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Spatial optimization of wind and solar power capacities in Europe

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Abstract

As the European power mix transitions towards higher shares of variable renewable energy (VRE), such as wind and solar power, the power system becomes increasingly weather dependent. The weather follows seasonal and geographical patterns caused by the earth's rotation and position to the sun. Increased weather dependence presents challenges in maintaining a safe, reliable, and affordable power system. This thesis investigates the wind and solar resources in Europe, both on a spatial and temporal scale. A case study is conducted where modern portfolio theory is used to find optimal allocations for wind and solar power capacities in Europe and to investigate the impact that different time resolutions have on the structure of optimal portfolios.

The weather analysis shows that wind and solar resources have a large negative correlation of -0.64 with a monthly time resolution. However, this relationship decreases as we move towards an hourly time resolution where the correlation coefficient becomes -0.05, indicating no statistical relationship. This is also the trend when comparing the volatility of wind and solar resources. There is a strong negative correlation for the occurrence of high and low volatility between wind and solar resources on a monthly time resolution, with a decreasing relationship as the time resolution increases.

The portfolio optimization shows that the existing fleet of wind and solar capacities is not the optimal distribution, given the assumptions in this study. Additionally, the portfolio optimization favors the regions in Portugal and Greece, which both have significantly higher wind output during summer months than the European average. By introducing significant wind power capacities in these regions, Europe will potentially have a more stable wind power output year-round.

The optimal portfolios outperform the existing fleet in both hourly, daily, weekly, and monthly time resolutions, with the most significant improvement at an hourly time resolution. Furthermore, the portfolios with lower time resolutions tend to favor higher shares (52%) of solar PV relative to portfolios with high time resolutions, receiving only 13% solar PV, indicating that solar PV is relatively more favorable in systems concerned about long-term volatility. At the same time, high shares of wind power are more beneficial in systems concerned about short-term volatility.

Sammendrag

Etter hvert som den Europeiske kraftmiksen beveger seg mot høyere andeler av variabel fornybar energi, som vind- og solkraft, blir kraftsystemet stadig mer væravhengig. Været følger sesongmessige og geografiske mønstre forårsaket av jordens rotasjon og posisjon til solen. Økt væravhengighet kan by på utfordringer med å opprettholde et trygt, pålitelig og rimelig kraftsystem. Denne oppgaven undersøker vind- og solressursene i Europa, både i romlig og tidsmessig skala. Det gjennomføres en casestudie hvor moderne porteføljeteori brukes for å finne optimale allokeringer for vind- og solkraftkapasiteter i Europa og hvilken innvirkning ulike tidsoppløsninger har på strukturen til de optimale porteføljene.

Væranalysen viser at vind- og solressurser har en negativ korrelasjon på -0.64 med månedlig tidsoppløsning. Imidlertid avtar dette forholdet når vi beveger oss mot en timebasert tidsoppløsning hvor korrelasjonskoeffisienten blir -0.05, noe som indikerer ingen sammenheng. Dette er også trenden når man sammenligner volatiliteten til vind- og solressurser. Det er en sterk negativ korrelasjon for når høy og lav volatilitet oppstår mellom vind- og solressurser på en månedlig tidsoppløsning, med avtagende sammenheng ettersom tidsoppløsningen øker.

Porteføljeoptimaliseringen viser at den eksisterende flåten av vind- og solkapasitet ikke er den optimale fordelingen, gitt forutsetningene i denne studien. I tillegg favoriserer porteføljeoptimaliseringen regionene i Portugal og Hellas, som begge har betydelig mer vind i sommermånedene enn det europeiske gjennomsnittet. Ved å ha store mengder vindkraftkapasitet i disse regionene vil Europa som helhet ha en mer stabil vindkraftproduksjon året rundt.

De mest optimale porteføljene utkonkurrerer den eksisterende flåten i både times-, daglig, ukentlig og månedlig tidsoppløsning, hvor den mest betydelige forbedringen ved timebasert tidsoppløsning. Videre har porteføljer med lavere tidsoppløsninger en tendens til å favorisere høyere andeler (52%) av solenergi i forhold til porteføljer med høy tidsoppløsning, som bare mottar 13% solenergi. Dette indikerer at høy andel solkraft er relativt mer gunstig i systemer som er bekymret for langsiktig volatilitet. Samtidig er høye andeler vindkraft mer fordelaktig i systemer som er opptatt av kortsiktig volatilitet.

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Abbreviations

VRE	Variable renewable energy
CF	Capacity factor
ENTSO-E	European Network of Transmission System Operators for Electricity
MPT	Modern portfolio theory
RLDC	Residual load duration curves
NVE	The Norwegian Energy Regulatory Authority
EFTA	European Free Trade Association
BESS	Battery energy storage system
PV	Photovoltaic
EU	European Union
GW	Gigawatt

1 Introduction

Europe is planning to minimize fossil fuels for energy purposes and replace them with renewable energy. This is to tackle climate change, mitigate emissions, and make the green transition. In line with the Paris agreement and as part of the European Green Deal, the European Union (EU) has proclaimed to achieve carbon neutrality by mid-century. In this agreement, a clean energy transition is described as critical. The Green Deal highlights three fundamental principles for the energy transition: (1) Ensuring a secure and affordable EU energy supply. (2) Developing a fully integrated, interconnected, and digitalized EU energy market. (3) Prioritizing energy efficiency, improving the energy performance of buildings and developing a power sector based largely on renewable sources (European Commision, 2019).

Wind and solar power are forecasted to be the primary source of power production by 2050 (DNV, 2021). Both these energy sources have weather dependency in common, resulting in substantial production output volatility. This volatility of production output brings challenges in terms of balancing the power system. According to Kirchhoff's first law, the power system requires a continuous balance between the production and consumption of electricity. If the EU and its surrounding nations are to achieve a secure, integrated, and renewable-based power market, these balancing challenges must be addressed and solved.

As of today, energy planning and energy security are not always factors judged together. While energy planning is mainly considered nationally and locally, it has never been clearer that energy security should be visioned in an international context, despite the turmoils of the current geopolitical situation. Therefore, energy planning should focus less on individual optimal alternatives and focus more on finding the combination of power production technologies and spatial distribution that is efficient and ensures energy security.

Huber et al. (2014) analyzed the flexibility requirements depending on the penetration of variable renewable energy (VRE). They discovered that flexibility requirements increased strongly when the share of VRE increased. Similar results have also been reported by Olsen et al. (2020) and Guerra et al. (2022).

Flexibility can be provided by numerous sources, both from the supply and demand side of the power system. Demand-side flexibility attracts attention with solutions that shift demand from high to low demand. Storage solutions such as batteries, hydrogen, pumped hydro, or other mechanical devices are also potential sources of flexibility in the future energy system. However, the flexibility needed depends on the time scale in question. Some solutions are more suitable for short-term frequency or ramping flexibility, and others for more long-term stability measures. Regardless, flexibility resources all have in common that an increased need for flexibility leads to higher costs.

Huber et al. (2014) found that the flexibility requirements decreased with the geographical power system size, especially in high wind power penetration systems. This coincides with Waldo Tobler's first law of geography, stating that "everything is related to everything else, but near things are more related than distant things" (Tobler, 1970).

Conclusively, decision- and policy-makers need a more holistic approach to their energy planning. One potential method could use modern portfolio theory in regional allocation planning for power capacities. While modern portfolio theory is a well-established methodology within finance, it has also gained traction in energy planning (Awerbuch & Berger, 2003). By focusing on how one asset of power production affects the power system as a whole, Europe could potentially get a more secure and balanced power system with less need for flexibility resources. This study examines the weather resources in Europe and the optimal spatial distribution of wind and solar capacity in Europe by using modern portfolio theory. Additionally, the optimization will be conducted in different time resolutions in order to analyze its effect on the optimal allocation of wind and solar power.

1.1 Existing literature

Wind-solar complementarity

Several studies have analyzed the variability and intermittency of wind and solar energy and the complications these sources bring in the energy system. In fact, Europe is the region with the highest number of wind-solar complementarity studies in the world (Weschenfelder et al., 2020). For example, Bett & Thornton (2016) analyzed the monthly climatological relationship between wind and solar irradiance in Great Britain. They discovered that solar irradiance and wind are negatively correlated, with correlation coefficients between -0,4 and -0,2 on a daily basis. Similarly, Koivisto et al. (2019) analyzed the correlation between onshore wind and solar power on an hourly basis in northern Europe, which resulted in a negative correlation of -0.24.

Additionally, Bett & Thornton (2016) found that daily variability decreased in all months of the year by incorporating solar capacity. Bett & Thornton emphasizes in their study, the importance of analyzing short-term correlations rather than monthly, which is more prevalent. However, Bett & Thornton (2016) argued that correlation patterns between wind and solar power in Great Britain are not reliable enough to secure a well-balanced energy supply.

Monforti et al. (2014) investigated the complementarity of wind and solar resources in Italy. They analyzed 100 potential complementary production sites of wind and solar power using a Monte Carlo simulation. The results revealed some cases where monthly correlation coefficients reached lower values than -0,8. In contrast, nationwide monthly correlation coefficients showed values between -0,65 and -0,6.

Furthermore, Kapica et al. (2021) analyzed the temporal complementarity of wind and solar resources globally. They suggested that the theoretical maximum, regarding the monthly temporal correlation of wind and solar resources, is found in the interval between -0,70 and -0,75 using Kendall's Tau correlations.

These studies all found a negative temporal correlation between wind speed and solar radiation and found that the generation pattern in these energy sources is suitable to complement each other to achieve an overall more balanced energy system. On the spatial scale, most studies typically find a smoothening effect of wind power with spatial distancing, resulting in lower positive correlations of wind speeds or wind power output with increased distance. In contrast, the spatial effect of solar power is more limited due to lower variability across distances for solar resources. On the other hand, the spatial distancing of solar power has some effect on mitigating the risk of cloud cover (Perez et al., 2016).

However, most complementarity studies focus on relatively small areas at a time and at a single time resolution.

Complementarity over larger areas

Heide et al. (2010) analyzed the optimal seasonal mix of wind and solar power in a highly renewable Europe. Similar to the more area-restrictive studies, they found that wind and solar power could counterbalance and smooth the seasonal power curve in Europe, with more wind power during winter months and more solar during summer months. However, Heide et al. (2010) did not consider the spatial distribution of wind and solar power, only the allocation of each power source.

Koestler et al. (2020) from The Norwegian Energy Regulatory Authority (NVE) studied the challenges of high shares of renewable energy in the Nordic power system. Their analysis included hydropower, one of the dominant power sources in northern Europe. Their results showed that wind power has significant variations in output within the country of Norway, as the country is highly elongated. Furthermore, their results showed that while solar power and load demand have a distinct daily output profile, wind power has no such regularity. In the same study, NVE also analyzed the typical weather patterns in northern Europe. NVE stated that countries in close proximity are primarily affected by the same weather systems and that flexible solutions will increasingly be necessary when the share of intermittent renewables increases.

Koivisto et al. (2018) also considered northern Europe when analyzing how the spatial allocation of offshore and onshore wind and solar power could minimize the aggregate generated output variability. They also found negative correlations between wind and solar power and that in a minimization scenario, there would be clear benefits of a spatially spread allocation and a mixture of VRE technologies.

Portfolio optimization in energy planning

Portfolio methodologies have been applied in energy planning concerning energy prices for some time. Awerbuch and Berger (2003) used portfolio theory to evaluate efficient portfolios in Europe from a cost perspective. Similarly, deLlano-Paz et al. (2017) analyzed the efficient cost-risk frontier and modern portfolio theory in energy planning.

Reichenberg et al. (2017) investigated the geographic distribution of wind power to avoid periods of low output. They used a multi-objective optimization model to improve the performance of aggregated wind power output in Europe. The results showed that an optimal allocation of wind power substantially reduced the frequency of low outputs. However, Reichenberg et al. (2017) only considered wind power and did not consider the complementarity of solar power or other technologies in the optimization model.

Zappa & van den Broek (2018) conducted a highly detailed optimization analysis of the spatial allocation of wind and solar power in a fully integrated European energy system, intending to minimize the residual load on an hourly basis. Surprisingly, their results showed that spatial optimization did not significantly reduce peak residual demand nor total residual demand. While the objective of Zappa & van den Broek’s study was to shape the power output so that it corresponds to the load demand, Miglietta et al. (2017) focused solely on smoothening the power output of wind and solar.

1.2 Contribution to existing literature

Previous studies suggest a significant negative correlation between wind speed and solar irradiation and that this meteorological complementarity can be exploited. Furthermore, spatial optimization models that consider wind power suggests that there are specific weather patterns in Europe and that there is an optimal spatial distribution of wind power. This thesis will consist of a wind and solar resource mapping and a portfolio optimization to find the optimal distribution of wind and solar power capacities in Europe. Unlike methods found in existing literature, the portfolio optimization in this thesis is conducted with different time resolutions to analyze its effect on the optimal portfolio allocation. Additionally, unlike Zappa & van den Broek's (2018) study, this thesis will not consider the demand. The optimization model will exclusively consider the weather resources available in Europe, and how optimal distributions and allocations of wind and solar power can get as high and smooth output as possible. Further justification for not including demand will be discussed in chapter 7.

1.3 Problem statement

The objective of this thesis is to analyze how decision-makers in energy planning could utilize portfolio optimization to allocate and distribute production capacities of wind and solar power in Europe. The aim is to find combinations of areas in Europe that can provide higher power output and less volatility. The portfolio optimization will be conducted with different time resolutions in order to analyze its effect on the optimal portfolio. This is done using modern portfolio theory, commonly used in finance, for energy planning purposes. More specifically, the thesis is divided into the following questions:

1. **What are the key characteristics of wind and solar resources in Europe?**
2. **How should wind and solar capacities be distributed to achieve a higher total capacity factor and lower volatility than the existing fleet?**
3. **How do different time resolutions affect the allocation of wind and solar power capacities in an optimal portfolio?**

1.4 Boundaries and assumptions

The geographical boundaries in this thesis are restricted to the 27- EU member nations, the UK, and the EFTA countries. Furthermore, due to lack of data, only the offshore regions of Belgium, Denmark, Germany, Netherlands, and the United Kingdom are included.

In the analysis of this thesis, several assumptions are made, including:

1. **No transmission loss or bottlenecks in the transmission grid**
2. **No area restrictions. All regions are suitable for wind and solar PV capacities**
3. **The future average weather is equal to the historical average weather**

The implications and justification of these assumptions will be discussed in chapter 7.

1.5 Thesis structure

The remainder of this thesis is structured through seven chapters, from chapter 2 to chapter 8. Chapter 2 contains the background for the thesis, including an introduction to the European power mix and to which degree high shares of intermittent renewables can affect the power market. Furthermore, the background also contains an introduction to weather systems and the characteristics of European weather.

