenario entails a 1-2GW yearly increase in the signed PPA capacity leading to a PPA market size of around 12 GW by 2027. In this case, the onshore permitting process problem is resolved, however, most of the onshore newbuild would be subscribing to governmental subsidies. This scenario reflects a PPA market size which is less than 34 TWh compared to the high scenario, representing an 18 GW of difference. The results of the low scenario highlight the importance of decreasing governmental subsidies as a way to allow the growth in the PPA market which will lead to the growth in the renewables market without high costs incurred on the government, and on the energy consumers in turn.

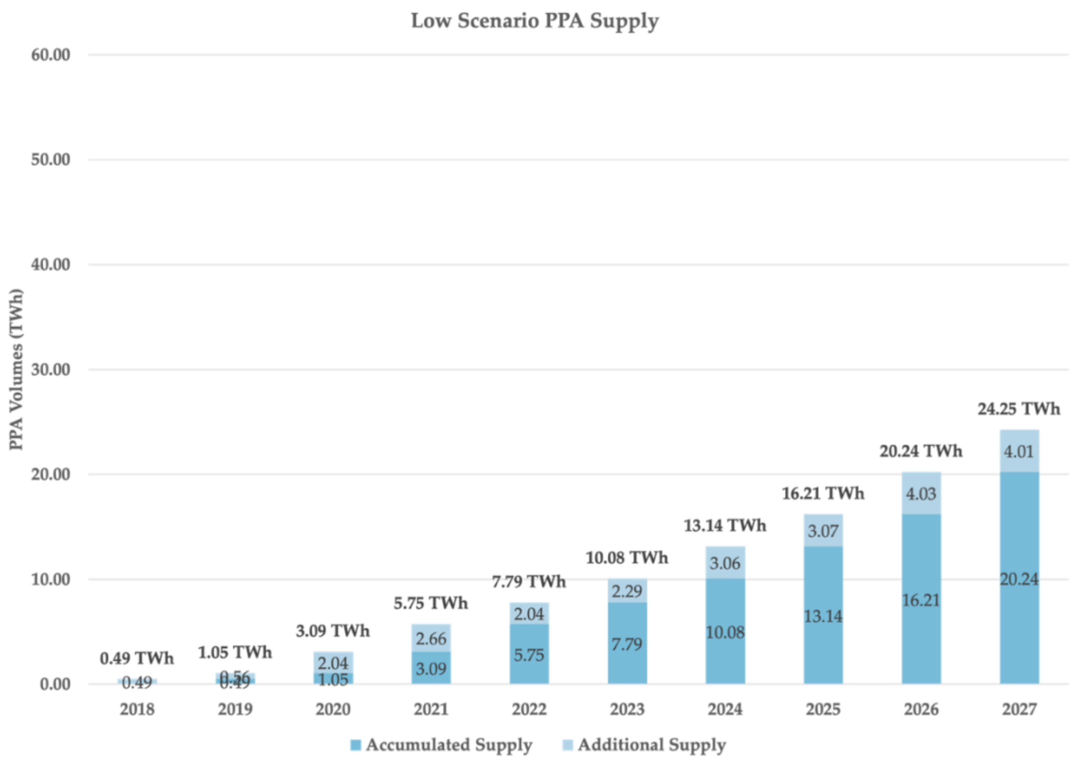

Figure 12-3: Low Scenario PPA Supply Results

12.2 German PPA Demand Forecasting

Also in the forecasting of the demand of PPAs in Germany, three scenarios emerged: high, reference, and low scenarios. Each of the scenarios has its own assumptions and considerations, therefore leading to differences in the demand of known corporate sectors active in the German industry.

HIGH DEMAND SCENARIO

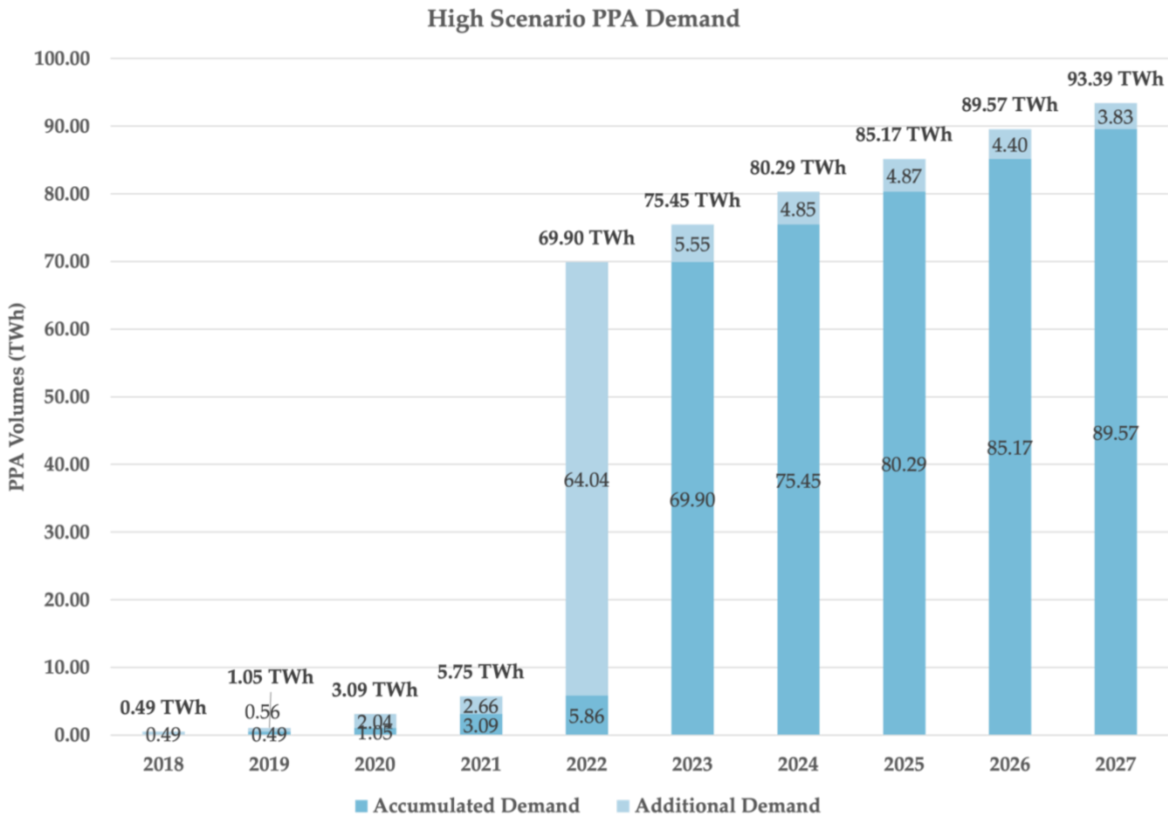

Figure 12-4: High Scenario PPA Demand Results

The high demand scenario represents the situation in which starting from 2022, the German sectors that were studied, which are the main corporate players in the PPA market, will shift their green energy purchasing habits to be coherent with the RE100 companies. This explains the 64.04 TWh of increase in purchasing in 2022, while in 2021 it was in the range of few TWh (2.66 TWh), representing an almost 64 TWh increase in market size by just one year. Although this scenario is ideal to reach climate neutrality, it appears to be out of reach. German corporate players could improve their green purchasing habits in the upcoming years; however, a sudden increase of this kind is most probably unattainable. Hence, this scenario represents an upper limit for the size of the German corporate PPA market in upcoming years till 2027.

REFERENCE DEMAND SCENARIO

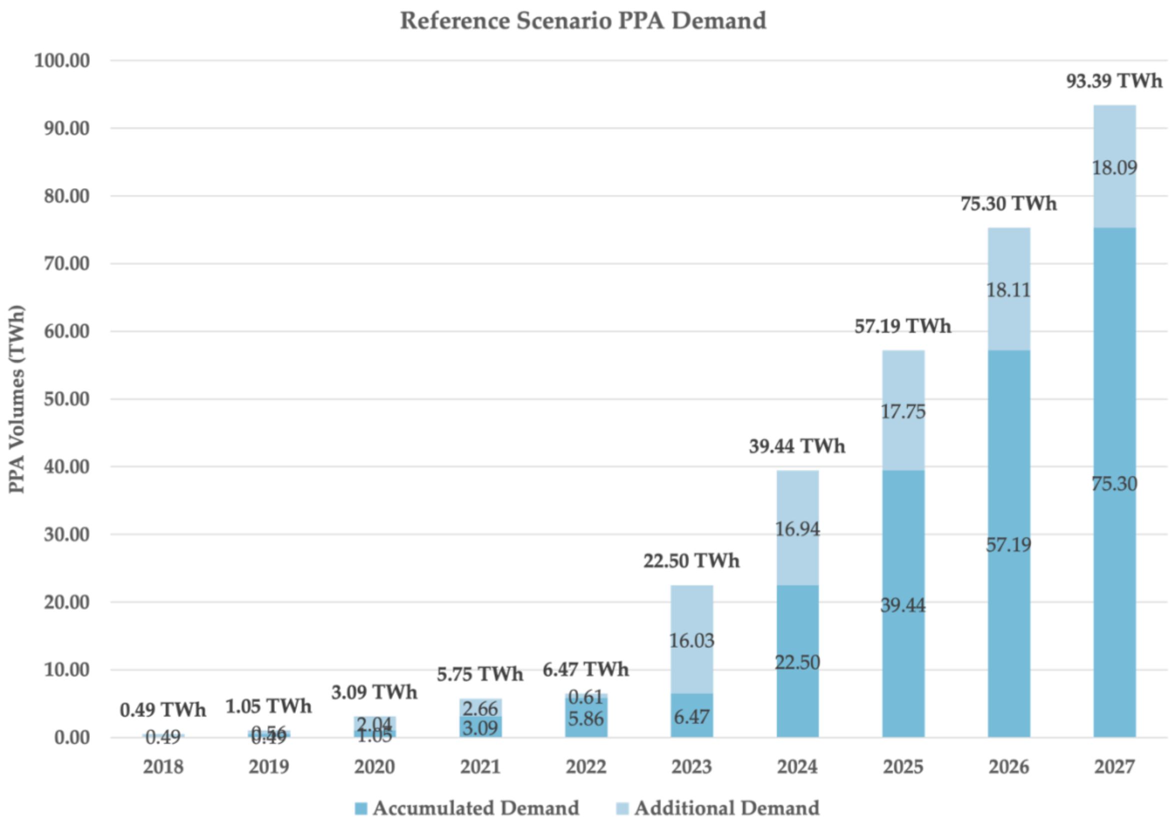

Figure 12-5: Reference Scenario PPA Demand Results

The reference scenario represents the case in which the corporate energy buyers in Germany will gradually improve their sustainable actions to finally meet the purchasing habits of the RE100 companies by 2027. In fact, for the year of 2027, both, the reference, and the high scenarios, have the same PPA market size of around 94 TWh. However, although this scenario also seems to be a positive one, it is more attainable compared to the high scenario due to the gradual growth in the demand through time. This scenario could be attainable especially if awareness is raised among industries highlighting the opportunities brought up by PPAs. In fact, PPAs ensure low and stable electricity costs with time, help industries to achieve lower cost of goods sold, and improve their green image which facilitates their financial procedures as banks are being more aware of such aspects.

LOW DEMAND SCENARIO

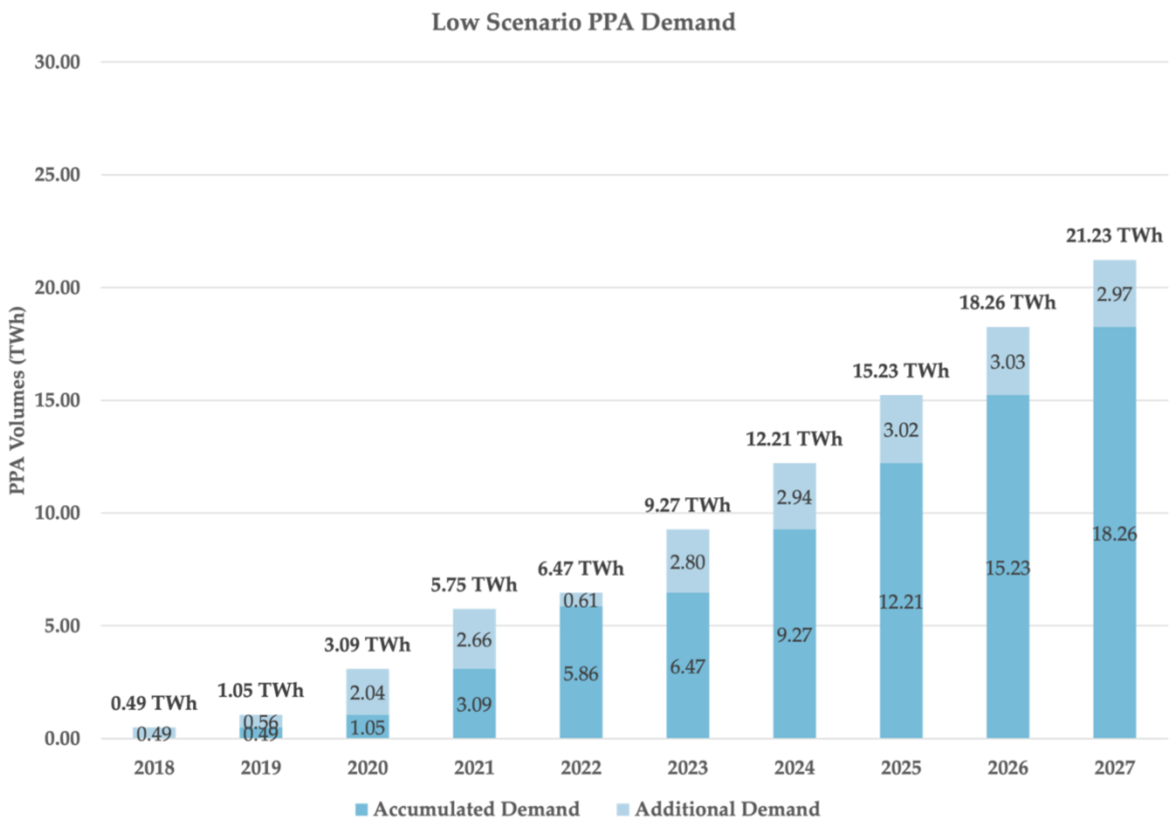

Figure 12-6: Reference Scenario PPA Demand Results

The low demand scenario will emerge if the corporate buyers in the German industry continue purchasing green energy following their past behavior observed. All industries, except for the Chemicals one, are still far from the commitment of the RE100 companies in reaching the target of 100% energy from renewables. In this scenario, the yearly increase in the PPA market volume is around 2-3 TWh per year which is comparable to the growth witnessed in the years of 2018 till 2021. This will lead to a PPA market size of around 21 TWh by year 2027 which is less than the other two scenarios by 72 TWh. This reflects the important role that corporate buyers have in facilitating the further expansion of renewables through purchasing their produced energy. We expect that the actual corporate purchasing in future years be somewhere between the low and reference scenarios as we expect more corporate players to be attentive to their image in terms of sustainability. This will be driven by the increasing restrictions imposed by financial institutions on companies who want to apply for loans, and by the increased customer concerns about green corporate image.

12.3 Discussion of Scenario-Building Results

In this section, the results of the supply and demand will be compared to draw conclusions on the evolution of the German PPA market. In each of the figures below, one case from the supply scenarios will be compared to the three possible evolutions of the demand.

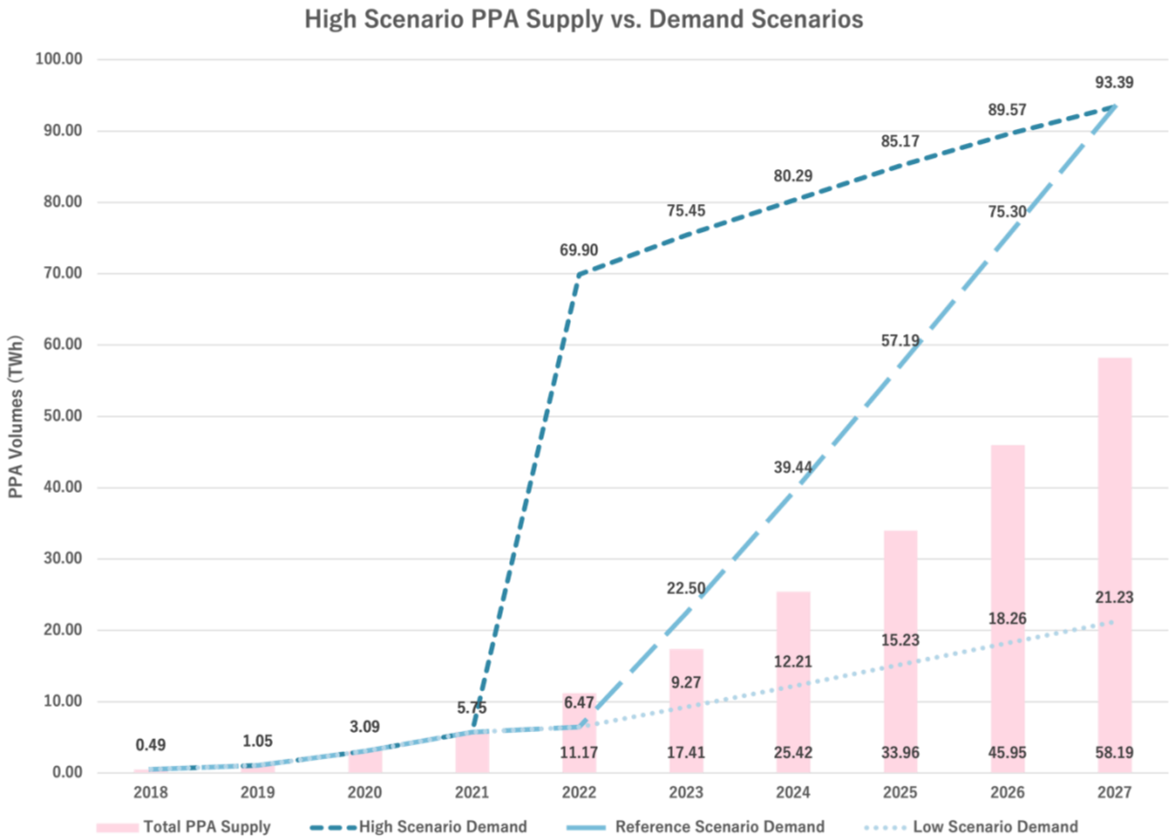

Figure 12-7: High Scenario PPA Supply vs. Demand Scenarios

In Figure 12-7, the high scenario of PPA supply is compared to the three demand scenarios. From the curve, we see that the only case where the corporate demand will be fully met by the supply volumes is when the corporates continue purchasing green energy following their past habits. In this case, the corporate players in Germany are still far from the RE100 performance. Hence, the PPA supply volumes will be partly supplied to corporate players, as seen in the graph, and the remaining supply volumes will be contracted by utilities. However, in the high and reference demand scenarios, the PPA supply volumes are not enough to cover the corporate needs. To mitigate this phenomenon, the German government could decrease the subsidy volume in upcoming years on the condition that the corporate contracting of PPAs is guaranteed. Otherwise, the governmental support will decrease, and no offtakers will be available on the market leading to unrealizable renewable projects. Moreover, if the corporate demand for PPAs increases and is not met by enough local PPA supply, then corporates will start looking for cross-border PPA deals to close. This negatively influences the German energy transition since its industries will be purchasing the needed green energy without supporting the local renewable projects. Hence, the German government should work in a dual mode, firstly decreasing subsidies while also incentivizing corporate players to enter into PPA contracts with developers.

As for the reference scenario for the supply which represents the current status of the PPA market in Germany, we see that also, only the low scenario of demand will be balanced by the needed volumes, Figure 12-8.

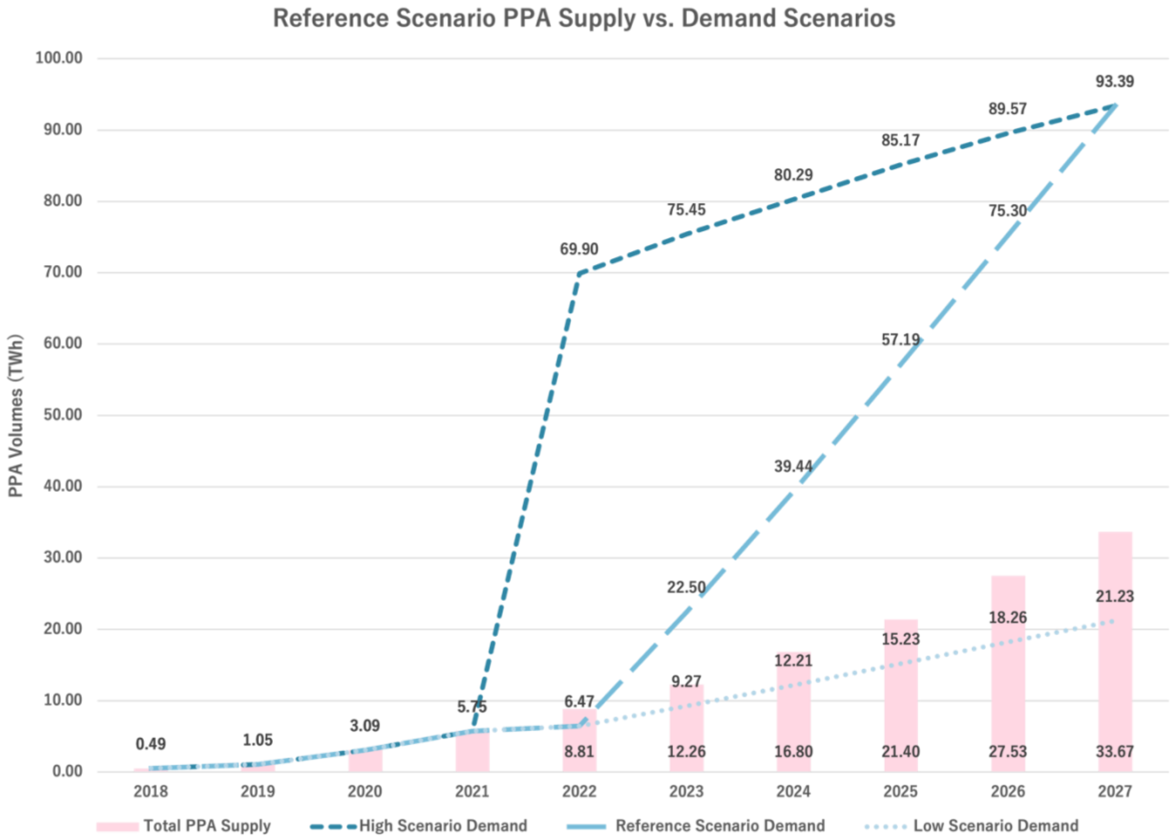

Figure 12-8: Reference Scenario PPA Supply vs. Demand Scenarios

In this case, the part of supply associated to utility players is limited, unlike the high scenario of supply, where this volume was greater. However, in this case, the gap between the supply and demand in the other two demand scenarios increases. The PPA market would be characterized by the high concentration of offtakers willing to purchase green energy, without having enough project developers supplying the required volumes. This has the potential of increasing the PPA prices observed on the market with the complete absence of cannibalization from renewable energy projects which might eventually push corporate players to pursue other actions to access to clean energy such as cross border PPAs, on-site renewable energy projects' development and creating industrial green energy communities. Such phenomenon ensure industries access green energy without actually contributing to the portion of grid electricity coming from renewables. To avoid the occurrence of such phenomenon, the German government could work on decreasing the renewable energy subsidies. This is true since subsidy support and PPAs appear to be mutually exclusive phenomena in most European markets. That is to say, when project developers ensure their access to governmental support, their interest in signing a PPA decreases. As a matter of fact, decreasing the renewable energy subsidies should not affect the development of such projects since most renewable technologies are reaching grid parity, given that the project is installed in a proper region with good capacity factor and production. In addition, the German government should work on decreasing restrictions related to onshore wind permitting and to the repowering of post-EEG plants to guarantee higher renewable volumes on the market. Decreasing the restrictions during permitting processes and gradually lifting the renewable subsidies will allow the proper balance in the German PPA market and ensure the country reaches its renewable targets.