Chapter 3 contains the main theory used in this study, including Modern portfolio theory, efficient frontiers, portfolio selection, and an introduction to Monte Carlo simulation. Chapter 4 presents the data used for the analysis, where it is collected from, and known issues associated with the data. Further in chapter 5, the thesis presents the methods that are used in the portfolio optimization and how the data are used in the analysis. The analysis is shown in chapter 6 and is split into two main parts. Part one analyzes the general characteristics of wind and solar resources in Europe, while part two uses the portfolio optimization model described in chapter 5 to model optimal portfolios of wind and solar capacities in Europe.

The discussion, in chapter 7, contains discussions of the characteristics of wind and solar resources in Europe, the optimization model, issues with the datasets, and potential further work. Lastly, chapter 8 presents the conclusion of this study.

2 Background

2.1 The European power market

A key aspect of the energy transition is to electrify the economy while having the power production as renewable as possible. Historically, the power mix in Europe has been mainly based on coal, nuclear, gas, and hydro. At the same time, intermittent renewables like wind and solar have experienced a steep increase in capacity in recent years, especially wind power (IEA, 2022). As of 2020, western Europe has the highest share of installed wind power capacity in Europe, with Denmark being the country with the highest relative share of wind power. Germany has the highest total capacity with 63 Gigawatt (GW), followed by Spain and the UK with 27 and 24 GW, respectively (WindEurope, 2021). Germany also has the highest installed capacity of solar PV with approximately 50 GW installed capacity, followed by Italy and the UK with about 21 and 14 GW, respectively (IRENA, 2022).

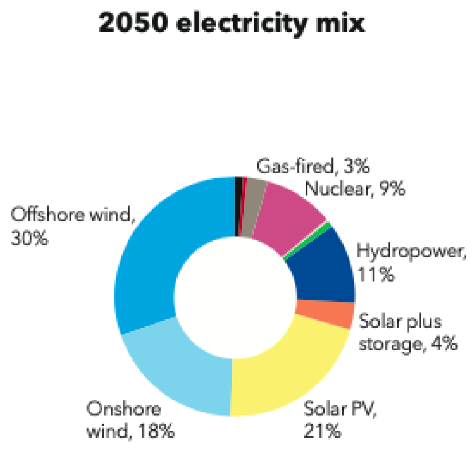

Figure 1: Estimated electricity mix in 2050. Source: DNV, 2021.

With the declining prices of wind and solar, more or less all prognoses point to these technologies being the dominant electricity source towards mid-century. As shown in Figure 1, DNV estimates that offshore and onshore wind will stand for 48% of electricity production, while solar PV and solar plus storage will stand for 25%. This brings the combined total of wind and solar to a share of 73% of electricity production by 2050 (DNV, 2021).

With a power system mainly based on two intermittent power sources, it is essential to understand the characteristics of these power sources and, therefore, because of their weather dependence, to understand the weather itself.

Balancing costs and grid-complementarity of wind and solar

As described previously, wind and solar resources are intermittent in their production output and solely dependent on weather conditions. The output volatility ranges from minutes to years. This imposes challenges for the grid operators. Balancing costs occur when power is either used or curtailed to restore the supply-demand equilibrium. These costs tend to increase when the power source is inflexible, such as wind and solar. The power supply from wind and solar for the next period is forecasted using weather forecasts. As in all forecasting, weather forecasts have uncertainties, and there are usually some deviations between the supply forecast and the actual production of wind and solar. Balancing market designs is different across Europe. However, the essence includes that transmission system operators need to either add or curtail production within a short notice to restore balance and maintain system frequency within a predefined range. Therefore, the transmission system operators need to procure these additional balancing capacities in advance through balancing markets. These capacities can either be generators, demand response facilities, or storage operators, which in their own way can provide some form of balancing service. In general, the greater the need for balancing services, the higher the costs to maintain a balanced system (ENTSO-E, 2018).

In the more traditional power systems, most of the flexibility has been provided by the conventional generators themselves, which can ramp production up and down on-demand. However, as the share of VRE increases, supply-side flexibility decreases, leading to a flexibility gap. Additionally, the increased weather-dependent power mix further increases the need for more flexible resources (Papaefthymiou et al., 2018). Consequently, new sources of flexibility are needed to fill the gap, as illustrated in Figure 2.

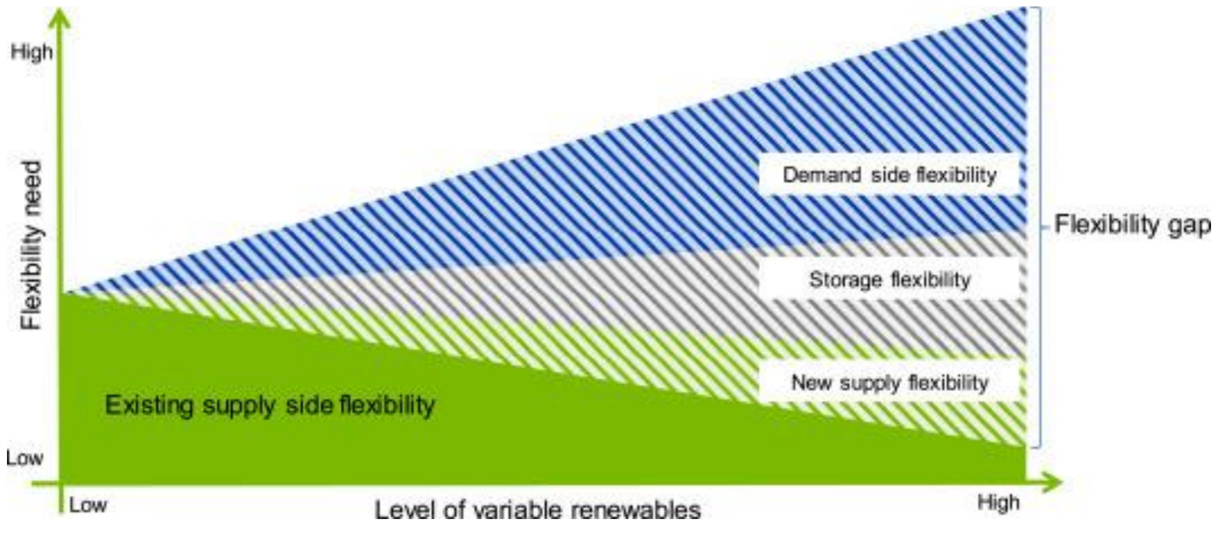

Figure 2: The increasing need of flexibility with higher shares of VRE. Source: (papaefthymiou et al., 2015)

The European transmission system

A continent-wide, fully integrated European power system is one of the goals of the European Green Deal. According to the European Network of Transmission System Operators for Electricity (ENTSO-E), Europe already has the largest interconnected electrical grid in the world. However, ENTSO-E argues that there is a substantial need for additional cross-border capacity in Europe. Towards 2025, there is 35 GW of cross-border capacity planned but studies show that an additional 93 GW is necessary by 2040 (ENTSO-E, 2021). This corresponds to an annual investment need of about 3.4 bn Euros from 2025 to 2040. Despite this substantial need for investments, Tröndle et al. (2020) argue that expanding cross-border transmission and renewable electricity supply on a continental scale has lower costs than regional or national scale supply.

Indirect costs of implementing wind and solar energy

The theoretical marginal cost of VRE is, by all practicality, zero. There is no additional cost of producing one more unit of power for a wind or solar power plant that is already operational. There are, however, integration costs involved. Studies have shown three critical characteristics of intermittent renewable energy that bring integration costs to the power system. (1) intermittent renewable energy production is variable and cannot follow load demand. Due to costly storage solutions, integration costs occur when accommodating production to demand, illustrated as "Profile costs" in Figure 2. (2) Production is uncertain until actual realization. Balancing costs occur when forecasted production deviates from actual production, illustrated as "Balancing costs" in Figure 3. (3) Production is location-specific and sometimes far from demand—resulting in transmission costs due to the distance between generator and demand, illustrated as "Grid related costs" in Figure 3 (Hirth et al., 2015).

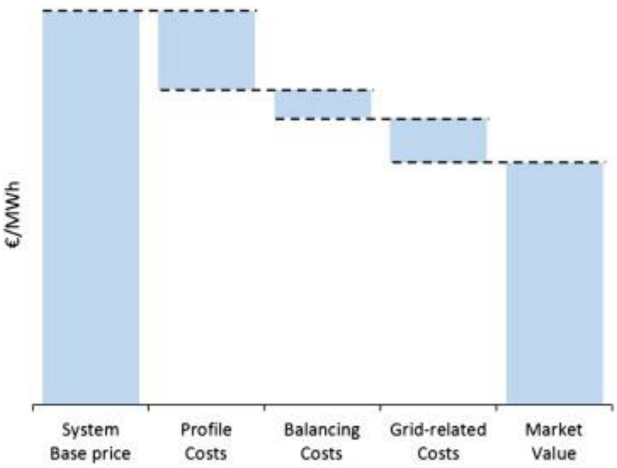

Figure 3: Integration costs of VRE. Source: Hirth et al. (2015)

Profile costs and merit-order effect

Hirth et al. (2013) investigated the market value of wind and solar power in relation to their market share. Market value in this context is described as the relative price compared to the system base price, also known as a value factor. The results revealed that the market value of wind and solar power declines as market share increases. Hirth et al. (2013) explain these results through two mechanisms. Firstly, the "correlation-effect" explains the correlation between production and demand characteristics. A positive correlation will result in a higher market value. Secondly, the "merit-order effect" is a result of low or non-marginal costs for wind and solar. When the wind blows or the sun shines, these production technologies have the lowest marginal costs and will always produce, shifting the supply curve to the right, resulting in lower system base prices.

Combined, Hirth et al. (2013) discovered that wind experiences value factors over one in low market share areas due to the correlation between wind and power prices during the winter months. At the same time, sun power experienced value factors below one because of the correlation between high sun irradiation and low power prices during the summer months. As market shares increased, Hirth et al. (2013) discovered that the value factor decreased substantially for both production technologies due to the merit-order effect, as illustrated for wind power in Figure 4. The decline in value factor for wind and solar power due to high penetration and market share is also found by Mills et al. (2012), which discovered similar results from a case study in California.

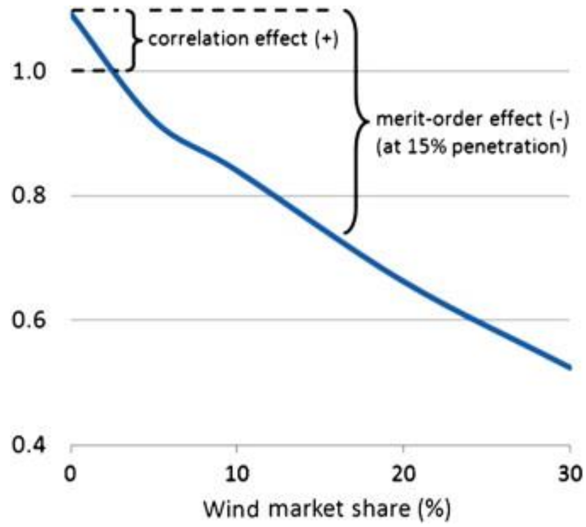

Figure 4: Value factor in relation to market share. Source: Hirth et al. (2013)

Conclusively, the EU plans to significantly increase the market shares of wind and solar power by 2050, which massively changes the dynamics in the power market. By being heavily dependent on two sources of power that both are intermittent in their production output, the power market is largely weather dependent. The increasing shares of wind and solar will, without a doubt, lead to increased needs for both short-term and long-term flexibility measures.

While literature argues the complementarity of wind and solar power, there are still significant challenges when planning to implement large shares of intermittent renewable energy to the existing power system.

2.2 European weather

Introduction to European weather

As random as it may seem, the weather follows specific patterns through time and space. For the most part, the weather is formed from the rotational tilt of the earth in relation to the sun and at what angle sunlight hits different parts of the globe. The most direct angle of sunlight is found around the equator and the lowest angle near the poles. In addition, elements such as elevation and heat capacity of different surface materials contribute to different pressure systems, with hot air rising resulting in low pressure and vice versa. It is the air moving from high-pressure systems to low-pressure systems that is wind (MetOffice, n.a.). The air circulation takes the form of three atmospheric cells in both the northern and southern hemispheres, as illustrated in Figure 5. Europe is primarily placed in the latitudinal interval of the Ferrel-circulation cell, indicated by number two in Figure 5, which is between the Polar cell and the Hadley cell. These cells give us semi-permanent areas of low and high pressure. Northern Europe is in a low-pressure area, resulting in a wetter climate. Opposite, Southern Europe is in a high-pressure area resulting in a dryer climate with largely clear skies.

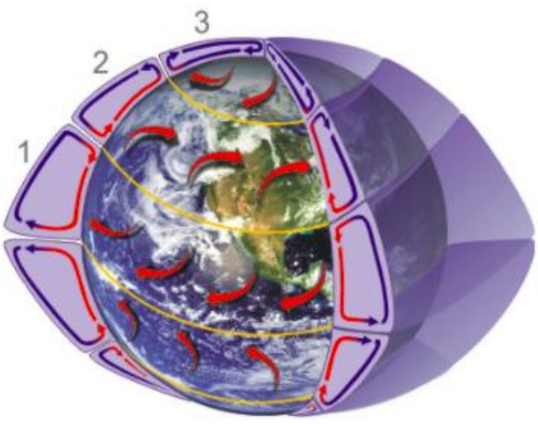

Figure 5: Atmospheric cells and prevailing winds. Source: (National Weather Services., n.a.)

Earth's rotation does also play a significant role in the global wind systems. The earth rotates from a western to eastern direction and at a higher speed at the equator than towards the poles due to the difference in circumference. Because of the difference in rotational speed at different latitudes, the air moving in the atmospheric cells does not move in a straight latitudinal line but rather in a curved line relative to the earth's surface, as illustrated by the curved red lines in Figure 5. This effect is called the Coriolis effect. As seen by the red lines in the Ferrel circulation, air moves in a north-eastward direction. In Europe, known as the prevailing westerly winds (ESA, n.a.).

European regional weather variability

Looking at the more regional resolution in Europe, the sub-seasonal variability in weather is characterized by recurrent circulation anomalies, also known as weather regimes. Grams et al. (2017) define weather regimes as variability in weather in the spatial scale of about 1000 km that occurs for more than five days. The weather regimes can be divided into two sub-groups, three regimes are so-called cyclonic regimes, and four are so-called blocking regimes. These regimes contain differences in surface weather and timescales. Blocked regimes are characterized by high surface pressure having cold and foggy conditions with strongly reduced winds during winter, illustrated by the yellow, green, dark green, and blue bars, with blue text in Figure 6. Opposite, cyclonic regimes are characterized by strong winds and mild conditions, illustrated by the purple, red, and orange bars with red text in Figure 6.