Figure 12-9 shows the low supply scenario along with the various possibilities for the demand evolution. In this case, there is very low dependence from the side of developers on PPAs. A significant volume of both, newly built assets, and post-EEG either stays merchant on the market or benefits from governmental support. In this case, the onshore wind subsidies are fully subscribed to, which decreases the volumes of unsubsidized assets willing to sign a PPA. Moreover, post-EEG assets prefer to remain merchant on the market instead of looking for a corporate offtaker. The result would be a PPA market that barely satisfies the demand coming from corporates, with a very small capacity remaining for utility in PPAs. Hence, the market is undersupplied with green energy volumes. As for the reference and high demand scenarios, they are very far off from the market's ability to supply green PPAs. This will surely lead to companies looking for other means to ensure their green sourcing. The German government should work on avoiding the evolution of such supply scenario since it would be creating a renewable energy industry that is highly dependent on the subsidies which usually leads to increase in the electricity prices for end-consumers. In fact, all European countries are working on gradually lifting the subsidies off from renewable energy investments since such projects have continuously proven to be profitable without any external support.

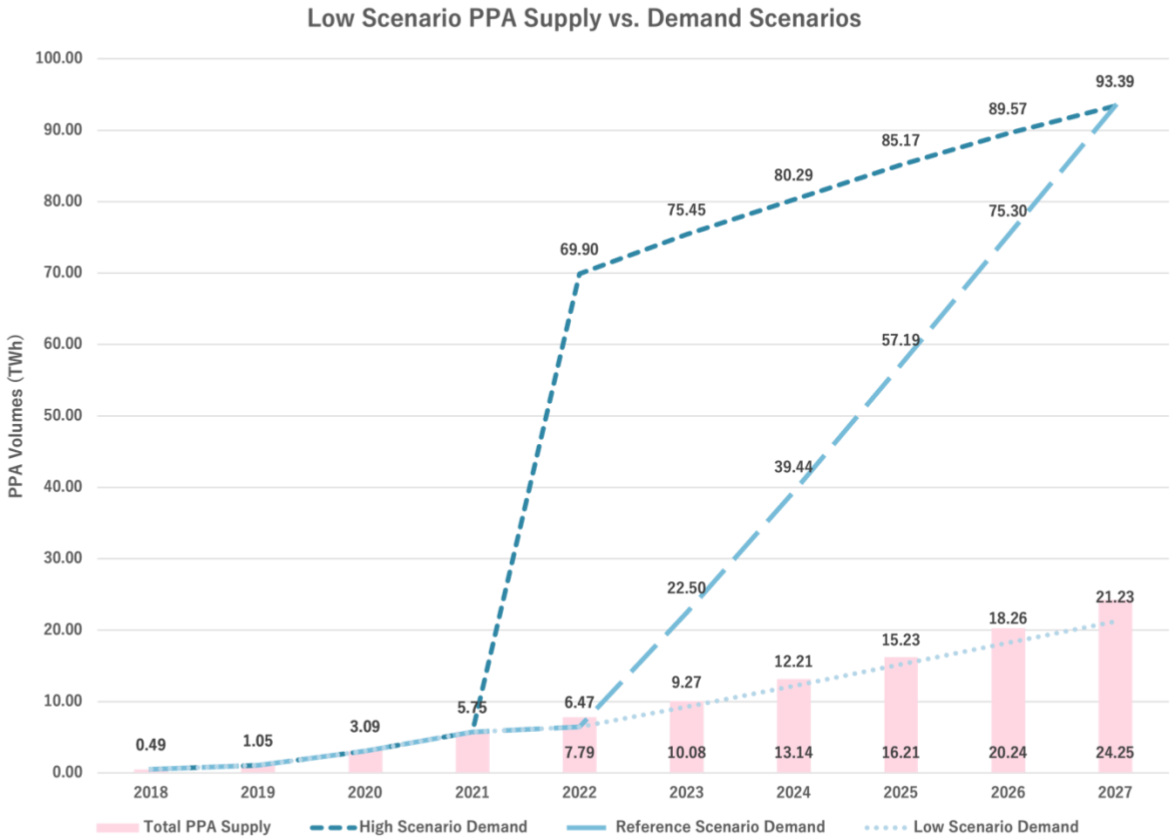

Figure 12-9: Low Scenario PPA Supply vs. Demand Scenarios

Hence, we can observe that in most cases, the German PPA market appears to be undersupplied with enough renewable volumes. In all supply scenarios, the corporate demand of PPAs, along with that of utilities is met by the local projects if the corporate green performance remains constant through time. However, in the cases where corporates gradually or abruptly increase their green energy purchasing, the local supply of renewable volumes appear to be insufficient, guiding companies into other forms of green electricity purchasing. The shortage in the supply of PPAs could be explained by the starting position of the German energy transition; eventhough the goals of year 2030 are very high in terms of renewable expansion, the current diffusion of renewables is still rather low, and it will take some years to be fully on track. This is best observable in the low scenario of the supply where the low scenario demand is barely met, especially in the front years of the forecast period. Considering the reference supply scenario which is the most likely to occur, we can see that the PPA market would be balanced if the industries continue purchasing at the same rate as in the past, or if only some industries work on improving their purchasing habits. However, only few volumes will be left to be purchased by utilities and it will be difficult for new players to enter the market due to the high concentration on the buying side, and the low availability of volumes on the supply side. This also highlights one of the major limitations of the analysis which is considering that all industries will equally grow in the future years, and not considering the possibility of new industries and players entering the PPA market. Those two phenomena will increase the corporate demand on PPAs and are a good justification for the high renewable goals set by the government.

Looking at the optimistic goals set by Germany, there are several considerations which should be highlighted that might delay reaching an 80% electricity consumption from renewable energy by 2030. An important problem is the lack of availability of space to accelerate the expansion of onshore wind. In order to make progress and reach Germany's goal of having 2% of its land covered by onshore installations, local authorities should loosen the regulations relating to the minimum distances, and this might take some time to be implemented. As for offshore wind the availability of tendering areas is essential to allow new projects to be developed. At the moment, offshore wind is competing with other forms of use of ocean floor; thus, Germany should give offshore wind turbines priority in the Exclusive Economic Zone (EEZ). And lastly, for solar projects, bureaucracy should be reduced to encourage the installation of solar plants on buildings. We can say that the scenario will only occur if actions and facilitations are taken on a national level to facilitate and encourage the renewable build out.

12.4 Extending the Analysis to Other Regions

With the proper research and proper application of experts' knowledge, the scenario-building technique could be extended to other European markets. Each market has its own characteristics and considerations that should be taken into account to be able to perform a proper forecasting exercise. Some of the main considerations for the major European PPA markets are listed in Table 12-1. The table only serves as a summary for the major aspects that the major European PPA markets are characterized with. However, if one wishes to re-apply the scenario-building technique to the countries mentioned below, more extensive research into its dynamics is required. The positive aspect which facilitates the forecasting procedure is the high similarity between various European countries, especially the neighboring ones. Hence, the research needed decreases as more countries are studied and introduced.

Market	Key Considerations
Spain	**Generation Tax Uncertainty:** Tax on the Value of production leading to an extra cost for all electricity producers. There are risks related to the changing in the value of the tax, or even its elimination which creates uncertainty in PPA contract terms.
	Future Auctions: The low bidding values seen in 2021 auctions have led to a change in offtaker pricing sentiment. Offtakers have revised their offer prices downward and were reluctant to sign a PPA as a rection to auction results.
	Saturation of Risk Appetite: Due to the significant amount of capture risk taken by offtakers, there is significant reduction in risk appetite of offtakers, especially in solar PPAs, which is leading to lower requested tenors.
	High presence of intrnational offtakers: The major driver behind recent deals is the non-local corporate procurement demand on a virtual basis in Spain.
Italy	**Permitting Delays:** The lack of permitted projects and the persistent permitting delays continue to negatively influence the PPA supply volumes.
	Low Presence of corrporate players: The local corporate market is largely inactive to date in Italy.
	Persistent Governmental Support: The government-backed auctions are the most viable route to the market for renewable investments and a strategic alternative to PPAs.
	High Cannibalization: The Italian market has relatively high cannbilization, especially regarding solar technology which affects the terms of the PPA negotiation.
France	**Persistent Governmental Support:** Developers can still access state-supportted mechanisms providing them favorable terms.
	High Future Corporate Appetite: Corporates are expected to increase ther uptake of PPAs to seek certainty in power supply as the next couple of years will witness knocking off of nuclear reactors.

	Post-Subsidy Assets: An additional PPA market is developing due to teh existing wind farms that are losng their subsidies and loooking for a short-term PPAs to cover the remainder of their lifetime.
Great Britain	**Increased Corporate Demand:** The corproate sustainability driven demand is expected to increase in upcoming years.
	Emergence of unsubsidized assets: The market has witnessed the first cases of subsidy free onshore wind, which is expected to increase in the future and increase the need for PPAs.
the Netherlands	**Concentration of offtakers:** The market is characterized by a wide pool of credit-worthy offtakers which are attracted to the country's developed infrastructure and competitive tax structure.
	Presence of energy-intensive industries: The netherlands is the hub for high-tech companies and chemical companieswhich are known for their ambitious renewable energy targets and high energy demand.
	Design of Governmental Support: The Dutch subsidy scheme systems (SDE++) is designed in a way to encourage the signing of PPAs between counterparties, making subsidies and PPAs not mutually exclusive.
	Innovative PPA structures: The market regulations encourage corporates to sign joint-PPAs hence allowing small to medium companies enter into such agreements.