Due to the patterns of the weather regimes, grams et al. argue that Europe is divided into three sub-areas for wind-power output. These are the western Mediterranean, southeastern Europe, and northern Europe. The analysis conducted by Grams et al. shows that these sub-regions have different wind-power outputs within the different regimes during winter days.

As seen in Figure 6, in blockage regimes, the northern countries face underproduction, while southeastern Europe and partly western Mediterranean have higher production during winter. However, during some of the blockage regimes, Grams et al. discovered that certain peripheral areas like northern Scandinavia and the Balkans experienced an increase in mean wind speed. This is caused by cyclonic activity occurring on the flanks of the blockage regime due to winds pushed from the outside of the regime.

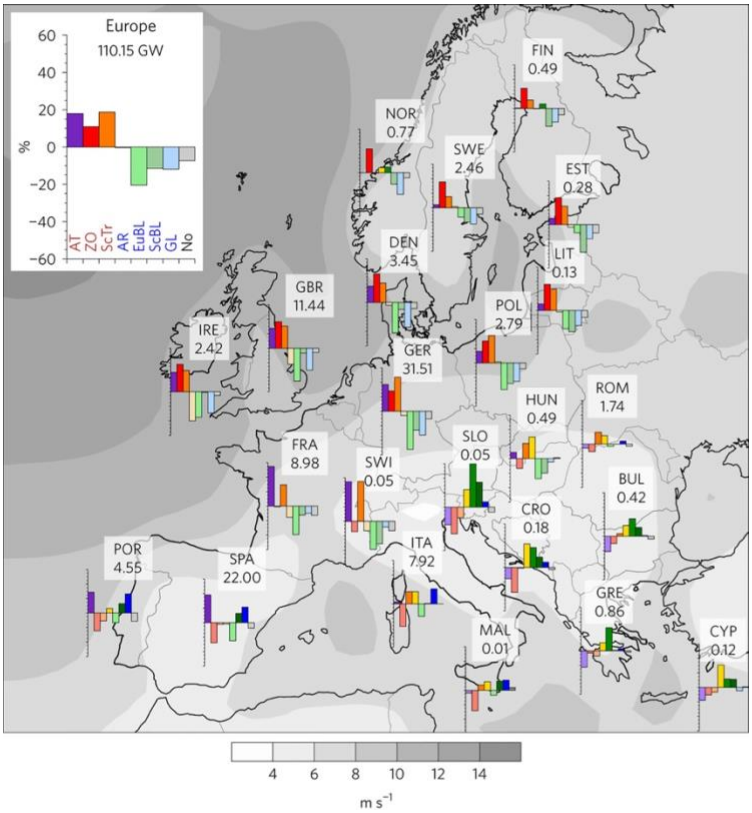

Figure 6: Country-specific relative change of CF during weather regimes. Source: Grams et al., 2017

Opposite, northern Europe faces overproduction under cyclonic regimes, while southeastern Europe experiences underproduction parts of the time during winter. On average, cyclone regimes lead to overproduction, and blockage regimes lead to underproduction in Europe. Grams et al. argue that the European energy system would strongly benefit from exploiting the weather-regime patterns with a planned spatial distribution of energy production.

3 Theory

3.1 Portfolio optimization

Modern portfolio theory

Modern portfolio theory (MPT) is a highly accepted methodology derived from financial economics, which is also useful outside the economic sphere. By dealing with energy planning for specific areas or regions as an investment problem, MPT gives a more holistic approach to energy planning and provides decision-makers with a sounder foundation (deLlano-Paz et al., 2017).

Harry Markowitz, awarded a Nobel Prize for his work on modern portfolio theory, created a methodology emphasizing that assets risk and return should not be viewed in silos, but be analyzed together to see how individual assets affect the overall portfolio. In energy planning, assets can be translated to specific areas and or technologies for production, while return can be viewed as production output and risk as production volatility. MPT is thus a theoretical framework to analyze the inter-relationship of risk and return. The risk and return of each asset are unique to that asset, and by conducting a portfolio optimization, one can get a combination of assets that fully or partly meet the desired characteristics of risk and output. By combining multiple assets, also known as diversification, it is the covariance between the assets that are of interest, not the individual asset alone.

In MPT, the risk is divided into two components: systematic risk and unsystematic risk. Systematic risk is a risk at a macro-level and is a risk that is not possible to diversify away. In the context of this study, risk is equivalent to the natural meteorological deviations of wind speed and solar irradiation around its mean. This is the risk that is not confined to one area but to some degree to a larger region. Opposite, unsystematic risk is a micro-level form of risk that is limited to a single asset or a small group of assets. In this study, micro-level risk corresponds to local weather patterns that are to some degree unique for that area but do not impact the total meteorological system in Europe. Accordingly, systematic risk can, for the most part, be mitigated by simply not choosing assets with unsatisfactory characteristics or by diversification of assets in a portfolio, exploiting the covariance of different assets (Mangram, 2013).

Efficient frontier

If each portfolio has a unique combination of assets, it will contain a unique portfolio expected return and standard deviation. The figure below illustrates this by plotting the unique assets' risk and return. Each colored dot is one asset. However, the black dotted line shows the so-called efficient frontier. The efficient frontier is the set of asset combinations with the highest return for a defined level of risk. All portfolios that are not on the efficient frontier are thus sub-optimal and do not provide the optimal expected returns for the given level of risk. As seen in the figure, no individual asset has an equally low standard deviation as the front part of the efficient frontier. This is due to the covariance between assets, which makes the aggregated standard deviation of some portfolios to be low.

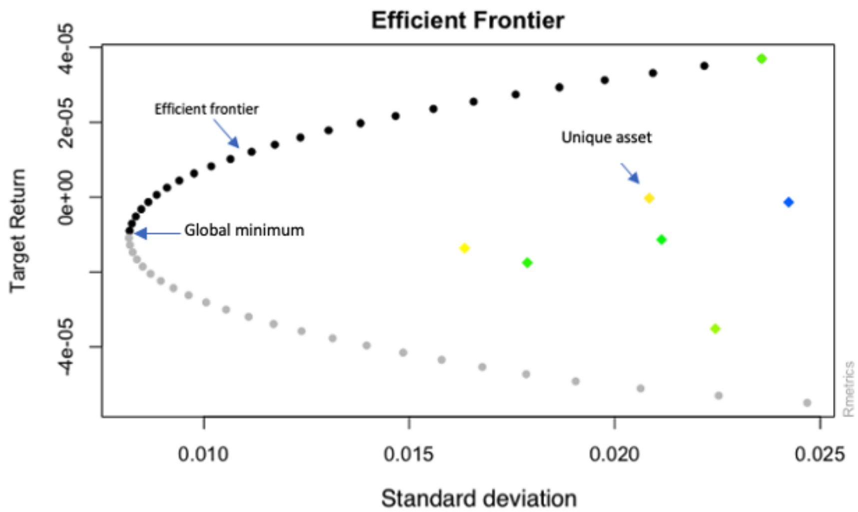

Figure 7: Efficient frontier illustration. Created with Rstudio (ggplot2), Authors own

The point on the efficient frontier with the lowest standard deviation, the global minimum, gives the portfolio with the lowest possible standard deviation. All portfolios below this point, illustrated by grey dots, are seen as irrelevant, as you could always get a portfolio with a higher expected return and lower standard deviation. However, it is important to mention that it is impossible to know that your portfolio is on the efficient frontier, as you will never know your future return (Kenton, 2022). The optimization model uses averaged historical data, with the assumption that the future will be like the past. Obviously, this is a bold assumption that is not likely to hold. Translated to energy planning, it is doubtful that the weather in the coming years will be exactly as the historical 30-year average as we cannot accurately predict weather far into the future. However, the notion that the next 30 years of weather is to some degree similar to the last 30 years is not that hard to imagine.

Conversion from finance to energy

The application of a methodology originally developed for financial purposes with financial data into energy planning is not straightforward. Modern portfolio theory is based on several assumptions that, to some extent, hold in efficient financial markets. That these assumptions also hold in the case of weather patterns and variability is, at best, doubtful. In the application to spatial energy planning, however, some of these assumptions are more important to consider than others.

The assumptions include that there exist perfect markets for trading assets with low or no transaction costs. Translated to energy planning, this could be like transmission loss and bottlenecks in the grid. While the transmission loss and bottlenecks are significant in the power system, these issues are not considered in this study, and the assumption of Europe as a copper plate makes the perfect market assumption hold.

Portfolio selection

Portfolio selection is the process where you define what the optimal portfolio is or what the objective function for your optimization is. Portfolio selection is, in that sense, quite individualistic, based on several factors. If you are a risk-averse investor, you would probably choose a portfolio with a low standard deviation and vice versa if you are a risk-taker. The following approaches are some of the most common in financial portfolio management.

Max Sharpe

The Sharpe ratio, created by William Sharpe in 1966, is by far one of the most used risk/return measures in finance (Lioudus, 2021). The ratio describes the amount of excess return one receives for the amount of volatility one must endure by holding a risky asset. The Sharpe ratio is given by the excess return of an asset divided by its standard deviation:

$$S(x) = \frac{r_x - r_f}{stdDev(r_x)}$$

Where:

$\boldsymbol{r_x}$ = The average rate of return for x

$\boldsymbol{r_f}$ = The risk-free rate

stdDev(r_x) = The standard deviation of r_x

The risk-free rate refers to investment returns that hold zero risk. In practice, this is a theoretical measure as all investment holds some sort of risk. In finance, T-bills or other governmental bill interest rates are usually used as proxies (Lioudus, 2021). In energy planning, however, the risk-free rate is not relevant. Thus, the measure used in this study is by the correct definition, not a Max Sharpe measure.

Value At Risk

Value at risk is a common measure and approach in portfolio investment to control the portfolio's risk exposure. As the risk in financial terms is defined as variance and standard deviation, it also includes upwards variance. However, in finance, upwards variation is not necessarily a negative feature, it's rather the opposite. In Value at Risk, one only measures the potential for downside loss and the probability of occurrences for a given amount of loss. This way, one can order the losses, from high to low, and compute the likelihood of those losses to occur. Further, you could choose the portfolio with the lowest possible loss within a threshold value or confidence level $\alpha \in (0, 1)$. This will result in a portfolio with the highest values at its 1-α lower quantile (Kenton, 2021). By using this method in energy planning, you can find a portfolio of production sites that will, within a confidence level, have a capacity factor above a certain value. However, this portfolio neglects the challenges of high variability and considers only the risk of low output. In addition, the measure says nothing about the risk below the quintile value.

Minimum Variance

The Minimum Variance portfolio is the combination of assets that provides the lowest possible variance among all possible combinations of risky assets. Therefore, one should never accept a portfolio that has lower expected return than the Minimum Variance portfolio (Clarke et al., 2011).

3.2 Monte Carlo methods

Monte Carlo methods have a long history in mathematical problem solving, including optimization problems. The methods are computational techniques for solving or getting an approximation of a solution to mathematical problems using random samples. The basic idea is to propose a random change in the variables for each iteration and look at how it affects the objective function.

While there are numerous different Monte Carlo methods, it will in this study be used to generate random portfolios by substituting wind and solar power market shares in different regions with random shares. The distribution of the weights is uniform, meaning that there is an equal chance of receiving all weights. This results in each iteration having a portfolio of regions, each with its random market share. In order to get the sum of each iteration to one, the market shares are scaled down proportionate to the sum of each portfolio.

4 Data

The data is mainly collected from the open dataset named EMHIRES, created by the European Commission Joint Research Center (JRC). EMHIRES is the first publicly available dataset that derives wind and solar power generation from meteorological datasets at relatively high resolutions. The dataset is available at national and NUTS-2 resolution levels, with hourly observations ranging over 30 years from 1986 to 2015 for onshore wind and solar PV. Offshore wind is only available for Belgium, Denmark, Germany, the Netherlands, and the United Kingdom. Additionally, geographical information datasets are collected for each type of power generation dataset, as shown in the table below.

Table 1: Datasets

Datasets	
Type	**Name of downloaded datasets**
Onshore wind capacity factors	EMHIRES_WIND_NUTS2_June2019_2.csv
Offshore wind capacity factors	TS.CF.OFFSHORE.30yr.date.txt
Solar PV capacity factors	EMHIRESPV_TSh_CF_Country_19862015.xlsx
NUTS-2 geometry coordinates	NUTS_RG_20M_2021_4326.shp
Economic zone geometry coordinates	EEZ_land_union_v3_202003/EEZ_Land_v3_202030.shp
Country-centroid coordinates	country_id.csv
Existing wind power capacities	Rystad internal dataset

All the datasets above are publicly available, with the exception of Rystad's dataset containing existing wind power capacities and their coordinates.

4.1 Wind data

The EMHIRES hourly wind data is extracted from the NASA-MERRA reanalysis dataset with meteorological observations, covering the whole world at a 60km x 70km grid. Wind speed is measured as U and V-components, measuring wind speed and direction. The general wind speed, disregarding direction, is calculated from the two components. Furthermore, the wind speed is vertically interpolated to hub heights to get the wind speed at different hub heights. The wind speed is then converted to wind power through a power curve for each region (Gonzalez-Aparicio et al., 2021). The region-specific power curves are derived from the existing fleet of wind farms that generated power in 2015.

The dataset initially consisted of 301 different regions. However, three areas are removed due to relevance or lack of data. These are IS00 (Iceland), LI00 (Lichtenstein), and MT00 (Malta).

4.2 Solar radiation

Solar PV capacity factors are also collected from the EMHIRES dataset. Originally consisted of 35 countries. However, Cyprus is removed due to a lack of data. The reason for choosing nationally aggregated data, not NUTS-2 regions, for solar PV capacity factors, is regarding data size management. For computational speed, reducing the number of variables, in this context, the number of regions, has a significant impact. However, low spatial resolution indeed brings with it higher uncertainty. The variability of solar irradiation over large areas is relatively low, which results in a high correlation in Solar PV capacity factors over long distances, as shown in the figure below.