Table 12-1: Key Characteristics of European PPA Markets

13. Conclusion

13.1 Research Contributions

The presented study attempts to make a contribution to the research gaps identified in the phase of literature review. Through the revision of literature, it was evident that not enough academic attention has been given to the topic of Power Purchase Agreements although such instruments have been playing a central role in achieving the European energy transition. Although several published research papers focus on solving forecasting problems focused on forecasting the future electricity consumption, the future production from renewable sources, and the future industrial consumption of electricity, forecasting the size of European PPA markets is not yet performed by any academic institution. Furthermore, there is the complete absence of a model that can predict both the demand and supply of PPA volumes. Such model has been mainly the interest of advisory and consulting companies which guide the decisions of renewable energy developers and energy buyers, whether corporates and utilities. Nevertheless, created models by such institutions are strictly confidential and not shared with the public. Even with clients, companies only share the results of their models without rigorously explaining the assumptions and mathematical considerations behind them due to the fear from competitors. Therefore, the focus in this research was to create a model that could predict the liquidity of PPA markets in European countries. To build an easily replicable model, the first focus was to create a model that requires minimum expert intervention. Such model would allow any party that is interested in the evolution of the PPA market in a certain European country to easily calculate it. In this regard, several linear regression and neural network models were introduced. The various models were built based on varying starting assumptions with the aim to identify the one with the most accuracy and lowest forecasting error. In general, building such models requires a big sized data set that would avoid overfitting and allow a fair split between testing and training subsets. This is one of the problems faced in building the two model types. The other issue faced was the absence of abundant data regarding the renewable energy market in some European countries. For example, there was clear absence of coherent LCOE data tracking in most countries, and the absence of clear roadmaps set by some countries regarding the future of renewable energy diffusion. The end result of the various trials to build a linear regression and neural network model was to obtain one most accurate model. A technology-neutral model formed at the European level turned out to be the most accurate forecasting model among all other linear regression and neural network models. This model is characterized with the highest coefficient of determination of 0.638 and an MAE of 0.081 meaning that the used independent variables predict around 65% of the variability in the PPA volumes with only 8% average error. Although this model had the best performance, comparing its forecasts to the actual PPA market volumes reflect an average predictability. The predicted future volumes are close to the actual ones, with some error that in some cases is negligible but in others no. One of the possible reasons for obtaining a relatively better performance in this model could be that the model was trained and tested using a considerably larger dataset compared to the other models. This was possible since the model was trained with data coming from all technologies in all European markets. Hence, this model can be used if one wishes to have a rough estimate of the size of the PPA market in a certain European market. The advantage of having such model is its ease of use where it can be used by individuals without the need of digging deep into the market under question. In addition, such model could be used to get rough estimates to help in guiding the governmental regulations on a high level. Moreover, it could be used by other researchers who wish to compare the evolution of different markets without studying the dynamics of each individually. After developing a high level model, a more accurate and more in-depth model was created to forecast the future size of PPA markets. The scenario-building technique was utilized to build two models: one to forecast the supply of PPAs and a second forecasting the corporate demand of PPAs. The main focus of the second model was on corporate PPAs due to the lack of persistent transparency from utilities regarding their energy purchasing activities. Each of the two models builds a high, low, and reference scenario for the parameter it wishes to forecast. The building of the scenarios is helpful since it allows the model to not only show the most probable outcome, but also the other outcomes which would result from some changes in the market dynamics. One of the drawbacks of building such models is the in-depth analysis for the market under study needed making the created model mainly a tool for experts, project developers, and knowledgeable corporate buyers. For example, project developers may wish to invest in markets where the corporate demand of PPAs is promising as this would guarantee the availability of potential energy buyers allowing the financing and execution of the project. In addition, the models forecasting the supply and demand could be utilized by governmental bodies to help steer their decisions to face some market challenges like the low concentration of potential buyers or the lack of abundance of PPA supply volumes. The supply-forecasting model starts from the governmental renewable energy targets and forecasted renewable support to predict the evolution of the PPA supply volumes. Nevertheless, a deep understanding of the past trends seen on the market are needed to build realistic scenarios that are not very far from the market reality. As for the demand forecasting, the scenarios are built based on the comparison

between the performance of top PPA offtakers industry in the market of study to their respective industry in the RE100 companies. In this regard, the RE100 companies are considered a benchmark whose performance is sought by non-RE100 companies. The result of the two models would be comparing the various demand and supply scenarios and draw conclusions on the best way to manage each of them in the future to ensure market balance and stability. The created models were created and tested on the German PPA market as it is one of the biggest PPA markets in Europe, and as the German Energy Agency (DENA) requested such analysis.
To conclude, on a high-level, two models were created to help in the analysis of future PPA markets. The first one is based on artificial neural networks and could be considered a quick tool to roughly assess the size of the PPA market in a certain European country. It is based on collecting some easily accessible parameters such as the wholesale electricity price, and the LCOE to get to the yearly PPA capacity. The other model is a more accurate and in-depth model that aims to forecast the yearly supply and demand of PPAs in a European country to better help in steering governmental decisions, developers' investments, and corporates' green purchasing. The two created models are complementary where one can be used when quick rough estimates of future PPA market capacity is needed while the other is utilized for more accurate results but with more computation time needed.

13.2 Limitations

The results of this research should be treated as a starting point towards the creation of predictive models to forecast the liquidity of European PPA markets. The main strength of this research is breaking the stigma of high confidentiality of market forecasting models due to the low concentration in the PPA advisory firms segment. Although the predicted models were created after one year of rigorous studies and analysis of European PPA markets through the internship at Pexapark, there are some limitations that were imposed by the nature of PPA markets. The lack of abundant public data and the infancy of the European PPA markets might have hindered the ability to obtain more accurate linear regression and neural network results. Future works might have larger datasets, along with more historical market data which would allow the building of more accurate predictive models. In addition, an increase in the historical data would allow the addition of more independent variables to better capture the variability of the PPA market size. Moreover, future work might improve the scenario-building methodology to decrease the interference of experts' opinion in the model's final results.

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s=B03&productionType.values=B04&productionType.values=B05&productionType.values=B06&productionType.values=B07&productionType.values=B08&productionType.values=B09&productionType.values=B10&productionType.values=B11&productionType.values=B12&productionType.values=B13&productionType.values=B14&productionType.values=B20&productionType.values=B15&productionType.values=B16&productionType.values=B17&productionType.values=B18&productionType.values=B19 (accessed 6.12.22).

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A. Appendix A: Literature Review Summary Table

Authors	Objective	Region of Analysis	Forecasting Model	Data Used	Forecasted Years	Reference
Felipe Leite, Coelho da Silva, Kleyton da Costa , Paulo Canas Rodrigues , Rodrigo Salas, Javier Linkolk López-Gonzales	Forecase Industrial Electricity Consumption	Brazil	Holt–Winters, SARIMA, Dynamic Linear Model, and TBATS, ARMA, Artificial Neural Networks	1979 - 2015	2019 - 2021	(Leite Coelho da Silva et al., 2022)
S.Sp.Pappas, L.Ekonomou, D.Ch.Karamousantas, G.E.Chatzarakis, S.K.Katsikas, P.Liatsis	Forecast Electricity Demand Load	Greece	ARMA	2004 - 2005	Backtesting	(Pappas et al., 2008)
Volkan Ş.Ediger, SertaçAkar	Forecast Primary Energy Demand by Fuel	Turkey	ARIMA	1950 - 2004	2005 - 2020	(Ediger and Akar, 2007)
Fazil Kaytez	Forecast Electricity Consumption	Turkey	ARIMA	2000- 2018	2019 - 2022	(Kaytez, 2020)
Lianyi Liu, Lifeng Wu	Forecast renewable energy consumption	Central Europe	Adjacent Non-homogeneous Gray Model	2008-2018	2019 - 2025	(Wu et al., 2013)
Jarosław Brodny, Magdalena Tutak, Saqib Ahmad Saki	Forecast renewable energy production	Poland	Artificial Neural Networks	1990-2018	2020 - 2025	(Brodny et al., 2020)
Nan Wei, Changjun Lia, Xiaolong Peng, Fanhua Zeng, Xinqian Luc	Review conventional models and AI-based models in	Global	Time Series Models, Regression	N/A	N/A	(Wei et al., 2019)

	energy consumption forecasting		Models, Gray Models			
Feng Song, Junxu Liu, Tingting Zhang, Jing Guo, Shuran Tian, Dang Xiong	Forecast Eletricity Consumption	City	Gray Model	2001-2011	Backtesting	(Song et al., 2020)

Table A-1: Literature Review Summary

B. Appendix B: Solar-Specific Model Data

1. Solar Raw Data

The following tables show the raw data that was used to build models that forecast the supply of solar PPAs in Europe. Data points not found are labeled as Data Not Found (DNF) while datapoints in grey imply that they were obtained in the data cleaning phase by either linear interpolation from surrounding years, or by assuming a constant value through time. The references used for Appendices B till E are listed at the end of Appendix E, in Section 3.

Solar Subsidies (GW)						
Year	**Germany**	**Great Britain**	**Spain**	**Italy**	**France**	**Portugal**
2017	0.60	DNF	DNF	DNF	DNF	0.00
2018	0.60	0.00	0.00	0.00	0.70	0.00
2019	1.48	0.00	0.00	0.01	0.50	1.30
2020	1.30	0.00	0.00	0.13	0.33	0.67
2021	1.85	3.50	2.90	1.04	0.64	0.26

Table B-1: Historical Solar Subsidies

Wholesale Electricity Price (Euros/MWh)						
Year	**Germany**	**Great Britain**	**Spain**	**Italy**	**France**	**Portugal**
2017	44.7	55.11	52.24	59.52	49.34	52.48
2018	37.6	69.29	57.29	61.53	116.1	57.45
2019	37.67	54.48	47.68	62.49	90.72	47.87
2020	30.47	43.96	33.96	51.07	74.01	33.99
2021	96.85	151.69	111.93	133.92	253.86	112.01

Table B-2: Historical Wholesale Electricity Prices

Solar LCOE (Eurocents/kWh)						
Year	**Germany**	**Great Britain**	**Spain**	**Italy**	**France**	**Portugal**
2017	4.29	9.50	10.00	DNF	DNF	DNF
2018	3.86	8.40	8.00	6.85	DNF	DNF
2019	3.90	8.20	4.90	6.11	DNF	1.47
2020	3.55	7.90	4.50	5.37	6.29	1.11
2021	4.57	7.80	3.90	4.63	6.29	3.62

Table B-3: Historical Solar LCOE

Solar Capacity Factor (%)						
Year	**Germany**	**Great Britain**	**Spain**	**Italy**	**France**	**Portugal**
2017	12.19	10.57	17.32	16.34	14.19	17.47
2018	13.07	11.11	16.34	14.7	13.89	16.45
2019	12.67	10.94	17.3	15.57	14.22	17.16
2020	12.67	11.24	20	15.57	14.65	17.16
2021	12.67	10.35	20	15.57	14.65	17.16

Table B-4: Historical Solar Capacity Factors

PPAs Signed (GW)						
Year	**Germany**	**Great Britain**	**Spain**	**Italy**	**France**	**Portugal**
2017	0	0	0	0	0	0
2018	0	0.16	0.40	0.12	0	0
2019	0.23	0.01	3.21	0.36	0.18	0.12
2020	0.62	0.05	1.80	0.07	0.13	0.11
2021	0.19	0.05	2.51	0.10	0.23	0.03

Table B-5: Historical Volumes of Solar PPAs

Solar Newbuild (GW)						
Year	**Germany**	**Great Britain**	**Spain**	**Italy**	**France**	**Portugal**
2020	4.81	0.24	2.80	0.63	0.16	DNF
2021	5.01	0.34	3.00	0.94	1.60	0.66
2022	7.00	2.00	5.50	3.00	2.96	0.66
2023	9.00	2.00	5.50	3.00	2.96	0.76

Table B-6: Historical Volumes of Solar Renewable Newbuild

2. Solar Trial 1

Country	LCOE (t)	Capacity Factor (t)	Wholesale Electricity Price (t-1)	Subsidy (t-1)	Newbuild (t+2)	PPA Signed (t)
Germany	3.86	13.07	44.70	0.60	4.81	0.00
Germany	3.90	12.67	37.60	0.60	5.01	0.23
Germany	3.55	12.67	37.67	1.48	7.00	0.62
Germany	4.57	12.67	30.47	1.30	9.00	0.19
Great Britain	8.20	10.94	69.29	0.00	0.34	0.01
Great Britain	7.90	11.24	54.48	0.00	2.00	0.05
Great Britain	7.80	10.35	43.96	0.00	2.00	0.05
Spain	4.90	17.30	57.29	0.00	3.00	3.21
Spain	4.50	20.00	47.68	0.00	5.50	1.79
Spain	3.90	20.00	33.96	0.00	5.50	2.51
France	6.29	14.65	90.72	0.50	2.96	0.13
France	6.29	14.65	74.01	0.33	2.96	0.23
Portugal	1.11	17.16	1.47	1.30	0.66	0.11
Portugal	3.62	17.16	1.11	0.67	0.76	0.03

Table B-7: Non-normalized Data Solar Trial 1

Wholesale Electricity Price (t-1)	LCOE (t)	Capacity Factor (t)	Subsidy (t-1)	Newbuild (t+2)	PPA Signed (t)
0.49	0.39	0.28	0.41	0.52	0.00
0.41	0.39	0.24	0.41	0.54	0.07
0.41	0.34	0.24	1.00	0.77	0.19

0.33	0.49	0.24	0.88	1.00	0.06
0.76	1.00	0.06	0.00	0.00	0.01
0.60	0.956	0.09	0.00	0.19	0.02
0.48	0.94	0.00	0.00	0.19	0.02
0.63	0.54	0.72	0.00	0.31	1.00
0.52	0.48	1.00	0.00	0.60	0.56
0.37	0.39	1.00	0.00	0.60	0.78
1.00	0.73	0.45	0.34	0.30	0.04
0.81	0.73	0.45	0.22	0.30	0.07
0.01	0.00	0.71	0.88	0.04	0.04
0.00	0.35	0.71	0.45	0.05	0.01