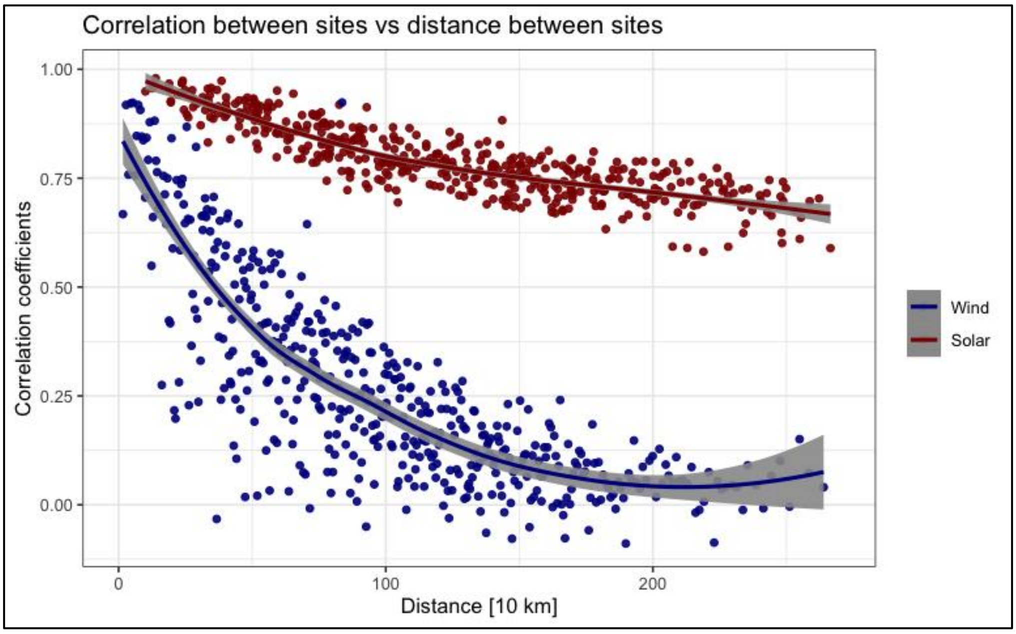

Figure 8: Hourly correlation-pair coefficient vs. distance between pairs. Created with Rstudio (ggplot2), Authors own

The figure shows the hourly correlation between capacity factors from different sites in Europe and the distances between each correlation pair. The figure clearly indicates that wind speed is highly correlated for sites closely situated but that the correlation strongly reduces the further apart they are. For solar irradiation, however, one can see that the correlation between sites stays relatively high even for areas that are more than 2 000 km apart. Note that the distances used are between the region centroid for wind resources and the country centroid for solar resources. These results indicate that the added uncertainty of low spatial resolution of solar PV capacity factors is limited. The solar resources within a given country are, to a large extent, similar.

4.3 Geographical data

The geographical data consist of three different datasets. National centroid coordinates for visualizing solar production by country, NUTS-2 geometry coordinates to visualize wind power by NUTS-2 region, and offshore economic zone geometry coordinates to visualize offshore wind. The figures are made with the “rnaturalearth”- and “sf”-packages in R. The figure below illustrates Europe and how it is divided into areas. The figure to the left is split into NUTS-2 areas with also the offshore economic zones of Belgium, Denmark, Germany, Netherlands, and the United Kingdom. The figure to the right shows the national borders in Europe, with points that represent the country centroid of each country.

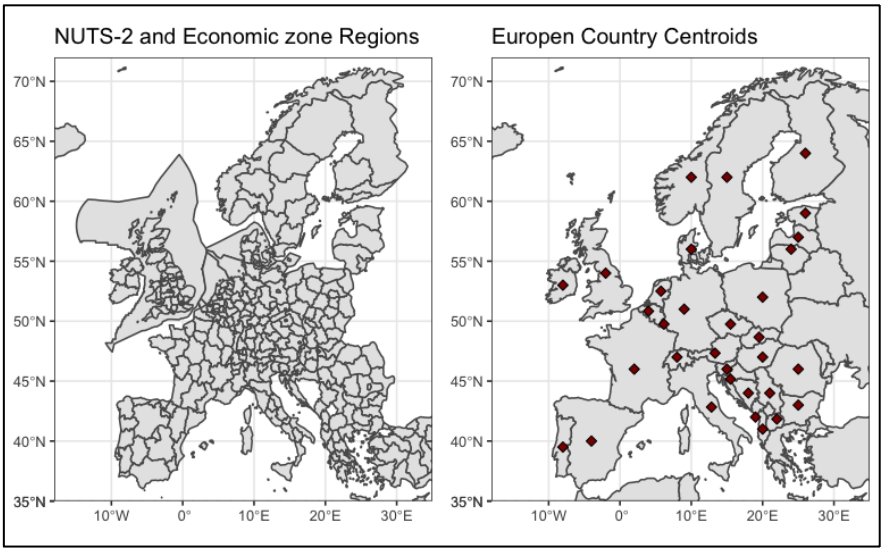

Figure 9: Geographical areas. Created with Rstudio (ggplot2), Authors own

4.4 The existing fleet of wind and solar

In order to compare and benchmark the optimal portfolios of wind and solar capacities and their measured results, one also needs to analyze the existing fleet and distribution of wind and solar capacities in Europe. A detailed dataset of all wind farms in Europe with their installed capacity and their coordinates are provided by Rystad, while solar PV capacities are collected from IRENAs online data query tool. The capacities of all areas are summarized to find the unique market share for each individual area.

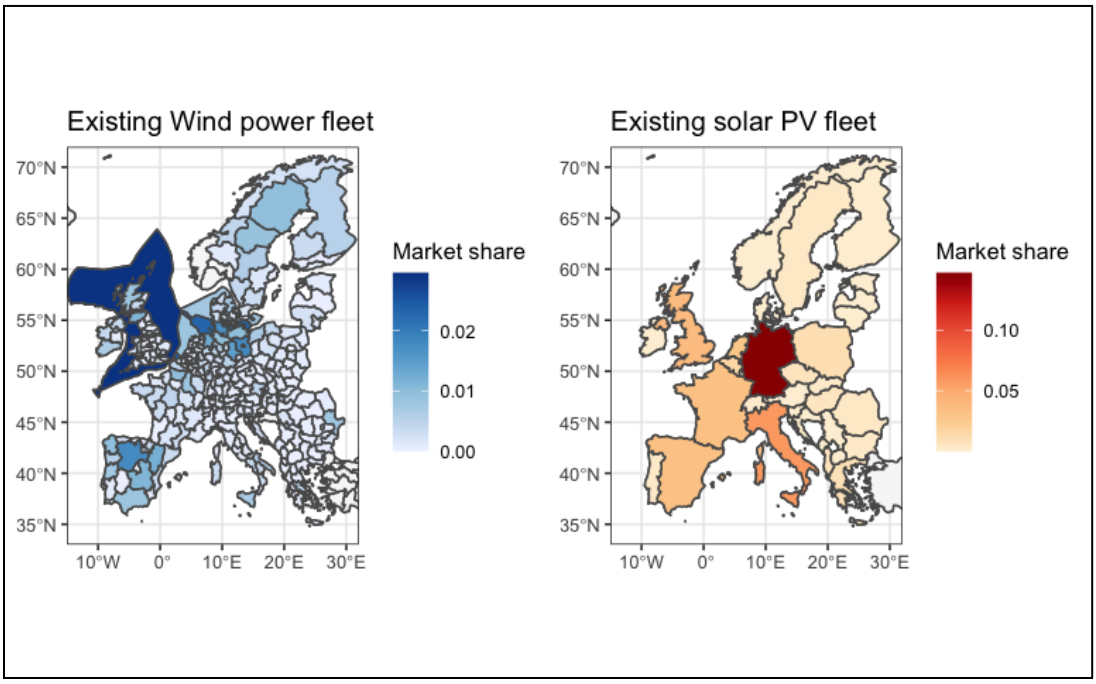

Figure 10: The current distribution of wind and solar capacities. Created with Rstudio (ggplot2), Authors own

As shown in the figure, Germany has installed roughly 14% of the power capacity in Europe in solar PV, which amounts to about 50 GW. As the distribution of solar PV is at a lower resolution than for wind power, the visualization must be interpreted accordingly. Additionally, even though it looks like the offshore region of the UK has huge amounts of wind power, it is actually not as much relative to the size of the area. Germany is the country with the highest share of wind power, but due to the small sizes of the NUTS-2 areas relative to the offshore areas, this is not as clear in Figure 10.

5 Method

5.1 Optimization model

The optimization model consists of the seven input files covered in the previous chapter. The three capacity factor datasets are first joined, making it a dataset consisting of 330 variables, not including metadata columns, and 30 years of hourly observations. Further, the mean for each hour in a year is calculated, aggregating the observation to 8760 (Appendix 1). Note that observations on the 29. of February are removed. In addition, all the different geographical information datasets are joined to one dataset, as seen in Figure 11. The entire model and data wrangling is computed in the free software R through Rstudio.

The optimal portfolio gets calculated in the portfolio optimization model that will be further explained below. From the portfolio, the location codes, in the form of NUTS-2 and ISO-A2 codes, get compared to the joined geographical information dataset to only filter the optimal portfolio areas (Appendix 2). Lastly, the chosen areas are mapped to visualize the optimal distribution of onshore and offshore wind and solar PV in Europe.

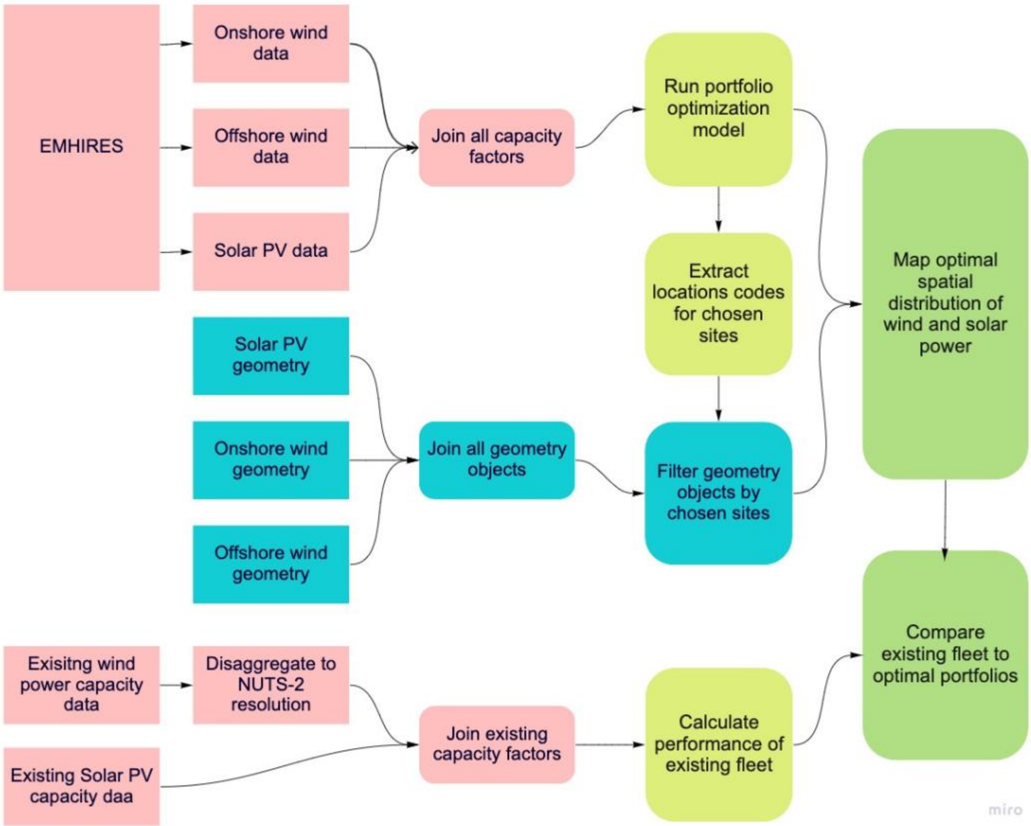

Figure 11: Method visualization, created with Miro.com. Authors own.

The portfolio model is based on Monte Carlo simulation methods, where 2 million iterations, each with changing variables, result in varying outcomes. The changing variable in this context is the market share of power generation for each area. For example, a random market share in NO2 relative to the entire portfolio of wind power in Europe or the market share of solar PV in Spain. For each iteration, the output gives a random portfolio of market shares in the 330 areas, totaling 100% (Appendix 4). Furthermore, to give the model a starting point, the existing fleet of wind and solar power capacities is used. From this, the model will randomly change between 10-200 variables, with random weights between 0-10%. The reason to cap the number of shares to 10% is due to the realism of higher market shares in a single area. These market shares are multiplied by the area's respective average capacity factor. Further, the portfolio standard deviation is calculated by multiplying the market shares by the area's individual covariance with the other areas, as illustrated in Figure 12 below.

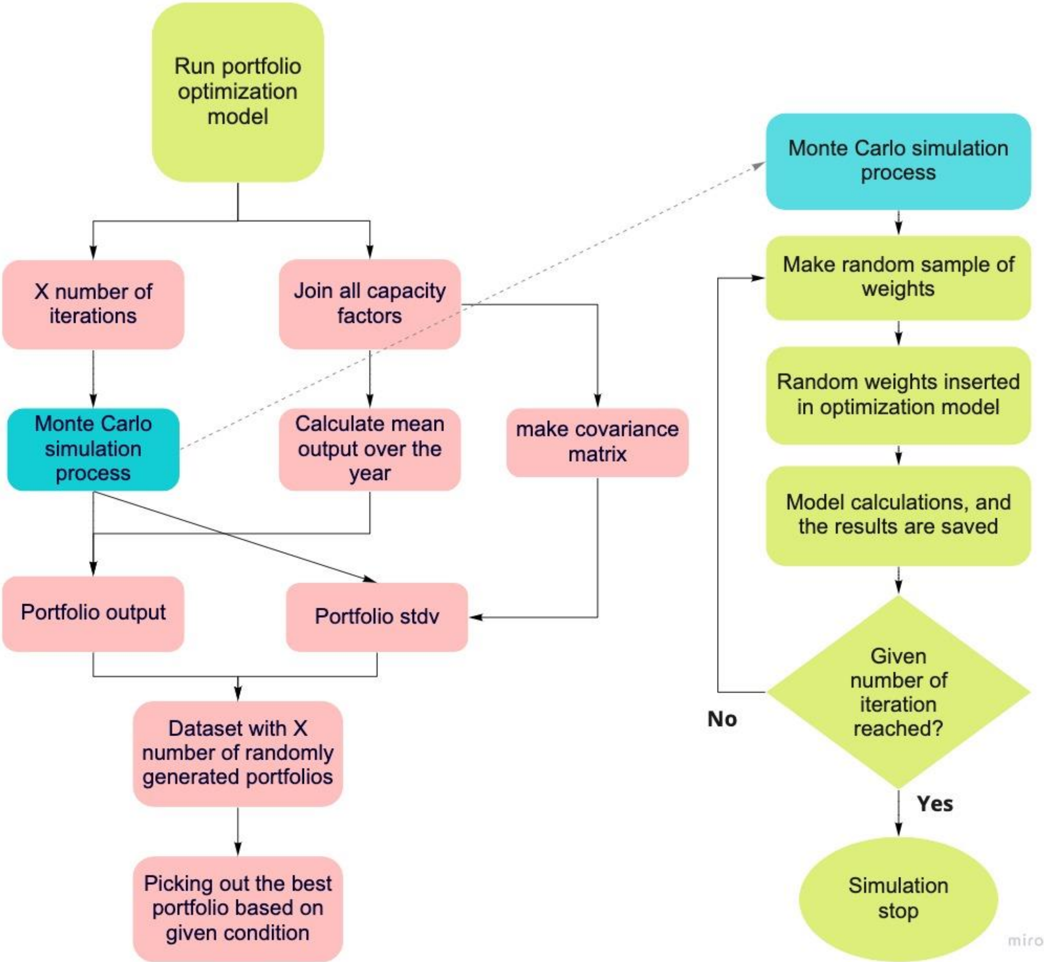

Figure 12: Portfolio model visualization, created with Miro.com. Authors own

The portfolio output P_R is the weighted average capacity factor

$$P_R = \sum w_i cf_i$$

Where w_i is the area's market share, cf_i is the area's 30-year average hourly capacity factor. Market share is defined as:

$$\sum_{i=1}^{N} w_i = 1 \qquad 0 \leq w_i \leq 0.1$$

Meaning that no single area can have more than 10% of the total share of wind and solar power capacity in Europe. This assumption is made both because of the realism of how much capacity there is room for in one area and to reduce the number of possible unique portfolios.