Table B-8: Normalized Data Solar Trial 1

3. Solar Trial 2

Country	Wholesale Electricity Price (t)	LCOE (t)	Capacity Factor (t)	Subsidy (t)	Newbuild (t+2)	PPA Signed (t)
Germany	37.60	3.86	13.07	0.60	4.81	0.00
Germany	37.67	3.90	12.67	1.48	5.01	0.23
Germany	30.47	3.55	12.67	1.30	7.00	0.62
Germany	96.85	4.57	12.67	1.85	9.00	0.19
Great Britain	69.29	8.40	11.11	0.00	0.24	0.16
Great Britain	54.48	8.20	10.94	0.00	0.34	0.01
Great Britain	43.96	7.90	11.24	0.00	2.00	0.05
Great Britain	151.69	7.80	10.35	3.50	2.00	0.05
Spain	57.29	8.00	16.34	0.00	2.80	0.40
Spain	47.68	4.90	17.30	0.00	3.00	3.21
Spain	33.96	4.50	20.00	0.00	5.50	1.79
Spain	111.93	3.90	20.00	2.90	5.50	2.51
France	74.01	6.29	14.65	0.33	2.96	0.13
France	253.86	6.29	14.65	0.64	2.96	0.23
Portugal	47.87	1.47	17.16	1.30	0.66	0.12
Portugal	33.99	1.11	17.16	0.67	0.66	0.11

Portugal	112.01	3.62	17.16	0.26	0.76	0.03

Table B-9: Non-normalized Data Solar Trial 2

Wholesale Electricity Price (t)	LCOE (t)	Capacity Factor (t)	Subsidy (t)	Newbuild (t+2)	PPA Signed (t)
0.03	0.38	0.28	0.17	0.52	0.00
0.03	0.38	0.24	0.42	0.54	0.07
0.00	0.33	0.24	0.37	0.77	0.19
0.30	0.47	0.24	0.53	1.00	0.06
0.17	1.00	0.08	0.00	0.00	0.05
0.11	0.97	0.06	0.00	0.01	0.00
0.06	0.93	0.09	0.00	0.20	0.02
0.54	0.92	0.00	1.00	0.20	0.02
0.12	0.95	0.62	0.00	0.29	0.12
0.08	0.52	0.72	0.00	0.32	1.00
0.02	0.47	1.00	0.00	0.60	0.56
0.36	0.38	1.00	0.83	0.60	0.78
0.19	0.71	0.45	0.09	0.31	0.04
1.00	0.71	0.45	0.18	0.31	0.07
0.08	0.05	0.71	0.37	0.05	0.04
0.02	0.00	0.71	0.19	0.05	0.04
0.37	0.34	0.71	0.08	0.06	0.01

Table B-10: Normalized Data Solar Trial 2

4. Solar Trial 3

Country	Wholesale Electricity Price (t)	LCOE (t)	Capacity Factor (t)	Subsidy (t-1)	Newbuild (t+1)	PPA Signed (t)
Germany	37.67	3.90	12.67	0.60	4.81	0.23
Germany	30.47	3.55	12.67	1.48	5.01	0.62
Germany	96.85	4.57	12.67	1.30	7.00	0.19
Great Britain	54.48	8.20	10.94	0.00	0.24	0.01

Great Britain	43.96	7.90	11.24	0.00	0.34	0.05
Great Britain	151.69	7.80	10.35	0.00	2.00	0.05
Spain	47.68	4.90	17.30	0.00	2.80	3.21
Spain	33.96	4.50	20.00	0.00	3.00	1.79
Spain	111.93	3.90	20.00	0.00	5.50	2.51
France	74.01	6.29	14.65	0.50	1.60	0.13
France	253.86	6.29	14.65	0.33	2.96	0.23
Portugal	33.99	1.11	17.16	1.30	0.66	0.11
Portugal	112.01	3.62	17.16	0.67	0.66	0.03

Table B-11: Non-normalized Data Solar Trial 3

Wholesale Electricity Price (t-1)	LCOE (t)	Capacity Factor (t)	Subsidy (t-1)	Newbuild (t+1)	PPA Signed (t)
0.03	0.39	0.24	0.41	0.68	0.07
0.00	0.34	0.24	1.00	0.71	0.19
0.30	0.49	0.24	0.88	1.00	0.06
0.11	1.00	0.06	0.00	0.00	0.00
0.06	0.96	0.09	0.00	0.01	0.01
0.54	0.94	0.00	0.00	0.26	0.01
0.08	0.53	0.72	0.00	0.38	1.00
0.02	0.48	1.00	0.00	0.41	0.56
0.36	0.39	1.00	0.00	0.78	0.78
0.19	0.73	0.45	0.34	0.20	0.04
1.00	0.73	0.45	0.22	0.40	0.07
0.02	0.00	0.71	0.88	0.06	0.03
0.37	0.35	0.71	0.45	0.06	0.00

Table B-12: Normalized Data Solar Trial 3

5. Solar Trial 4

Country	Wholesale Electricity Price (t)	LCOE (t)	Capacity Factor (t)	Subsidy (t-1)	Newbuild (t+2)	PPA Signed (t)
Germany	37.60	3.86	13.07	0.60	4.81	0.00
Germany	37.67	3.90	12.67	0.60	5.01	0.23
Germany	30.47	3.55	12.67	1.48	7.00	0.62
Germany	96.85	4.57	12.67	1.30	9.00	0.19
Great Britain	54.48	8.20	10.94	0.00	0.34	0.01
Great Britain	43.96	7.90	11.24	0.00	2.00	0.05
Great Britain	151.69	7.80	10.35	0.00	2.00	0.05
Spain	47.68	4.90	17.30	0.00	3.00	3.21
Spain	33.96	4.50	20.00	0.00	5.50	1.79
Spain	111.93	3.90	20.00	0.00	5.50	2.51
France	74.01	6.29	14.65	0.50	2.96	0.13
France	253.86	6.29	14.65	0.33	2.96	0.23
Portugal	47.87	1.47	17.16	0.00	0.66	0.12
Portugal	33.99	1.11	17.16	1.30	0.66	0.11
Portugal	112.01	3.62	17.16	0.67	0.76	0.03

Table B-13: Non-normalized Data Solar Trial 4

Wholesale Electricity Price (t)	LCOE (t)	Capacity Factor (t)	Subsidy (t-1)	Newbuild (t+2)	PPA Signed (t)
0.03	0.39	0.28	0.41	0.52	0.00
0.03	0.39	0.24	0.41	0.54	0.07
0.00	0.34	0.24	1.00	0.77	0.19
0.30	0.49	0.24	0.88	1.00	0.06
0.11	1.00	0.06	0.00	0.00	0.00
0.06	0.96	0.09	0.00	0.19	0.02
0.54	0.94	0.00	0.00	0.19	0.02
0.08	0.53	0.72	0.00	0.31	1.00
0.02	0.48	1.00	0.00	0.60	0.56

0.36	0.39	1.00	0.00	0.60	0.78
0.19	0.73	0.45	0.34	0.30	0.04
1.00	0.73	0.45	0.22	0.30	0.07
0.08	0.05	0.71	0.00	0.04	0.04
0.02	0.00	0.71	0.88	0.04	0.04
0.37	0.35	0.71	0.45	0.05	0.01

Table B-14: Normalized Data Solar Trial 4

C. Appendix C: Offshore-Specific Model Data

1. Offshore Raw Data

The following tables show the raw data that was used to build models that forecast the supply of offshore wind PPAs in Europe. Data points not found are labeled as Data Not Found (DNF) while datapoints in grey imply that they were obtained in the data cleaning phase by either linear interpolation from surrounding years, or by assuming a constant value through time. The references used for Appendices B till E are listed at the end of Appendix E, in Section 3.

Offshore Subsidies (GW)				
Year	Great Britain	Netherlands	Belgium	Germany
2017	3.20	0.70	0.00	1.49
2018	0.00	0.00	0.00	1.61
2019	5.74	0.70	0.00	0.00
2020	0.00	0.70	0.00	0.00
2021	8.00	1.40	0.00	0.96

Table C-1: Historical Offshore Subsidies

Wholesale Electricity Price (Euros/MWh)				
Year	Great Britain	Netherlands	Belgium	Germany
2017	55.11	39.33	44.58	44.7
2018	69.29	52.54	55.28	37.6
2019	54.48	41.19	39.35	37.67
2020	43.96	32.58	31.9	30.47
2021	151.69	102.65	98.2	96.85

Table C-2: Historical Wholesale Electricity Prices

Offshore LCOE (Eurocents/kwh)				
Year	Great Britain	Netherlands	Belgium	Germany
2017	16.30			11.70
2018	15.90			11.20
2019	15.50		7.90	10.70
2020	15.10	9.48		10.20
2021	14.40	8.30		9.80

Table C-3: Historical Offshore Wind LCOE

Offshore Capacity Factor (%)				
Year	Great Britain	Netherlands	Belgium	Germany
2017	37.28	31.40	30.14	33.31
2018	35.85	31.27	29.57	31.71
2019	36.23	32.42	30.99	33.70
2020	36.23	32.42	30.99	33.70
2021	36.23	32.42	30.99	33.70

Table C-4: Historical Offshore Capacity Factor

PPAs Signed (GW)				
Year	Great Britain	Netherlands	Belgium	Germany
2017	0.00	0.00	0.00	0.00
2018	0.00	0.00	0.58	0.00
2019	1.34	0.47	0.22	0.13
2020	0.58	0.00	0.14	0.32
2021	0.44	1.15	0.00	0.57

Table C-5: Historical Volumes of Offshore Wind PPAs

Offshore Newbuild (GW)				
Year	Great Britain	Netherlands	Belgium	Germany
2020	0.00	1.98	0.71	0.20
2021	1.86	0.65	0.64	0.00
2022	1.39	2.18	0.64	0.50
2023	1.54	2.18	0.64	0.50

2024	2.40	2.18	0.64	0.50
2025	4.16	2.18	0.64	1.90

Table C-6: Historical Volumes of Offshore Wind Renewable Newbuild

1. Offshore Wind Trial 1

Country	Wholesale Electricity Price (t)	LCOE (t)	Capacity Factor (t)	Subsidy (t-1)	Newbuild (t+3)	PPA Signed (t)
Great Britain	69.29	15.90	35.85	3.20	1.86	0.00
Great Britain	54.48	15.50	36.23	0.00	1.39	1.34
Great Britain	43.96	15.10	36.23	5.74	1.54	0.58
Great Britain	151.69	14.40	36.23	0.00	2.40	0.44
Netherlands	32.58	9.48	32.42	0.70	2.18	0.00
Netherlands	102.65	8.30	32.42	0.70	2.18	1.15
Belgium	39.35	7.90	30.99	0.00	0.64	0.22
Germany	37.60	11.20	31.71	1.49	0.00	0.00
Germany	37.67	10.70	33.70	1.61	0.50	0.13
Germany	30.47	10.20	33.70	0.00	0.50	0.32
Germany	96.85	9.80	33.70	0.00	0.50	0.57

Table C-7: Non-normalized Data Offshore Wind Trial 1

Wholesale Electricity Price (t)	LCOE (t)	Capacity Factor (t)	Subsidy (t-1)	Newbuild (t+3)	PPA Signed (t)
0.32	1.00	0.93	0.56	0.78	0.00
0.20	0.95	1.00	0.00	0.58	1.00
0.11	0.90	1.00	1.00	0.64	0.43
1.00	0.81	1.00	0.00	1.00	0.33
0.02	0.20	0.27	0.12	0.91	0.00
0.60	0.05	0.27	0.12	0.91	0.86
0.07	0.00	0.00	0.00	0.27	0.16
0.06	0.41	0.14	0.26	0.00	0.00
0.06	0.35	0.52	0.28	0.21	0.09
0.00	0.29	0.52	0.00	0.21	0.24

0.55	0.24	0.52	0.00	0.21	0.43

Table C-8: Normalized Data Offshore Wind Trial 1

2. Offshore Wind Trial 2

Country	Wholesale Electricity Price (t)	LCOE (t)	Capacity Factor (t)	Subsidy (t-1)	Newbuild (t+4)	PPA Signed (t)
Great Britain	55.11	16.30	37.28	0.00	1.39	0.00
Great Britain	69.29	15.90	35.85	3.20	1.54	0.00
Great Britain	54.48	15.50	36.23	0.00	2.40	1.34
Great Britain	43.96	15.10	36.23	5.74	4.16	0.58
Netherlands	39.33	9.48	31.40	1.40	2.18	0.00
Netherlands	52.54	9.48	31.27	0.70	2.18	0.00
Netherlands	41.19	9.48	32.42	0.00	2.18	0.47
Netherlands	32.58	9.48	32.42	0.70	2.18	0.00
Belgium	44.58	7.90	30.14	0.00	0.64	0.00
Belgium	55.28	7.90	29.57	0.00	0.64	0.58
Belgium	39.35	7.90	30.99	0.00	0.64	0.22
Belgium	31.90	7.90	30.99	0.00	0.64	0.14
Germany	44.70	11.70	33.31	0.00	0.50	0.00
Germany	37.60	11.20	31.71	1.49	0.50	0.00
Germany	37.67	10.70	33.70	1.61	0.50	0.13
Germany	30.47	10.20	33.70	0.00	1.90	0.32

Table C-9: Non-normalized Data Offshore Wind Trial 2

Wholesale Electricity Price (t)	LCOE (t)	Capacity Factor (t)	Subsidy (t-1)	Newbuild (t+4)	PPA Signed (t)
0.63	1.00	1.00	0.00	0.24	0.00
1.00	0.95	0.81	0.56	0.28	0.00
0.62	0.90	0.86	0.00	0.52	1.00
0.35	0.86	0.86	1.00	1.00	0.43
0.23	0.19	0.24	0.24	0.46	0.00

0.57	0.19	0.22	0.12	0.46	0.00
0.28	0.19	0.37	0.00	0.46	0.35
0.05	0.19	0.37	0.12	0.46	0.00
0.36	0.00	0.07	0.00	0.04	0.00
0.64	0.00	0.00	0.00	0.04	0.43
0.23	0.00	0.18	0.00	0.04	0.16
0.04	0.00	0.18	0.00	0.04	0.10
0.37	0.45	0.49	0.00	0.00	0.00
0.18	0.39	0.28	0.26	0.00	0.00
0.19	0.33	0.54	0.28	0.00	0.09
0.00	0.27	0.54	0.00	0.38	0.24

Table C-10: Normalized Data Offshore Wind Trial 2

3. Offshore Wind Trial 3

Country	Wholesale Electricity Price (t)	LCOE (t)	Capacity Factor (t)	Subsidy (t-1)	Newbuild (t+3)	PPA Signed (t)
Great Britain	55.11	16.30	37.28	0.00	0.00	0.00
Great Britain	69.29	15.90	35.85	3.20	1.86	0.00
Great Britain	54.48	15.50	36.23	0.00	1.39	1.34
Great Britain	43.96	15.10	36.23	5.74	1.54	0.58
Great Britain	151.69	14.40	36.23	0.00	2.40	0.44
Netherlands	39.33	9.48	31.40	1.40	1.98	0.00
Netherlands	52.54	9.48	31.27	0.70	0.65	0.00
Netherlands	41.19	9.48	32.42	0.00	2.18	0.47
Netherlands	32.58	9.48	32.42	0.70	2.18	0.00
Netherlands	102.65	8.30	32.42	0.70	2.18	1.15
Belgium	44.58	7.90	30.14	0.00	0.71	0.00
Belgium	55.28	7.90	29.57	0.00	0.64	0.58
Belgium	39.35	7.90	30.99	0.00	0.64	0.22
Belgium	31.90	7.90	30.99	0.00	0.64	0.14
Belgium	98.20	7.90	30.99	0.00	0.64	0.00

Germany	44.70	11.70	33.31	0.00	0.20	0.00
Germany	37.60	11.20	31.71	1.49	0.00	0.00
Germany	37.67	10.70	33.70	1.61	0.50	0.13
Germany	30.47	10.20	33.70	0.00	0.50	0.32
Germany	96.85	9.80	33.70	0.00	0.50	0.57

Table C-11: Non-normalized Data Offshore Wind Trial 3

Wholesale Electricity Price (t)	LCOE (t)	Capacity Factor (t)	Subsidy (t-1)	Newbuild (t+2)	PPA Signed (t)
0.20	1.00	1.00	0.00	0.00	0.00
0.32	0.95	0.81	0.56	0.78	0.00
0.20	0.90	0.86	0.00	0.58	1.00
0.11	0.86	0.86	1.00	0.64	0.43
1.00	0.77	0.86	0.00	1.00	0.33
0.07	0.19	0.24	0.24	0.83	0.00
0.18	0.19	0.22	0.12	0.27	0.00
0.09	0.19	0.37	0.00	0.91	0.35
0.02	0.19	0.37	0.12	0.91	0.00
0.60	0.05	0.37	0.12	0.91	0.86
0.12	0.00	0.07	0.00	0.29	0.00
0.20	0.00	0.00	0.00	0.27	0.43
0.07	0.00	0.18	0.00	0.27	0.16
0.01	0.00	0.18	0.00	0.27	0.10
0.56	0.00	0.18	0.00	0.27	0.00
0.12	0.45	0.49	0.00	0.08	0.00
0.06	0.39	0.28	0.26	0.00	0.00
0.06	0.33	0.54	0.28	0.21	0.09
0.00	0.27	0.54	0.00	0.21	0.24
0.55	0.23	0.54	0.00	0.21	0.43

Table C-12: Normalized Data Offshore Wind Trial 3

D. Appendix D: Onshore-Specific Model Data

1. Onshore Wind Raw Data

The following tables show the raw data that was used to build models that forecast the supply of onshore wind PPAs in Europe. Data points not found are labeled as Data Not Found (DNF) while datapoints in grey imply that they were obtained in the data cleaning phase by either linear interpolation from surrounding years, or by assuming a constant value through time. The references used for Appendices B till E are listed at the end of Appendix E, in Section 3.

Onshore Wind Subsidies (GW)						
Year	**Sweden**	**Spain**	**Norway**	**Finland**	**Netherlands**	**Great Britain**
2017	DNF	DNF	DNF	DNF	DNF	DNF
2018	DNF	0.00	DNF	DNF	0.83	0.00
2019	DNF	0.00	DNF	DNF	0.73	0.00
2020	DNF	0.00	DNF	DNF	0.22	0.00
2021	DNF	3.20	DNF	DNF	0.03	3.50

Table D-1: Historical Onshore Subsidies

Wholesale Electricity Price (Euros/MWh)						
Year	**Sweden**	**Spain**	**Norway**	**Finland**	**Netherlands**	**Great Britain**
2017	31.28	52.24	28.39	33.19	39.33	55.11
2018	44.84	57.29	43.55	46.80	52.54	69.29
2019	38.51	47.68	38.93	44.04	41.19	54.48
2020	17.78	33.96	9.22	28.02	32.58	43.96
2021	54.42	111.93	86.57	72.34	102.65	151.69

Table D-2: Historical Wholesale Electricity Prices

Onshore LCOE (Eurocents/kWh)						
Year	**Sweden**	**Spain**	**Norway**	**Finland**	**Netherlands**	**Great Britain**

2017	DNF	DNF	DNF	DNF	8.00	DNF
2018	DNF	DNF	DNF	DNF	7.00	8.33
2019	DNF	DNF	DNF	DNF	6.40	7.97
2020	2.90	DNF	DNF	3.00	5.20	5.95
2021	DNF	3.02	DNF	DNF	DNF	DNF

Table D-3: Historical Onshore Wind LCOE

Onshore Capacity Factor (%)						
Year	**Sweden**	**Spain**	**Norway**	**Finland**	**Netherlands**	**Great Britain**
2017	26.17	24.91	26.9	30.95	23.06	29.99
2018	23.74	25.77	26.15	30.78	22.74	28.87
2019	25.38	27.74	25.78	31.58	24.12	28.33
2020	25.38	27.74	25.78	31.58	24.12	28.33
2021	25.38	27.74	25.78	31.58	24.12	28.33

Table D-4: Historical Onshore Wind Capacity Factors

PPAs Signed (GW)						
Year	**Sweden**	**Spain**	**Norway**	**Finland**	**Netherlands**	**Great Britain**
2017	0.00	0.00	0.00	0.00	0.00	0.00
2018	0.53	0.39	1.24	0.19	0.00	0.01
2019	1.06	0.06	0.00	0.45	0.40	0.27
2020	0.43	0.26	0.20	0.50	0.22	0.13
2021	1.89	1.27	0.36	0.56	0.09	0.13

Table D-5: Historical Volumes of Onshore Wind PPAs

Onshore Newbuild (GW)						
Year	**Sweden**	**Spain**	**Norway**	**Finland**	**Netherlands**	**Great Britain**
2020	0.90	1.49	0.00	0.13	0.30	0.20
2021	2.30	2.22	0.67	0.28	0.53	0.10
2022	2.50	DNF	DNF	DNF	DNF	DNF
2023	1.20	DNF	DNF	DNF	DNF	DNF

Table D-6: Historical Volumes of Onshore Renewable Newbuild

E. Appendix E: Technology Neutral Model

The basis of the raw data found in the two sections below is the raw data of each technology found in the previous Appendices.

1. German Technology-Neutral Data

	Wholesale Electricity Price (t)	LCOE (t)	Capacity Factor (t)	Subsidy (t-1)	Newbuild (t+2)	PPA Signed (t)
Offshore Wind	37.60	11.20	31.71	1.49	0.00	0.00
	37.67	10.70	33.70	1.61	0.50	0.13
	30.47	10.20	33.70	0.00	0.50	0.32
	96.85	9.80	33.70	0.00	0.50	0.57
Solar	37.60	3.86	13.07	0.60	4.81	0.00
	37.67	3.90	12.67	0.60	5.01	0.23
	30.47	3.55	12.67	1.48	7.00	0.62
	96.85	4.57	12.67	1.30	9.00	0.19
Onshore Wind	37.60	5.00	17.92	2.82	1.30	0.01
	37.67	5.00	19.55	2.34	1.70	0.06
	30.47	5.00	19.55	1.85	3.00	0.00
	96.85	5.00	19.55	2.67	5.00	0.01

Table E-1: Non-normalized Data German Technology-Neutral

Wholesale Electricity Price (t)	LCOE (t)	Capacity Factor (t)	Subsidy (t-1)	Newbuild(t+2)	PPA Signed (t)
0.11	1.00	0.91	0.53	0.00	0.00
0.11	0.93	1.00	0.57	0.06	0.20
0.00	0.87	1.00	0.00	0.06	0.51
1.00	0.82	1.00	0.00	0.06	0.92

0.11	0.04	0.02	0.21	0.53	0.00
0.11	0.05	0.00	0.21	0.56	0.37
0.00	0.00	0.00	0.52	0.78	1.00
1.00	0.13	0.00	0.46	1.00	0.30
0.11	0.19	0.25	1.00	0.14	0.01
0.11	0.19	0.33	0.83	0.19	0.10
0.00	0.19	0.33	0.65	0.33	0.00
1.00	0.19	0.33	0.95	0.56	0.01