Further, the portfolio variance is calculated from the covariance matrix, $Cov(cf_i, cf_j)$ between each area in the portfolio.

$$\sigma_p^2 = \sum_{j=1}^{n} \sum_{i=1}^{n} w_j w_i \; Cov(cf_i, cf_j)$$

The final result from the portfolio model is 2 million unique portfolios, each with a different combination of areas with different market shares and with an associated mean capacity factor, standard deviation, Sharpe ratio, and value at risk metric (Appendix 3). Lastly, the model extracts the best-performing portfolios based on the different portfolio selection criteria explained in chapter 3.1.

6 Analysis and results

The analysis is split into two main parts. Part one will analyze wind and solar resources in Europe within both temporal and spatial characteristics. Secondly, part two will contain an analysis using the portfolio optimization model as described in chapter 5.1.

6.1 European wind and solar resource characteristics

The spatial distribution of wind resources is, for the most part, spread out amongst the north-western coastal areas of Europe. Note here that the wind resources in Norway are not correctly specified, and the interior parts of Norway have less wind resources than pictured. Additionally, note that the only offshore regions in the dataset are concentrated around the North Sea and that there are substantial offshore wind conditions elsewhere as well, such as outside of the Iberian Peninsula, which are not included. Conclusively, while the figure below shows the results from the data available through the EMHIRES dataset, it does not completely describe the full picture in Europe and should therefore be interpreted accordingly.

Not surprisingly are, the solar resources highly influenced by the latitude of the country. The further south, the higher the average capacity factor each area seems to be.

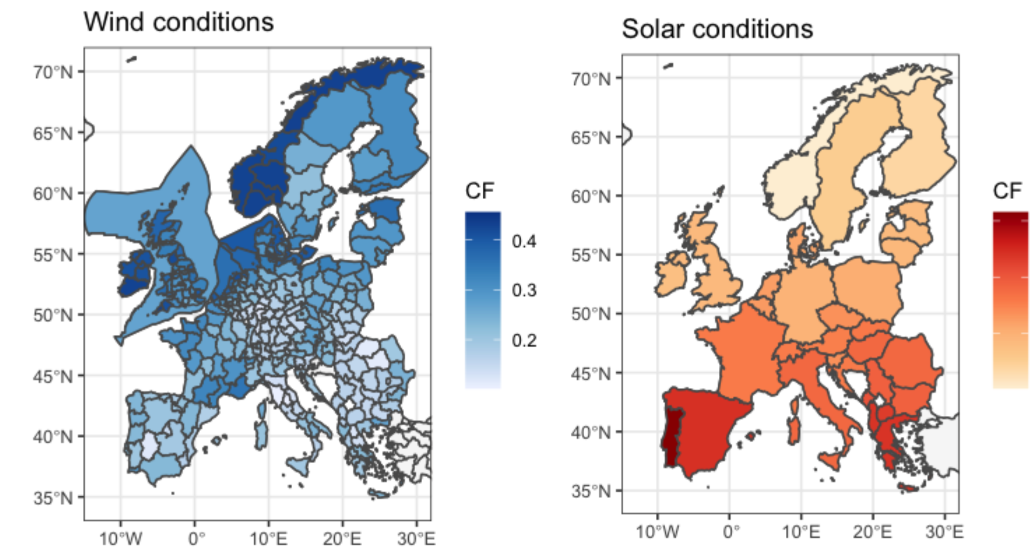

Figure 13: Wind and solar resources in Europe, from the EMHIRES dataset. Created with Rstudio (ggplot2), Authors own

By plotting the duration curves for the hourly mean capacity factors for wind and solar resources across Europe, Figure 14 clearly illustrates that there is always wind somewhere in Europe, as the capacity factor never reaches 0. However, Solar PV has 0 capacity factor just under 50% of the time, which of course comes from night-time.

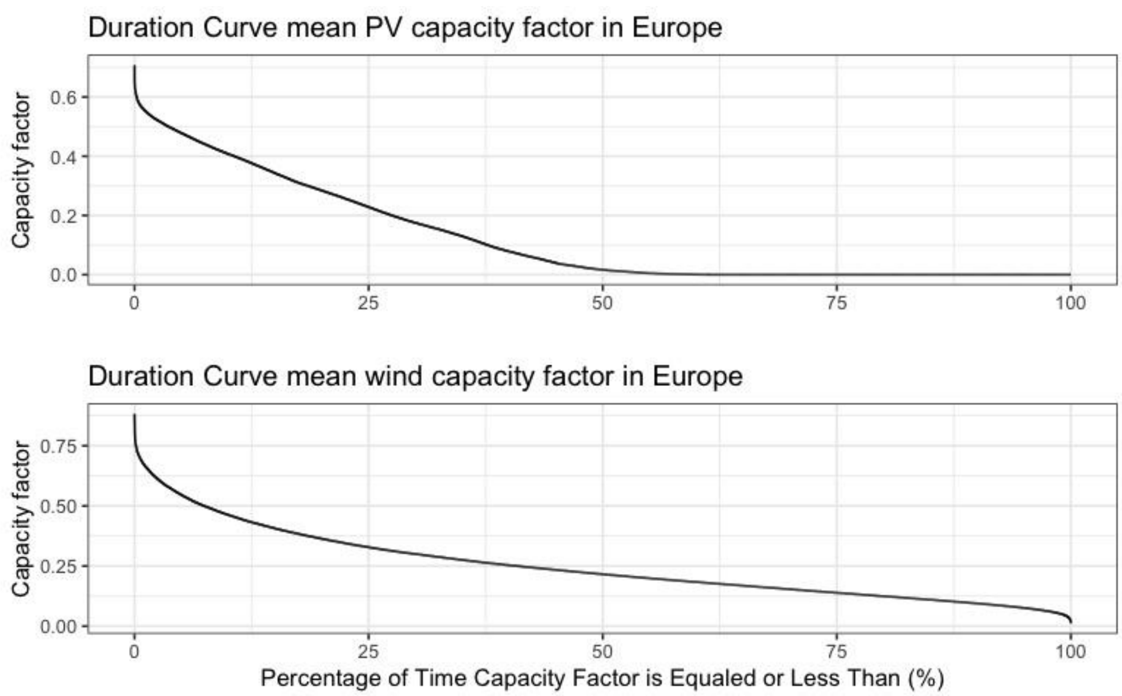

Figure 14: Duration curve, wind and solar capacity factors, 30 years of hourly observations. Created with Rstudio (ggplot2), Authors own

As discussed in chapter 3.2, the weather follows specific patterns due to seasonality and the Coriolis effect. In Figure 15, all areas in Europe are aggregated in order to get an overview of the resource profiles on a monthly basis from a sample period between 2009 and 2015. The figure shows high power capacity factors for wind in the winter months and high power capacity factors for solar PV in the summer months. This clearly illustrates the compatibility of wind and solar power over longer periods. The monthly mean capacity factor for wind and solar resources across Europe is also illustrated with a dotted line. This shows how the combination of wind and solar resources dramatically reduces the overall volatility relative to each resource's individual volatility.

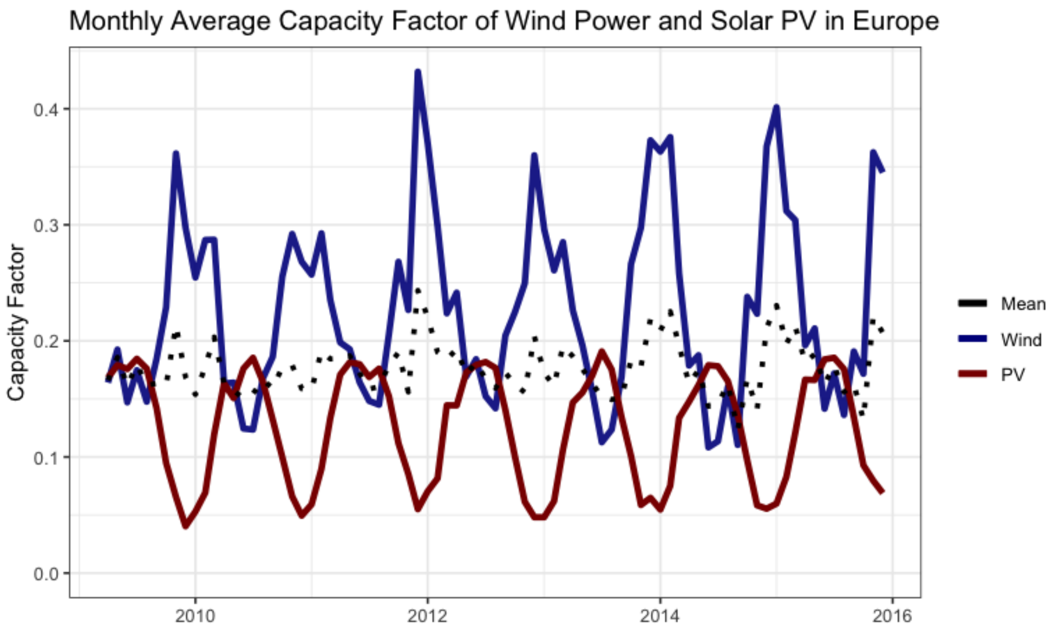

Figure 15: Mean wind and solar capacity factor in Europe on a monthly basis between 2009-2015. Created with Rstudio (ggplot2), Authors own

Although the monthly compatibility of wind and solar is promising in regards to minimizing the need for flexibility, higher temporal resolution shows that in the short-term, the correlation coefficients move towards 0, as seen in the table below. This indicates that the wind-solar compatibility could give a smoothening effect and reduce the need for flexibility, but that the impact is more significant for long-term variability than short-term variability. The correlation coefficients are calculated using the average capacity factors across Europe while using different time resolutions. Correlation coefficients close to zero indicate no relationship for hourly capacity factors between wind and solar resources.

Table 2: Wind and solar resources correlation

Aggregate wind and solar resources correlations	
Type	Kendall's Tau Correlation
Monthly average	-0.64
Weekly average	-0.46
Daily average	-0.38
Hourly average	-0.05

Further, the variability in wind and solar capacity factors shows significant volatility on monthly, weekly, daily and hourly timescales (Figure 16). However, while wind seems to have the most significant change in capacity factor from one month, week, and day to the next, solar PV capacity factors have noticeably greater hourly change than wind power capacity factors, as seen in the figure below. This is probably a result of the large increases and decreases in solar PV capacity factors during sunrise and sunset, and possibly from changes caused by cloud cover.

Further, it seems that the short-term variation is higher than the long-term variation, with monthly change in capacity factor for the most part ranging between +-0.05 for solar and +-0.15 for wind. For daily time resolution, the volatility for wind varies between seasons, but for the most part observing changes in the range of +- 0.2, while solar seems to experience changes below +-0.05. However, looking at hourly capacity factor changes, solar experience seasonal fluctuations and have, as mentioned, larger hourly variations than wind in the +-0.2 range, while wind experience hourly variations in the +-0.05 range. Furthermore, the figures reveal that there are some differences in when wind and solar resources show distinct profile regularity.

Similar to what is mentioned in the existing literature, it turns out that solar resources show specific daily patterns, while wind does not. On the contrary, wind resources seem to have higher seasonal patterns in their daily volatility relative to solar resources. This might suggest that the optimal market share allocation of wind and solar power depends on the time resolution used in the optimization model.

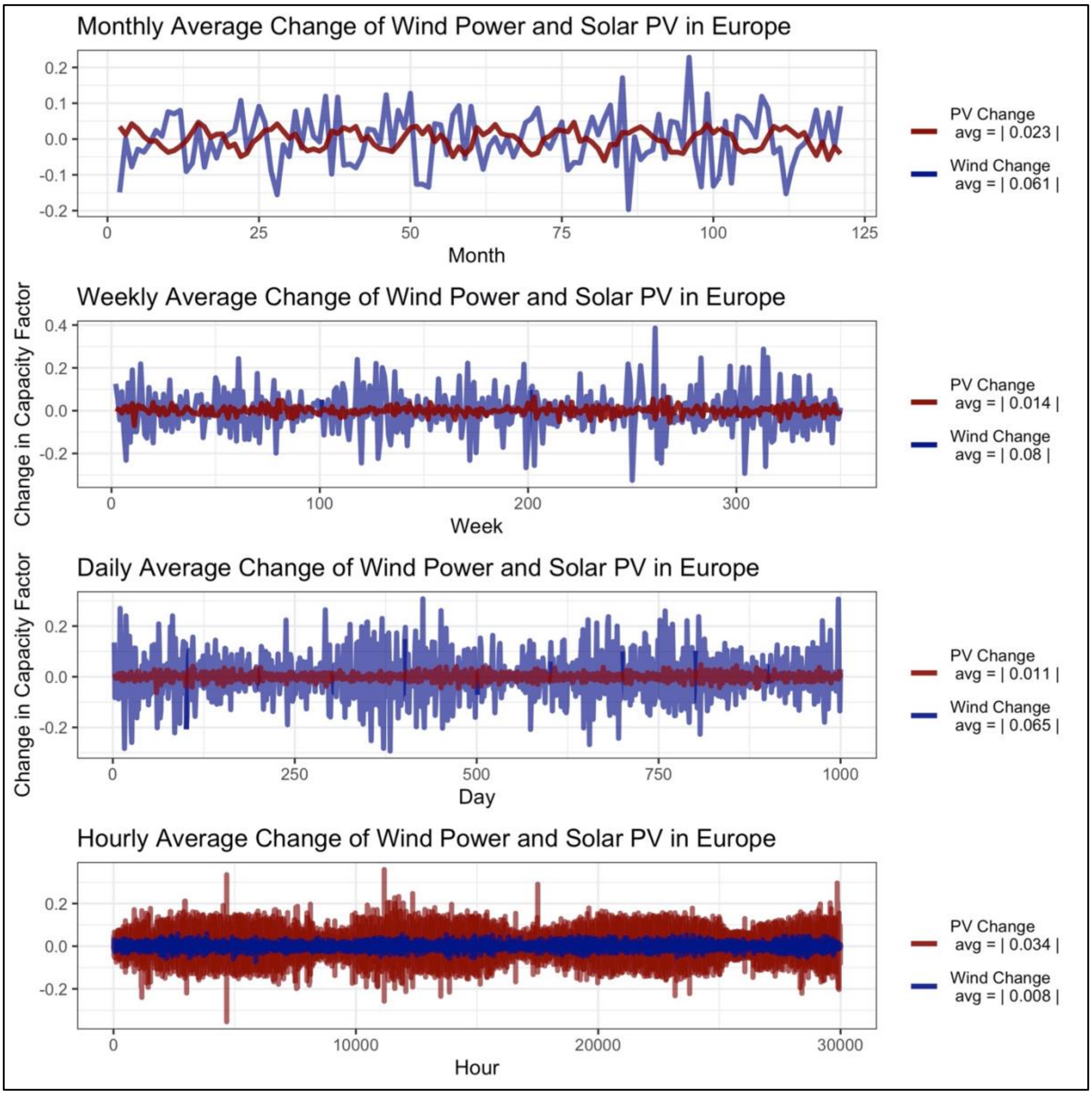

Figure 16: Wind and solar monthly, weekly, daily and hourly volatility illustration (Sample period from 1986). Average absolute change calculated from full dataset (1986-2015). Created with Rstudio (ggplot2), Authors own

Figure 16 also shows the absolute average volatility for each time resolution. The results show that the absolute average change is higher for wind resources than for solar resources in all time resolutions, except on an hourly basis. Additionally, the results show that the absolute average change is at its absolute highest for wind resources at a weekly time resolution. In simple terms, the average change is at its largest when looking at weekly time resolutions.

Similar to the monthly correlation for wind power and solar PV capacity factors, the monthly changes have a relatively strong negative correlation coefficient, as seen below. Meaning that, on average, significant variability in solar PV and wind power capacities is not likely to happen simultaneously, which is preferable from a flexibility perspective. However, the effect is reduced with higher temporal resolution. Indicating that there is little to no correlation between the variability of wind and solar in the short term. As also mentioned previously, this might indicate that the optimal portfolio will change with different time resolutions used in the optimization model.

Table 3: Wind and solar resource volatility correlation

Aggregate wind and solar resources volatility correlation	
Type	Kendall's Tau Correlation
Monthly change	-0.36
Weekly change	-0.13
Daily change	-0.08
Hourly change	0.07

6.2 The existing fleet of wind and solar power

By comparing the wind and solar resources to the existing market shares of production seen in Figure 17 below, there is no direct relationship between good resource conditions and high capacities, especially for solar PV. For example, Germany holds over 15% of aggregate production capacity solely in solar PV. Note that this is nationally aggregated data, which means that while it looks like Germany has more solar PV capacity than wind, this is not the case. However, the figure shows how it appears that it is not pan-European considerations that are used as a basis for power development but rather national considerations. Additionally, local incentives, political will, and cost profiles are major factors for where capacities are built. As in Norway, which seems to have some of the best wind resources in Europe, has very low wind capacities, which could be traced back to high competitiveness with hydropower and lack of local and political will. Similarly, Portugal, which seems to have great potential in solar power, has small amounts of solar power capacities.

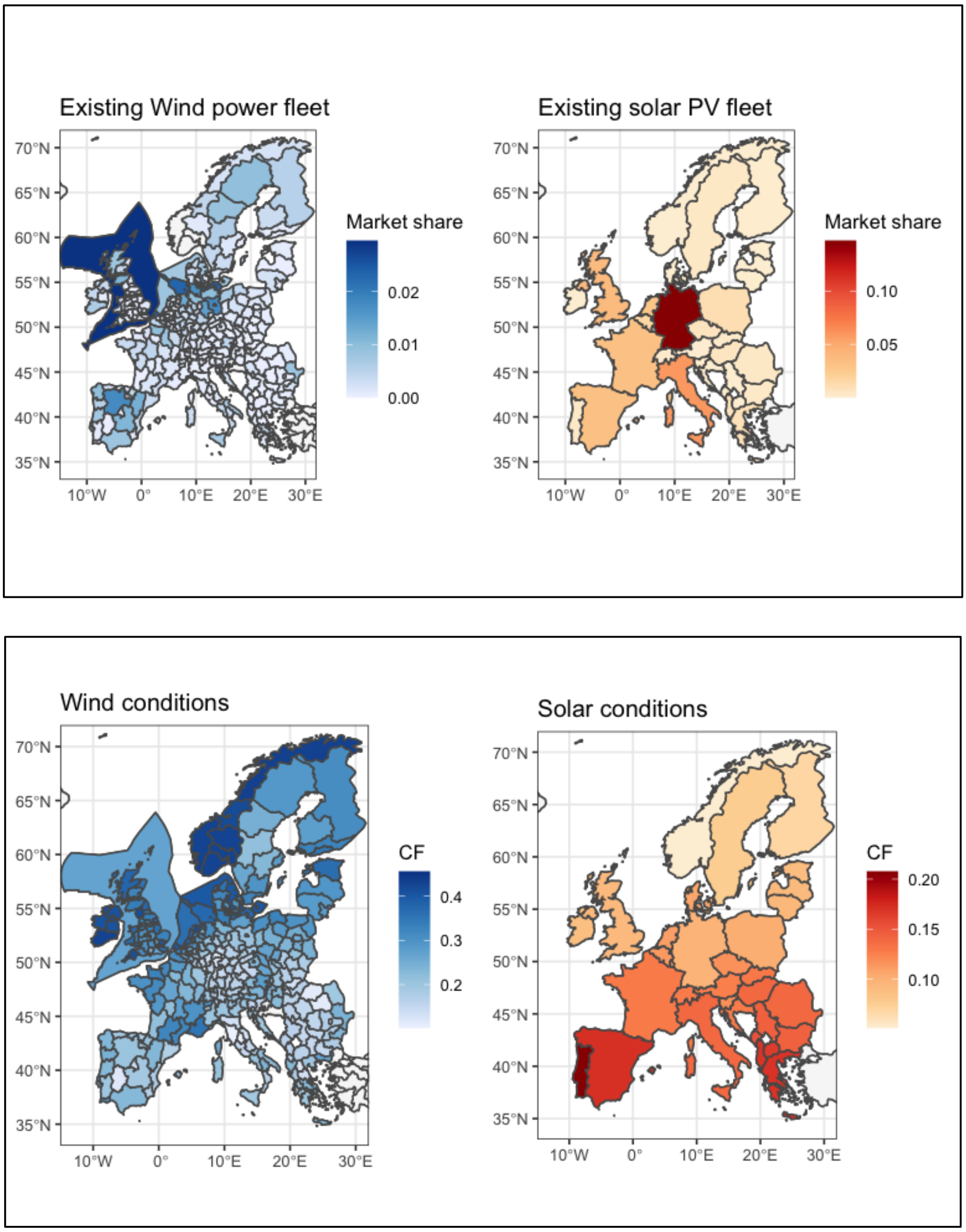

Figure 17: Existing fleet of capacities compared to wind and solar resources. Created with Rstudio (ggplot2), Authors own

6.3 Portfolio optimization

By simulating 2 million random portfolios, Figure 18 below pictures the efficient frontier, with a global minimum, the Max Sharpe, and the Value at Risk portfolio. Additionally, the performance of the existing fleet per 2020 is added. The graph clearly indicates that by planning for areas that should have wind and solar production using a portfolio optimization approach, one can identify portfolios that have significantly lower standard deviation with the same or higher expected average capacity factor. The reason for the poor performance of the existing portfolio is probably due to the extremely high share of solar PV in Germany, which gives the existing portfolio a low average capacity factor. Not surprisingly do we find the minimum variance portfolio furthest to the left, as the portfolio with the lowest possible standard deviation. However, the Minimum variance portfolio also has an average capacity factor that is relatively low, at just under 0.20. The Max Sharpe portfolio awards high capacity factors and penalizes high standard deviations, which places this optimal portfolio above the Minimum variance portfolio but with higher standard deviations. The Value at Risk portfolio does not take standard deviations into consideration but rather the probability of low outputs. This puts the Value at Risk portfolio with the highest average capacity factor but with a higher standard deviation than the two other optimal portfolios. However, even the Value at Risk portfolio experiences a lower standard deviation than the Existing fleet.

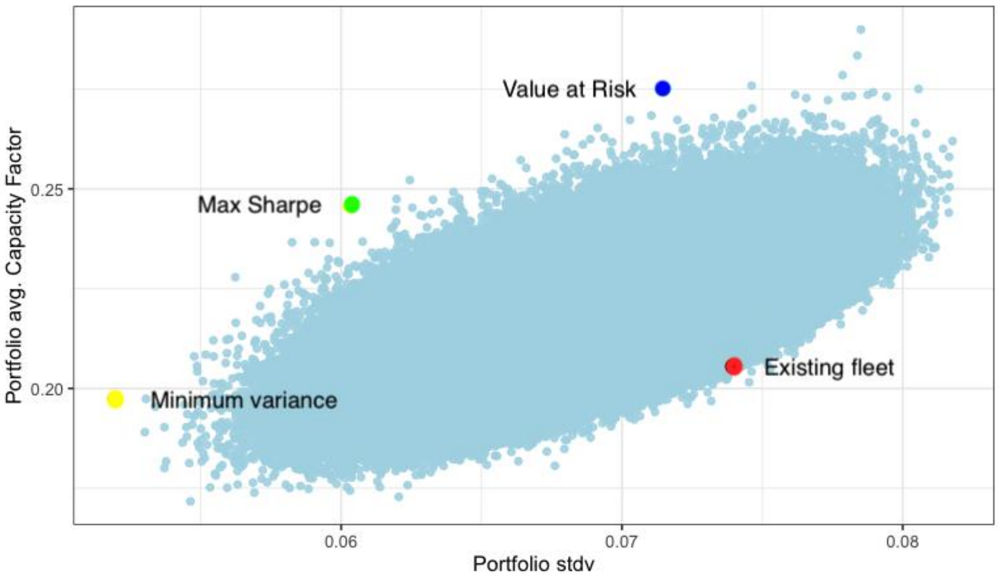

Figure 18: Efficient frontier optimal portfolios. Created with Rstudio (ggplot2), Authors own

While the figure shows significant improvements relative to the existing fleet, it is clear that the frontier is not as smooth as expected. This is probably due to the infinite number of theoretical combinations of wind and solar capacities in Europe. There is, therefore, no way of telling if the selected portfolios are the true optimal.

6.4 Optimal portfolio performance

The table below summarizes the mean capacity factors and the standard deviation for all the optimal portfolios, as well as the Existing fleet portfolio. The existing fleet of wind and solar capacities in Europe has both a higher standard deviation (0.078) and lower mean capacity factor (0.210) than the Max Sharpe portfolio and the Value at Risk portfolio, with standard deviations of 0.070 and 0.071, respectively. Further, the Max Sharpe portfolio and the Value at Risk portfolio have mean capacity factors of 0.241and 0.246, respectively.

Table 4: Optimal portfolio performances

Portfolio optimization, hourly time resolution				
	Existing fleet	**Max Sharpe**	**Value At Risk**	**Minimum Variance**
MEAN CAPACITY FACTOR	0.210	0.241	0.246	0.202
STANDARD DEVIATION	0.078	0.07	0.071	0.063
MEDIAN	0.198	0.219	0.227	0.186
VAR ($\boldsymbol{\alpha = 0.99}$)	0.028	0.080	0.081	0.055
WIND SHARE	0.589	0.869	0.848	0.823
SOLAR SHARE	0.411	0.131	0.152	0.177

For the respective aggregated wind and solar power shares, the optimal portfolios receive significantly higher shares of wind power than solar power compared to the existing fleet. The existing fleet has a wind power share of about 59% and 41% solar PV. While all the optimal portfolios with hourly time resolution receive shares of about 82-86% wind power.

The density plot in Figure 19 shows the probability distribution of capacity factors for the Existing fleet portfolio (red), Max Sharpe portfolio (green), and the Value at Risk portfolio (blue). The distribution is calculated by applying the given portfolio weights to the historically observed capacity factors for each site.

The distributions show that the Existing fleet historically has the highest chance of experiencing capacity factors less than 0.1, while the Value at Risk has the lowest probability of low outputs overall. The Max Sharpe portfolio has the probability distribution, which is the most centered, compared to the Value at Risk portfolio. This indicates that the Max Sharpe portfolio has more consistency in its outputs and, therefore, could be the most suitable portfolio.

All the measured portfolios are right-skewed, meaning that the tails of the distribution are longest on the right-hand side, as also mentioned in the table above. Depending on the skewness, we know that the mean of the distribution is greater than the median. Therefore, the mean observations mentioned above could be biased due to extreme right-tail values.

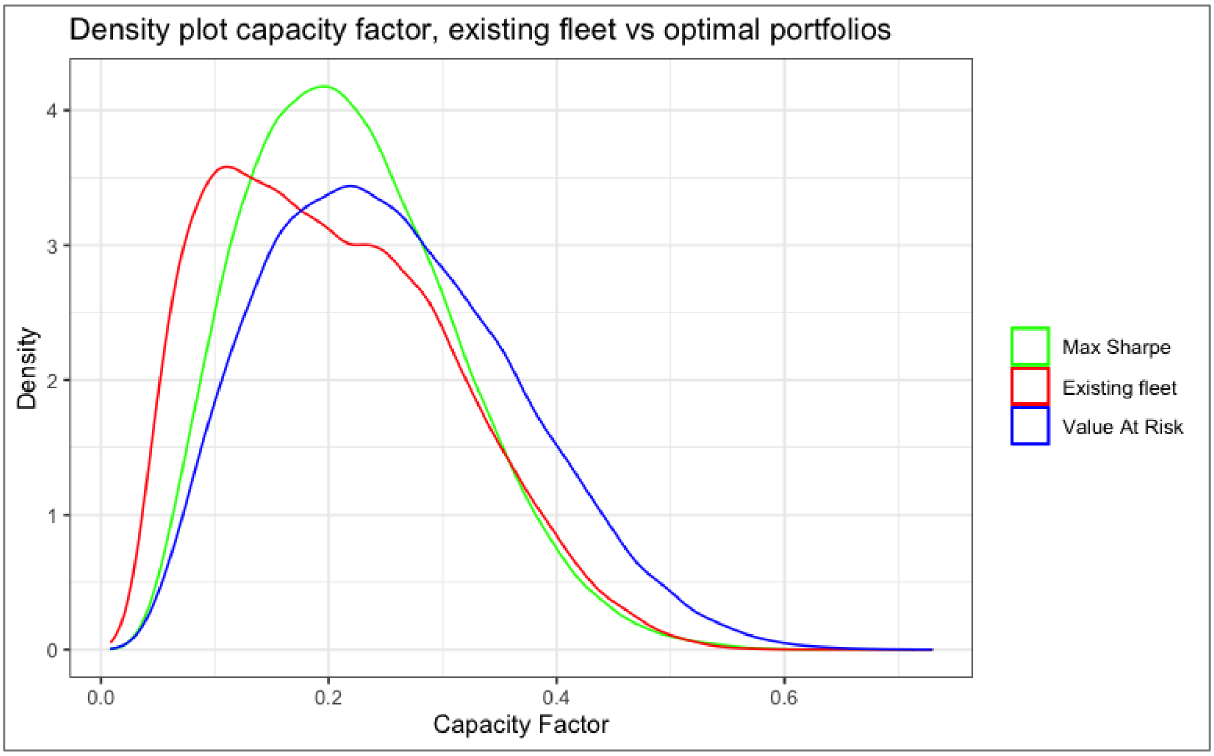

Figure 19: Density plot capacity factors, 30 years of hourly observation between 1986-2015. Created with Rstudio (ggplot2), Authors own

The Max Sharpe portfolio also shows significant improvements in terms of volatility relative to the Existing fleet, as shown in the figure below. Volatility is measured here using the absolute difference from one to the next. The absolute difference is an intuitive way of picturing volatility. However, it does not provide any information about the relative magnitude of the difference. The reason for not using relative difference is because of the frequent levels at zero for solar PV during nighttime. Relative difference from zero is, by most accounts, meaningless.