Table E-2: Normalized Data German Technology-Neutral

2. European Technology-Neutral Data

	Wholesale Electricity Price (t)	LCOE (t)	Capacity Factor (t)	PPA Signed (t)	Subsidy (t-1)	Newbuild (t+2)
Solar	37.60	3.86	13.07	0.00	0.60	4.81
	37.67	3.90	12.67	0.23	0.60	5.01
	30.47	3.55	12.67	0.62	1.48	7.00
	96.85	4.57	12.67	0.19	1.30	9.00
	54.48	8.20	10.94	0.01	0.00	0.34
	43.96	7.90	11.24	0.05	0.00	2.00
	151.69	7.80	10.35	0.05	0.00	2.00
	47.68	4.90	17.30	3.21	0.00	3.00
	33.96	4.50	20.00	1.79	0.00	5.50
	111.93	3.90	20.00	2.51	0.00	5.50
	74.01	6.29	14.65	0.13	0.50	2.96
	253.86	6.29	14.65	0.23	0.33	2.96
Onshore Wind	41.19	6.40	24.12	0.40	0.83	0.53
	69.29	8.33	28.87	0.01	0.00	0.20
	54.48	7.97	28.33	0.27	0.00	0.10
Offshore Wind	69.29	15.90	35.85	0.00	3.20	1.86
	54.48	15.50	36.23	1.34	0.00	1.39
	43.96	15.10	36.23	0.58	5.74	1.54
	151.69	14.40	36.23	0.44	0.00	2.40

	32.58	9.48	32.42	0.00	0.70	2.18
	102.65	8.30	32.42	1.15	0.70	2.18
	39.35	7.90	30.99	0.22	0.00	0.64
	37.60	11.20	31.71	0.00	1.49	0.00
	37.67	10.70	33.70	0.13	1.61	0.50
	30.47	10.20	33.70	0.32	0.00	0.50
	96.85	9.80	33.70	0.57	0.00	0.50

Table E-3: Non-normalized Data European Technology-Neutral

Wholesale Electricity Price (t)	LCOE (t)	Capacity Factor (t)	PPA Signed (t)	Subsidy (t-1)	Newbuild (t+2)
0.03	0.03	0.11	0.00	0.10	0.53
0.03	0.03	0.09	0.07	0.10	0.56
0.00	0.00	0.09	0.19	0.26	0.78
0.30	0.08	0.09	0.06	0.23	1.00
0.11	0.38	0.02	0.00	0.00	0.04
0.06	0.35	0.03	0.02	0.00	0.22
0.54	0.34	0.00	0.02	0.00	0.22
0.08	0.11	0.27	1.00	0.00	0.33
0.02	0.08	0.37	0.56	0.00	0.61
0.36	0.03	0.37	0.78	0.00	0.61
0.19	0.22	0.17	0.04	0.09	0.33
1.00	0.22	0.17	0.07	0.06	0.33
0.05	0.23	0.53	0.12	0.14	0.06
0.17	0.39	0.72	0.00	0.00	0.02
0.11	0.36	0.69	0.08	0.00	0.01
0.17	1.00	0.99	0.00	0.56	0.21
0.11	0.97	1.00	0.42	0.00	0.15
0.06	0.94	1.00	0.18	1.00	0.17
0.54	0.88	1.00	0.14	0.00	0.27
0.01	0.48	0.85	0.00	0.12	0.24
0.32	0.38	0.85	0.36	0.12	0.24
0.04	0.35	0.80	0.07	0.00	0.07

0.03	0.62	0.83	0.00	0.26	0.00
0.03	0.58	0.90	0.04	0.28	0.06
0.00	0.54	0.90	0.10	0.00	0.06
0.30	0.51	0.90	0.18	0.00	0.06

Table E-4: Normalized Data European Technology-Neutral

3. References for all Raw Data

Raw Data References		
Location	**Parameter**	**Source**
Europe	Renewable Newbuild	(Komusanac et al., 2022) ("Installed Capacity per Production Type," n.d.)
	Capacity Factors	("Renewables.ninja," n.d.)
	Wholesale Electricity Prices	("Average Spot Market Prices | Energy-Charts," n.d.)
Sweden	Onshore Wind Newbuild	(Kulin, 2021)
	Wholesale Electricity Prices	(Alves, 2022)
	Onshore Wind LCOE	(Craig, 2020)
Great Britain	Renewable Subsidies	("Digest of UK Energy Statistics (DUKES)," 2021)
	Renewable Newbuild	("Contracts for Difference," 2022) ("Solar photovoltaic (PV) cost data," 2022) (McCann, n.d.)
	Renewable LCOE	("Forecast: LCOE generation costs in the UK 2016," 2016)
	Wholesale Electricity Prices	("Wholesale market indicators," n.d.)
Netherlands	Renewable Subsidies	(Zaken, 2017)
	Renewable Newbuild	(Durakovic, 2021) ("Wind energy in Europe 2020 Statistics and the outlook for 2021-2025," 2021)
	Renewable LCOE	(Zegerius, 2020)
Germany	Renewable Newbuild	("Zeitreihen Erneuerbare Energien," 2022)
	Renewable Subsidies	("Zeitreihen Erneuerbare Energien," 2022)
	Renewable LCOE	("Federal Network Agency - Tenders," n.d.)
Belgium	Renewable Newbuild	("Offshore wind energy trends in Belgium and the Netherlands," 2022) ("Belgium to raise its offshore wind target in the light of war," 2022)
	Renewable Subsidies	(Bellini, 2021)

	Renewable LCOE	(Vermeylen, 2017)
	Wholesale Electricity Prices	(“Nuclear accounted for 52% of Belgium power mix in 2021,” 2022)
Finland	Renewable LCOE	(Craig, 2020)
Spain	Renewable Newbuild	(“Informe del Sistema Eléctrico Español 2017,” 2018)
	Renewable Subsidies	(“Summary 2021 (Part II),” 2021)
	Renewable LCOE	(“Iberdrola to Build Europe’s Largest Solar Farm,” 2019)
	Wholesale Electricity Prices	(“Day-ahead minimum, average and maximum price | OMIE,” n.d.)
France	Renewable Newbuild	(Deboutte, 2022)
	Renewable Subsidies	(“France solar PV auction results, 2017-2020,” 2020) (“Big-scale floating wind is kicking off in France,” 2021)
	Renewable LCOE	(*Projected Costs of Generating Electricity*, 2020)
	Wholesale Electricity Prices	(“Producer price index in industrial production sold in France,” 2022)
Portugal	Renewable Newbuild	(“Portugal to add significant solar PV capacity during 2021-2030,” 2021)
	Renewable Subsidies	(“Full 2020 Portuguese solar auction results - Antuko,” 2020)
	Renewable LCOE	(Bellini, 2020)
	Wholesale Electricity Prices	(“Day-ahead minimum, average and maximum price | OMIE,” n.d.)

Table E-5: Models’ Raw Data Sources

F. Appendix F: RE100 Companies

Company	Sector	Industry Group
3M Company	Industrials	Capital Goods
AB SKF	Industrials	Capital Goods
Accenture	Information Technology	Software and Services
Adobe	Information Technology	Software and Services
Advantest	Information Technology	Semiconductors and Semiconductor Equipment
Aeon Co., Ltd.	Communication Services	Media and Entertainment
Ajinomoto	Materials	Materials
AkzoNobel	Materials	Materials
Allianz SE	Financials	Insurance
Alstria	Real Estate	Real Estate
Amalgamated Bank	Financials	Banks
American Eagle	Consumer Discretionary	Retailing
American Express	Financials	Diversified Financials
Anheuser-Busch InBev	Consumer Staples	Food, Beverage and Tobacco
Anthem, Inc	Financials	Insurance
ANZ	Financials	Banks
Apple	Information Technology	Technology Hardware and Equipment
Asashi Kasei Homes	Real Estate	Real Estate
Asics Corporation	Consumer Discretionary	Consumer Durables and Apparel
ASKUL	Consumer Discretionary	Retailing
Asset Mangement One Co., Ltd.	Financials	Diversified Financials
AstraZeneca PLC	Health Care	Pharmaceuticals, Biotechnology and Life Sciences
Atlassian Corporation PLC	Information Technology	Software and Services

Aurora Organic Dairy	Consumer Staples	Food, Beverage and Tobacco
Autodesk Inc.	Information Technology	Software and Services
Aviva plc	Financials	Insurance
AXA Group	Financials	Insurance
Bank Australia	Financials	Banks
Bank of America	Financials	Banks
Bankia	Financials	Banks
Barclays PLC	Financials	Banks
BayWa	Industrials	Capital Goods
BBVA	Financials	Banks
BESTSELLER	Consumer Discretionary	Retailing
Biogen	Health Care	Pharmaceuticals, Biotechnology and Life Sciences
Bloomberg	Communication Services	Media and Entertainment
BMW AG	Consumer Discretionary	Automobiles and Components
British Land	Real Estate	Real Estate
Broad Group	Industrials	Capital Goods
BT Group	Communication Services	Telecommunication Services
Burberry Group	Consumer Discretionary	Consumer Durables and Apparel
Caixa Bank	Financials	Banks
Califia Farms	Consumer Staples	Food, Beverage and Tobacco
Canary Wharf Group	Real Estate	Real Estate
Capital One Financial	Financials	Banks
Carlsberg Breweries A/S	Consumer Staples	Food, Beverage and Tobacco
CHANEL	Consumer Discretionary	Consumer Durables and Apparel
Citigroup Inc.	Financials	Banks
Clif Bar & Company	Consumer Staples	Food, Beverage and Tobacco
Coca-Cola European Partners	Consumer Staples	Food, Beverage and Tobacco

Colruyt Group	Industrials	Capital Goods
Commerzbank	Financials	Banks
Commonwealth Bank of Australia	Financials	Banks
Continental	Consumer Discretionary	Automobiles and Components
Coop Sapporo	Consumer Staples	Food, Beverage and Tobacco
Corbion	Materials	Materials
Coty Inc.	Consumer Staples	Household and Personal Products
Credit Agricole	Financials	Banks
Credit Suisse	Financials	Banks
Crown Holdings, Inc.	Materials	Materials
Dai-ichi Life	Financials	Insurance
Daito Trust Construction Co., Ltd.	Industrials	Capital Goods
Daiwa House	Industrials	Capital Goods
Dalmia Cement	Materials	Materials
Danfoss	Industrials	Capital Goods
Danone	Consumer Staples	Food, Beverage and Tobacco
Danske Bank	Financials	Banks
Goldman Sachs	Financials	Diversified Financials
Google	Communication Services	Media and Entertainment
Grape King	Health Care	Pharmaceuticals, Biotechnology and Life Sciences
Grupo Bimbo	Consumer Staples	Food, Beverage and Tobacco
Grupo Cajamar	Financials	Banks
Gurmen Group	Consumer Discretionary	Retailing
H & M	Consumer Discretionary	Retailing
Hair O'right International Corp.	Consumer Staples	Household and Personal Products
Hazama Ando Corporation	Industrials	Capital Goods
Heathrow Airport Helvetia	Industrials	Transportation
Helvetia	Financials	Insurance

Hewlett Packard Enterprise	Information Technology	Software and Services
Hyundai Motor Manufacturing Czech	Consumer Discretionary	Automobiles and Components
HNI Corporation	Consumer Discretionary	Consumer Durables and Apparel
HP	Information Technology	Technology Hardware and Equipment
HSBC	Financials	Banks
Hudson Pacific Properties	Real Estate	Real Estate
Hulic	Real Estate	Real Estate
IHS Markit	Industrials	Commercial and Professional Services
Infosys	Information Technology	Software and Services
ING	Financials	Banks
Ingka Group	Consumer Discretionary	Retailing
Intel Corporation	Information Technology	Software and Services
Interactive	Information Technology	Software and Services
Interface	Consumer Discretionary	Retailing
International Flavors & Fragrances Inc.	Materials	Materials
Iron Mountain	Information Technology	Software and Services
JCDecaux	Communication Services	Media and Entertainment
JD Sports Fashion	Consumer Discretionary	Retailing
Jinko Solar	Industrials	Capital Goods
Johnson & Johnson	Health Care	Pharmaceuticals, Biotechnology and Life Sciences
JP Morgan Chase & Co	Financials	Diversified Financials
Jupiter Asset Management	Financials	Diversified Financials
Kellogg Company	Consumer Staples	Food, Beverage and Tobacco
Kerring	Consumer Discretionary	Consumer Durables and Apparel
Keurig Dr Pepper	Consumer Staples	Food, Beverage and Tobacco