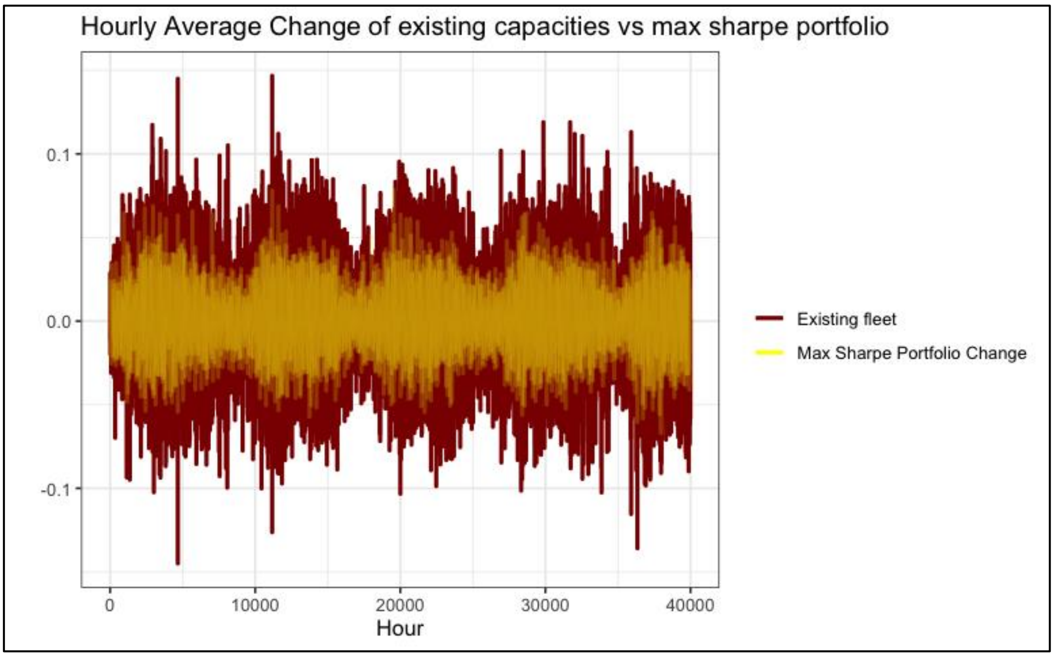

Figure 20: Hourly change for optimal portfolio and existing fleet, sample period starting from 1. January 1986. Created with Rstudio (ggplot2), Authors own

In Figure 21 below, the spatial distribution of wind and solar capacities in the Max Sharpe portfolio are mapped. Showing wind capacities to the left, with dark blue indicating high market shares of wind. On the map to the right, the spatial distribution of solar PV is mapped, with dark red areas indicating a high market share of solar PV.

The figure shows that no region has more than about 4% of the aggregated capacity. This leads to wind and solar capacities that are quite spread out. More so for wind power than solar PV, which shows significantly higher shares of solar PV in the areas around Spain and Portugal, and more surprisingly, in the Netherlands. On the other hand, Germany, which has the most solar power capacities to date, receives almost no solar power in the optimal portfolio.

However, as described earlier, the differences between output and standard deviations of solar resources are minor, which could lead to optimal portfolios with sub-optimal solar capacities.

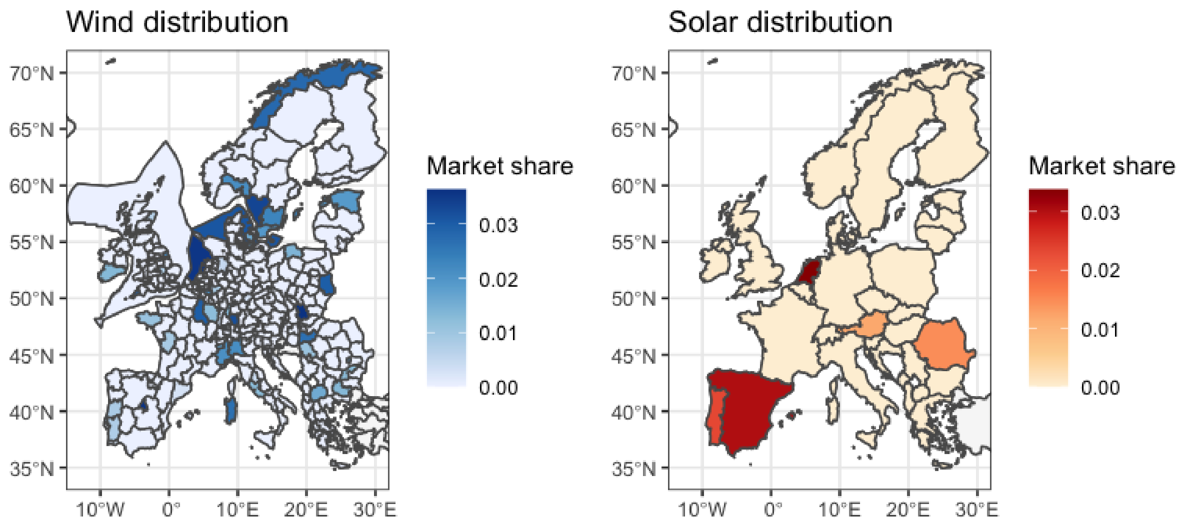

Figure 21: Optimal allocation of wind and solar capacities, hourly time resolution. Created with Rstudio (ggplot2), Authors own

As mentioned in chapter 6.1, there is a bug with the Norwegian wind resources which originates from the EMHIRES dataset. This means that the results for Norway cannot be trusted. For example, it seems strange that the south-eastern parts of Norway should be assigned as high wind shares as it has been in the optimal portfolio depicted in Figure 21. However, the bug only means that the southern parts of Norway have received the capacity factors for western Norway. Meaning that the results from this optimal portfolio could indicate that western Norway should have high shares of wind power, not the south-eastern parts.

Additionally, the results show that a large part of the wind power capacities in the optimal portfolio is based around the North Sea but also in more peripheral parts of Europe. For example, the results show that some of the regions with the most wind power in the optimal portfolio are SK03 in Slovakia and NO07 in northern Norway, two regions with small amounts of wind power today.

6.5 Best performing regions

Because of the instabilities in the model due to the infinite number of possible portfolios, the 1000 best-performing portfolios are extracted and analyzed. This is done by ranking all portfolios by the Max Sharpe ratio and calculating the mean market share for each area in the 1000 best portfolios. This should give more robust insight into individual areas that consistently perform well in the portfolio optimization.

The table below shows the five regions that have the highest average market share in the 1000 best portfolios, rated by the Max Sharpe criteria.

Table 5: The best performing regions on average

Country	Area code	Type
Greece	EL42	Wind
Portugal	PT15	Wind
Portugal	PT17	Wind
Greece	EL41	Wind
Portugal	PT16	Wind

Interestingly, Greece and Portugal occupy all the top five appearing regions from the optimization, indicating that these two regions are highly attractive for wind power from a portfolio perspective.

Looking at the 30-year average output from these two regions over a year (Figure 22), both EL41 and PT15 have some clear differences from the European average wind output. EL41, in Greece, seems to have its windiest months in the period around August, which is one of the least windy months in Europe, on average. Additionally, PT15 in Portugal also seems to have quite a stable mean wind resources year-round, compared to the European average. By including these two regions in an optimal portfolio, one undoubtedly gets an aggregate output with a lower dip through the summer months, which could make them attractive in a portfolio context.

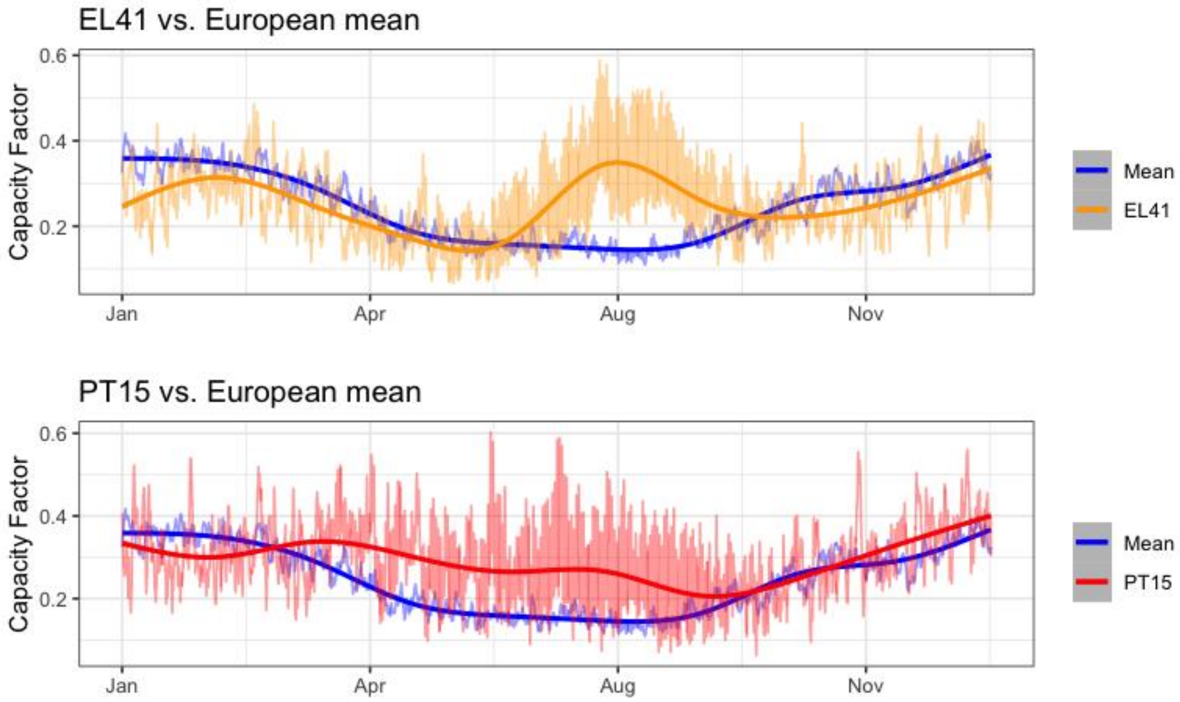

Figure 22: Best performing regions compared to the European average wind capacity factor. 30-year average (1986-2015), hourly observations. Authors own

6.6 Changing time resolution in the optimization model

The results from the weather characteristics analysis showed that there are some differences in the output volatility in both wind and solar resources at different time resolutions. At hourly time resolution, solar resources seemed to have higher volatility than wind. However, with lower time resolutions, like daily, weekly, or monthly data, wind was the resource with the highest volatility.

The optimization model is run at different time resolutions in order to analyze how the existing fleet performs relative to optimal portfolios. The results show that the optimal portfolios outperform the existing fleet in all-time resolutions, where the Minimum variance, Max Sharpe, and Value at Risk represent the optimal portfolios, which are marked in yellow, green, and blue, respectively (Figure 23). However, the possible improvement from the existing fleet, marked in red, is significantly larger on an hourly time resolution.

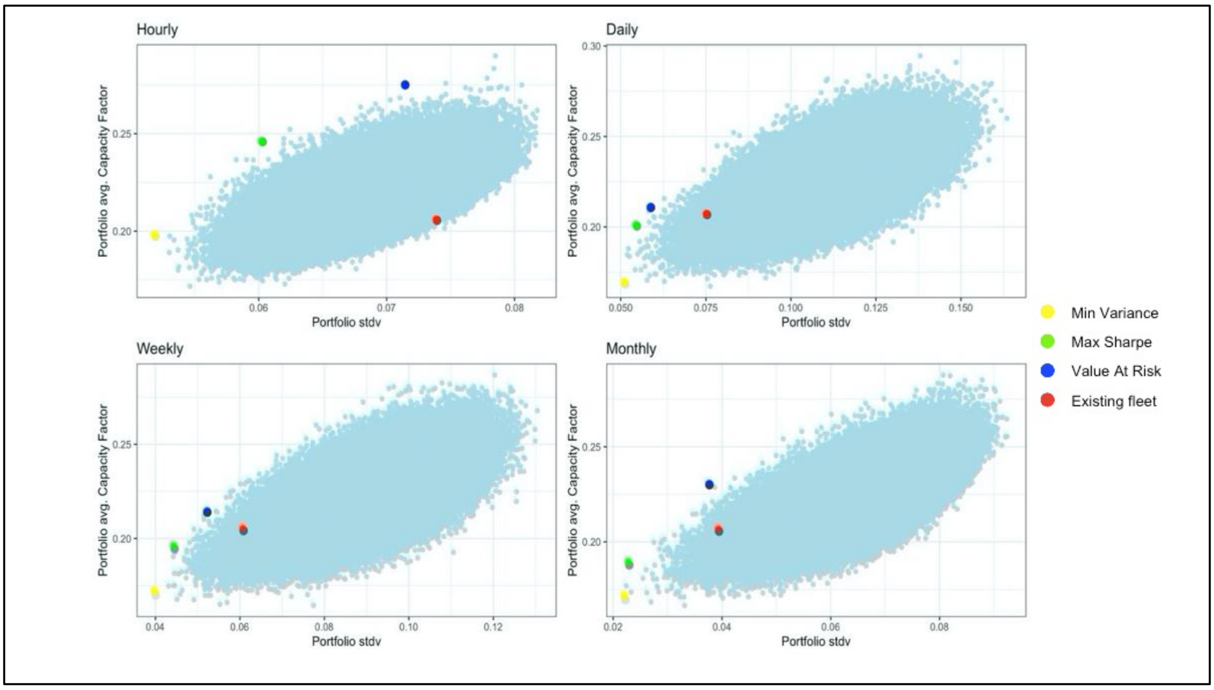

Figure 23: Optimal portfolios in different time resolutions. Created with Rstudio (ggplot2), Authors own.