Kingspan	Industrials	Capital Goods
Konica Minolta	Information Technology	Technology Hardware and Equipment
Koninklijke DSM	Materials	Materials
Koninklijke KPN N.V.	Communication Services	Telecommunication Services
L´Occitane Group	Consumer Staples	Household and Personal Products
La Poste	Industrials	Commercial and Professional Services
Landsec	Real Estate	Real Estate
Lego Group	Consumer Discretionary	Consumer Durables and Apparel
LIXIL	Industrials	Capital Goods
Lloyds Banking Group	Financials	Banks
Logitech	Information Technology	Technology Hardware and Equipment
LONGi	Industrials	Capital Goods
Lululemon	Consumer Discretionary	Consumer Durables and Apparel
Lyft	Industrials	Transportation
M&G	Financials	Diversified Financials
MacCain Foods	Consumer Staples	Food, Beverage and Tobacco
Mace Group	Industrials	Capital Goods
Macquarie	Financials	Diversified Financials
Mahindra Holidays & Resorts	Consumer Discretionary	Consumer Services
Mars, Inc.	Consumer Staples	Food, Beverage and Tobacco
Marui Group	Consumer Discretionary	Retailing
Mastercard	Financials	Diversified Financials
McKinsey & Company	Industrials	Capital Goods
Microsoft	Information Technology	Software and Services
Mirvac	Industrials	Capital Goods
Mitie	Industrials	Capital Goods
Mitsubishi Estate	Real Estate	Real Estate
Mitsui Fudosan	Real Estate	Real Estate
Morgan Stanley	Financials	Diversified Financials

NAB Australia	Financials	Banks
NatWest Group	Financials	Diversified Financials
Nestlé	Consumer Staples	Food, Beverage and Tobacco
New Balance Athletics, Inc.	Consumer Discretionary	Consumer Durables and Apparel
Next PLC	Consumer Discretionary	Retailing
Nihon Unisys	Information Technology	Software and Services
Nike	Consumer Discretionary	Consumer Durables and Apparel
Nomura Research Institute	Industrials	Commercial and Professional Services
Nordea	Financials	Banks
Nordic Real Estate Partners (NREP)	Real Estate	Real Estate
Novo Nordisk A/S	Health Care	Pharmaceuticals, Biotechnology and Life Sciences
Novozymes A/S	Health Care	Pharmaceuticals, Biotechnology and Life Sciences
Ono Pharmaceutical Co., Ltd.	Health Care	Pharmaceuticals, Biotechnology and Life Sciences
Organic Valley	Consumer Staples	Food, Beverage and Tobacco
Panasonic	Consumer Discretionary	Consumer Durables and Apparel
Pearson	Consumer Discretionary	Consumer Services
PepsiCo	Consumer Staples	Food, Beverage and Tobacco
Pernod Ricard	Consumer Staples	Food, Beverage and Tobacco
PNC Financial Services Group	Financials	Diversified Financials
Procter & Gamble	Consumer Staples	Household and Personal Products
Proximus	Communication Services	Telecommunication Services
PVH	Consumer Discretionary	Consumer Durables and Apparel

PwC	Industrials	Commercial and Professional Services
QBE	Financials	Insurance
QTS	Health Care	Healthcare Equipment and Services
Rackspace Hosting Inc	Information Technology	Software and Services
Radio Flyer	Consumer Discretionary	Consumer Durables and Apparel
Rakuten	Consumer Discretionary	Retailing
Ralph Lauren	Consumer Discretionary	Consumer Durables and Apparel
Reckitt Benckiser	Consumer Staples	Household and Personal Products
Refinitiv	Industrials	Commercial and Professional Services
RELX Group	Industrials	Commercial and Professional Services
Ricoh	Information Technology	Software and Services
Royal Philips	Consumer Discretionary	Consumer Durables and Apparel
Salesforce	Information Technology	Software and Services
Sanofi		
SAP SE	Information Technology	Software and Services
Schneider Electric	Health Care	Pharmaceuticals, Biotechnology and Life Sciences
Schroders	Financials	Banks
Sekisui Chemical Co., Ltd.	Materials	Materials
Sekisui House, Ltd.	Industrials	Capital Goods
SGS	Industrials	Commercial and Professional Services
Signify	Consumer Discretionary	Consumer Durables and Apparel
Sky	Communication Services	Media and Entertainment
Slaughter and May	Industrials	Commercial and Professional Services
Sony Corporation	Consumer Discretionary	Consumer Durables and Apparel

Starbucks Corporation	Consumer Discretionary	Consumer Services
Steelcase	Consumer Discretionary	Consumer Durables and Apparel
Sumitomo Forestry	Materials	Materials
Suncorp	Financials	Diversified Financials
Sungrow	Industrials	Capital Goods
Swiss Post	Industrials	Transportation
Swiss Re	Financials	Insurance
Swisscom Ltd.	Communication Services	Telecommunication Services
Symrise	Consumer Staples	Household and Personal Products
T-Mobile	Communication Services	Telecommunication Services
Takashimaya	Consumer Discretionary	Consumer Services
Target	Consumer Discretionary	Retailing
Tata Motors	Consumer Discretionary	Automobiles and Components
TCI Co.,	Materials	Materials
TD Bank Group	Financials	Banks
Telefonica	Communication Services	Telecommunication Services
Tesco	Consumer Staples	Food, Beverage and Tobacco
Tetra Pak	Materials	Materials
The Bozzuto Group	Real Estate	Real Estate
The Crown Estate	Financials	Diversified Financials
The Estée Lauder Companies	Consumer Staples	Household and Personal Products
The Johnan Shinkin Bank	Financials	Banks
The Mayor and Commonalty and Citizens of the City of London	Industrials	Commercial and Professional Services
The VELUX Group	Consumer Discretionary	Consumer Durables and Apparel
The Wonderful Company	Consumer Staples	Food, Beverage and Tobacco
Toda Corporation Japan	Industrials	Capital Goods
Tokyu Corporation	Industrials	Transportation
Tokyu Land Corporation	Real Estate	Real Estate

Trane Technologies	Industrials	Capital Goods
TRIDL	Consumer Staples	Household and Personal Products
TSMC	Information Technology	Semiconductors and Semiconductor Equipment
UBS	Financials	Banks
Unilever	Industrials	Capital Goods
Vail Resorts	Consumer Discretionary	Consumer Durables and Apparel
Vaisala	Industrials	Commercial and Professional Services
Vestas	Industrials	Capital Goods
VF Corporation	Consumer Discretionary	Retailing
Virgin Media	Communication Services	Telecommunication Services
Visa	Financials	Diversified Financials
Vmware	Information Technology	Software and Services
Vodafone Group	Communication Services	Telecommunication Services
Voya Financial	Financials	Diversified Financials
Wal-Mart	Consumer Discretionary	Retailing
Watami Co., Ltd.	Consumer Discretionary	Consumer Durables and Apparel
Wells Fargo	Financials	Diversified Financials
Westpac	Financials	Banks
WeWork	Real Estate	Real Estate
Workday	Information Technology	Software and Services
WPP	Communication Services	Media and Entertainment
YOOX NET-A-PORTER GROUP	Consumer Discretionary	Consumer Durables and Apparel
Zalando	Consumer Discretionary	Retailing
Zurich Insurance Company Ltd	Financials	Insurance
General Motors	Consumer Discretionary	Automobiles and Components
Kia	Consumer Discretionary	Automobiles and Components

Table F-1: Sectors and Industries of RE100 Companies

G. Appendix G: German Data

	Onshore Wind (GW)	Offshore Wind (GW)
2000	1.7	0.0
2001	2.6	0.0
2002	3.2	0.0
2003	2.4	0.0
2004	2.1	0.0
2005	1.9	0.0
2006	2.2	0.0
2007	1.7	0.0
2008	0.7	0.0
2009	2.9	0.0
2010	1.1	0.0
2011	1.8	0.1
2012	2.2	0.1
2013	2.2	0.2
2014	4.6	0.5
2015	3.7	2.3
2016	4.0	0.8
2017	4.9	1.3
2018	2.2	0.9
2019	0.9	1.2
2020	1.3	0.2
2021	1.7	0.0
2022	3.0	0.5
2023	5.0	0.5
2024	6.0	0.5
2025	7.0	1.9
2026	9.0	1.0
2027	10.0	0.9
2028	10.0	4.0

2029	10.0	6.0
2030	9.0	7.0

Table G-1: German Offshore and Onshore Wind Yearly Expansion

Onshore Wind Auctions (MW)						
Tender Date	Amount Advertised	Submitted bids amount	Amount Awarded	Undersubscription Amount (MW)	Ra (awarded relative to advertised)	Rs (awarded relative to submitted)
Feb-21	1500	718	692	782	46%	96%
May-21	1243	1161	1110	82	89%	96%
Feb-20	900	527	523	373	58%	99%
Mar-20	300	194	151	106	50%	78%
Jun-20	826	467	464	359	56%	99%
Jul-20	275	191	191	84	69%	100%
Sept-20	367	310	285	57	78%	92%
Oct-20	826	769	659	57	80%	86%
Dec-20	367	657	400	N/A	109%	61%
Feb-19	700	500	476	200	68%	95%
May-19	650	295	270	355	42%	92%
Aug-19	650	239	208	411	32%	87%
Sept-19	500	188	180	312	36%	96%
Oct-19	675	204	204	471	30%	100%
Dec-19	500	686	509	N/A	102%	74%

Table G-2: Historical Results of Onshore Auctions in Germany

Index	Year	Company Level Goal	Yfit	Residual	Residual Squared
1	2015	0.22	0.20510	0.01490	0.00022
2	2016	0.26	0.24417	0.01583	0.00025
2	2016	0.2	0.24417	-0.04417	0.00195
2	2016	0.4	0.24417	0.15583	0.02428
2	2016	0.08	0.24417	-0.16417	0.02695
3	2017	0.34	0.28799	0.05201	0.00271
3	2017	0.3	0.28799	0.01201	0.00014
3	2017	0.58	0.28799	0.29201	0.08527
3	2017	0.21	0.28799	-0.07799	0.00608
4	2018	0.1	0.33617	-0.23617	0.05578
4	2018	0.45	0.33617	0.11383	0.01296
4	2018	0.42	0.33617	0.08383	0.00703
4	2018	0.5	0.33617	0.16383	0.02684
4	2018	0.41	0.33617	0.07383	0.00545
5	2019	0.1	0.38802	-0.28802	0.08296
5	2019	0.5	0.38802	0.11198	0.01254
5	2019	0.36	0.38802	-0.02802	0.00079
5	2019	0.58	0.38802	0.19198	0.03685
5	2019	0.37	0.38802	-0.01802	0.00032
5	2019	0.01	0.38802	-0.37802	0.14290
6	2020	0.3	0.44254	-0.14254	0.02032
6	2020	0.5	0.44254	0.05746	0.00330
6	2020	0.45	0.44254	0.00746	0.00006
11	2025	0.75	0.70951	0.04049	0.00164
16	2030	1	0.88256	0.11744	0.01379
16	2030	0.75	0.88256	-0.13256	0.01757
16	2030	1	0.88256	0.11744	0.01379
36	2050	1	0.99852	0.00148	0.00000
36	2050	1	0.99852	0.00148	0.00000
36	2050	1	0.99852	0.00148	0.00000
36	2050	1	0.99852	0.00148	0.00000
A	**B**	**C**	**Sum of Residual Squared (SRS)**		
1.25885081	**0.22477097**	**1.349280322**	**0.60276**		

Table G-3: RE100 Chemicals Industry Analysis

Yearly PPA Additions (GW)	2022	2023	2024	2025	2026	2027
High Scenario	3.15	4.08	4.91	5.45	6.52	6.44
Reference Scenario	1.88	2.30	2.87	2.98	3.48	3.39
Low Scenario	1.30	1.56	1.98	2.04	2.38	2.30

Table G-4: Yearly PPA Supply Additions (GW)