The optimization model has also been run on daily, weekly, and monthly data to investigate whether these differences impact the choice of optimal allocation of wind and solar PV. For this analysis, only the Max Sharpe portfolio is run on each time resolution.

Table 6: Technology allocation in different time resolutions

Wind and solar power capacity allocation in different time resolutions				
	Hourly	Daily	Weekly	Monthly
WIND SHARE	0.869	0.653	0.598	0.480
SOLAR SHARE	0.131	0.347	0.402	0.520

The table above shows how changing the time resolution in the portfolio optimization model affects the allocation of wind, and solar PV aggerated market shares. As indicated in the weather characteristics analysis, wind power is most suitable for short-term performance, giving the optimal portfolio about 87% wind power. This is probably due to the high hourly volatility in solar resources commented on previously. However, when shifting to lower time resolution, the share of wind power decreases substantially for daily averages, reducing the amount of wind power to 65%. While weekly averages get an optimal portfolio of about 60%. For monthly averages, the optimal portfolio receives a wind power share of 48%.

7 Discussion

The discussion is divided into four main parts. Where the first discusses the results from the weather analysis and the optimization model. The second part discusses the model limitations and the approaches used in this thesis. The third part discusses how the results from this thesis could be used in further work. Lastly, the fourth part considers known issues with the data used in this thesis.

7.1 The optimal allocation of wind and solar power capacities

Key characteristics of wind and solar resources

The weather resources in this study are analyzed in broad and general terms, which means that inter-annual variations and weather regimes such as described in chapter 2.2 are not included. There are, of course, large deviations of wind and solar resources from year to year and within years. This means that conclusions based on a 30-year average are uncertain. On the other hand, it does give some interesting insights into the broad trends in the weather system.

The spatial and temporal characteristics of wind and solar resources are analyzed across Europe. Like existing literature, this analysis shows that wind and solar resources have a significant negative correlation on a monthly time resolution. However, when moving to higher time resolutions, the effect decreases to the point where there is no relationship at all. Similarly, the correlation between volatility in the wind and solar resources has a significant negative coefficient at monthly averages but experiences a decrease in the relationship as the time resolution increases. This means that on a monthly basis, wind and solar resources are to a large extent compatible, but that the compatibility decreases with higher time resolutions. However, while the decreasing compatibility means that the combination of wind and solar does not solve all problems, the general diversification of power supply is by all accounts positive.

The wind is the most volatile resource in all the measured time resolutions except on an hourly basis. Additionally, wind experiences the biggest volatility on a weekly basis which also is the largest volatility overall, while solar experiences its highest volatility on an hourly basis. However, large parts of the volatility in hourly solar power are due to the differences between sunrise and sunset, which is highly predictable. Predictable volatility is, of course, easier to cope with in a power system context than the volatility that is harder to predict. This could potentially be dealt with by removing data from the nighttime and in the periods of sunrise and sunset. By doing this, you could get a better picture of volatility caused by cloud cover.

Given that these results are based on aggregated data for the whole of Europe, it does not capture the compatibility in smaller regions. There are, however, ample studies that have analyzed more regional compatibility and volatility of wind and solar resources in Europe.

Optimal portfolios on an hourly basis

The optimal portfolios in hourly time resolution are analyzed and compared to the existing fleet of wind and solar power capacities in Europe. The results showed that it is theoretically possible to allocate wind and solar capacities in a way that both increases the aggregated average capacity factor and decreases its standard deviation. By distributing the capacities, especially for wind power, over larger areas, the power system could potentially handle situations of regional blockage regimes, as described in Chapter 3. However, this conclusion is drawn under the assumption that the transmission capacity is sufficient.

Furthermore, distributing wind power over larger areas could also be beneficial from an economic point of view due to the previously mentioned merit order effect, where large regional accumulations of capacities may lead to drops in the received power price for wind power plants. Implementing such effects on the received power price in the investment decision could lead to that previously rejected area becoming more attractive due to their complementary to more developed areas. Such an analysis, finding complementary sites, could be done with the type of model used in this study.

The analysis of the best performing regions from a portfolio perspective shows that regions in Greece and Portugal have great potential for wind power. Greece shows wind profiles highly compatible with the European average with windy summer months when the rest of Europe typically has less wind. On the one hand, high wind power output during the summer months could also lead to overproduction, assuming that the southern parts of Europe will have significant solar PV capacity. On the other hand, sufficient transmission capacity between northern and southern Europe will mean that wind power in Greece and Portugal is highly attractive.

Optimal portfolios in different time resolutions

The analysis showed that the time resolution of the data is crucial for the optimal allocation between aggregated wind and solar capacities in Europe. In general, to achieve smoother long-term output, the share of Solar PV should be higher than in an hourly time resolution. This indicates that decision-makers need to consider at what time resolution flexibility is most difficult to maintain with a comfortable margin in order to ensure safe operations of the power system. For example, if short-term flexibility is easier and cheaper to obtain in a future power system, it could be beneficial to plan the allocation of wind and solar capacities in a way that is optimal, looking at a low time resolution. However, the relationship between time resolution and allocation shares of wind and solar capacities is not thoroughly analyzed but could be interesting for further work.

7.2 Model limitations and approach

Variance as risk

While modern portfolio theory is an easy and not too complicated method for energy planning and finding efficient portfolios, it has its limitations. One criticism is that MPT usually assesses portfolios based on variance and no downside risk. In finance, upside volatility is actually no risk at all. One way of only considering downside risk is by measuring the Value at Risk portfolio. However, in energy planning, upside volatility is not necessarily a positive feature. While wind power is a suitable asset for curtailment, this could lead to higher balancing costs. Upside volatility could also be dealt with through different flexibility measures, like battery energy storage systems (BESS) and demand response. However, regardless of the direction of the volatility, this will most likely increase the complexity of maintaining a balanced system. Therefore, variance could seem to be an adequate measure of risk in energy planning after all.

Demand exclusion

A limitation of the analysis is that the model does not take demand into account, which in the end is the parameter power generators are built to cover. A reason for focusing on the resources only, and not demand, is to explore the potential resources available, which demand eventually will have to adjust to. Assuming that demand flexibility comes at cost, it is useful to know more about the potential for reducing the overall supply volatility. Additionally, by designing a power system to fit a given demand pattern, one could make the system vulnerable to changes in consumption and demand patterns. This is a relevant risk to consider, given the extensive electrification in sectors previously dependent on other energy sources. In the long-term perspective, it is not given that it makes more sense to design the power supply to follow the current demand rather than to adapt demand to follow the weather-driven future power supply.

On the other hand, there are some demand patterns that most likely are constant, such as higher demand for energy due to heating during winter months in the north and higher demand during summer months in the south due to cooling. It seems unrealistic to believe that flexibility can handle long-term demand volatility, not to mention seasonal variations. In that context, the optimal portfolios should, to some extent, try to match demand and not only try to maximize output while minimizing volatility. However, as mentioned previously, Zappa & van den

Broek's (2018) results showed that spatial optimization did not significantly reduce peak residual demand nor total residual demand, which is strange considering that they also found portfolios with lower volatility than the existing fleet. However, in their study, demand is a fixed metric, which, in reality, is not the case.

Nevertheless, lower supply output volatility should lead to lower forecast errors, improving the efficiency of the power system. Furthermore, the model has shown that the power system can get more power out of a system that is optimally distributed than one that is not, with the same amount of input. Additionally, the type of model used in this study is useful in the context of analyzing the complementarity of different production sites and how capacities in one region may affect the power system as a whole.

Historical average

Another weakness of the model is the use of historical data to make the expected output for each asset. This procedure assumes that historical observations are true for the future. This is, of course, a bold statement in finance, but also in energy planning. While there are enormous resources going into mapping the consequences of global warming and climate changes, this is beyond the scope of this study. Nevertheless, studies have found that climate change may decrease the output of solar PV in Europe, but not at a significant level (Jerez et al., 2015). Regarding wind power, Tobin et al. (2015) argue that climate change will not significantly change the overall production of wind power in Europe, but some regional changes in wind resources may occur. Conclusively, to truly analyze the weather in Europe and the future optimal distribution of capacities, climate change is something that should be included, but the overall consequences of not including it are limited.

Furthermore, the approach used in this study uses the average of all years of data when calculating mean returns and variability for each asset, mainly to reduce calculation time and to simplify the model. In reality, there are significant differences between years and within the year. The weather regimes described in Chapter 2.2 show that Europe experiences large deviations from the overall average, which is not soundly captured in the model used in this study. This could, in the end, result in instabilities within the covariance matrix used in the model and thus the overall results. Similarly, variations in the average capacity factors will result in significant deviations in the model output. The model in its current state is, as a result, not as robust as one could hope for, and the results should be interpreted accordingly. However, the historical average can still give some insight into the general wind and solar resources in Europe and how they behave in relation to each other.

Area restrictions

By not taking area restrictions and limitations into account when modeling the optimal portfolio, this study makes a significant simplification. This means that the model does not limit the number of market shares one region can receive due to factors such as high population density, natural reserves, and so on. While there is possible to add such constraints to the model, there has been a need to scale down the complexity of the model used in this study. Additionally, the aim of this study is not primarily to find the exact locations of sites for wind and solar PV capacities but rather to conduct a resource mapping and to analyze whether time resolution changes the optimal distribution. Furthermore, the geographical resolution used in this study is too low for it to be of any practical use in including such constraints. However, such considerations can instead be taken by more in-depth analyzes.

Europe as a copper plate

Another main assumption in this study is that Europe functions as a copper plate with no transmission loss or bottlenecks. While this assumption is highly unrealistic, this study has a future perspective and focuses primarily on the resources available.

On the one hand, by including transmission capacity, the model would tend to reduce the overall value of spatial distribution, as resources in close proximity naturally are more attractive than more distant resources. On the other hand, a future power system predominantly based on intermittent renewables will, in any case, require a significant expansion of the transmission capacity, as described in chapter 2.1. Therefore, it is not given that the saved costs from near resources outweigh the added performance of distributed capacity. The starting point should thus be to find where the resources are located, regardless of the current situation. An analysis that combines resource mapping and grid design is outside the scope of this thesis.

Cost profiles

The model used in this thesis does not take any cost perspective into account. The assumption that wind and solar power have equal cost profiles all over Europe is by no means realistic. In energy planning, cost profiles in different regions would naturally be a significant factor to consider, and the current distribution of wind and solar power capacities depicts just that, with high shares in areas where there are both favorable cost profiles and political will. But again, as this is more a resource mapping, cost profiles are not considered relevant in this thesis.

Additionally, cost profiles are not constant. Given that this thesis focuses on a future power system, current cost profiles are not necessarily adding value to the model. One could potentially try to forecast cost profiles in different parts of Europe towards 2050, but this is outside the scope of this thesis.

Conclusively, the results from the analysis convincingly show that the method can be used to increase the performance of the current allocation of wind and solar capacities in Europe. However, the simplification of the model and assumptions included suggest that the model should be used with care and not be the only knowledge base in decision situations. The approaches used in the model are, however, suitable for resource mapping and for evaluating the existing fleet performance relative to the theoretical possibilities.

Computational limitations

Due to the author's lack of models that handle the number of variables used in this study, the optimization model uses a Monte Carlo simulation approach. Additionally, due to a lack of experience in machine learning and evolutionary optimization, this has resulted in every iteration being saved for then being considered. The computing power available has thus not been sufficient to assess more than 2 million portfolios for each time resolution. With the fact that the number of possible combinations of wind and solar power areas in Europe is almost infinite, the results in the "optimal" portfolios are most likely not the true optimum. However, as mentioned previously, the main point of this study is not to find the exact areas for wind and solar power but rather to analyze the potential functionality of the method in energy planning.

7.3 Further work

There is no question that holistic energy planning in Europe is beneficial. In a power system that's increasingly weather-dependent, diversification of risk is crucial. The methods used in this thesis give some insights into how diversification can take place, but have some obvious shortcomings as mentioned above.

There are no economic perspectives taken into account in this study. It could be interesting to implement cost profiles in different areas to analyze the low-hanging fruits in Europe. This could be done both on direct generation costs for wind and solar power or for transmission capacity. By penalizing capacities far away from load centers, one can find regions that do not necessarily have transmission capacity today but are close to where the demand is located.

There have been conducted similar studies with the implementation of residual demand without managing to lower peak residual demand or total residual demand. However, there is most likely a need to implement demand in some form to soundly capture the power system dynamics.

Furthermore, only wind and solar power are analyzed in this study, while the future power system will consist of additional production technologies such as hydropower, nuclear and flexibility resources.

As computing power and advanced modeling get more accessible, high-resolution models with additional asset classes and attributes could use modern portfolio theory and portfolio optimization to find higher-performing allocations and spatial distributions of the power system. Additionally, the results from this thesis show that the time resolution used in the optimization significantly influences the optimal portfolios. Further analysis into how these effects behave could be interesting.

7.4 Known issues with data

All data, except current capacities and geographical information, is based on the EMHIRES dataset. Through the analysis, some issues with the dataset have appeared.

N01-NO4 has the same values. In NUTS-2 area codes, NO1-NO4 only covers the areas south of Trøndelag. However, this means that the results from the optimization model cannot be trusted in Norway, especially in the south-eastern parts.

Furthermore, the offshore economic zone of the UK is vast and stretches all around the UK. This may potentially undermine the potential in some areas with better wind resources. The offshore regions of Germany and the Netherlands show a higher capacity factor than the offshore region of the UK. This is probably a result of the extent of the area.

Additionally, geometry information on the NUTS-2 location of Kosovo is not present, resulting in the exclusion of this region for wind power.

These issues surely bring with them some uncertainties in the results, especially in the optimization model. As mentioned previously, the model is quite sensitive to changes in the input, which means that small errors or issues with the data may affect the results significantly.

8 Conclusion

Through this study, the complementarity of wind and solar resources has been analyzed using portfolio optimization of wind and solar power in Europe using different time resolutions. The complementarity analysis is in line with existing literature showing a high negative correlation between wind and solar resources on a monthly basis. The negative correlation has, however, a decreasing relationship with an increased time resolution. European wind resources are most profound in the coastal areas of north-western Europe, while solar resources are directly linked to latitude, with better solar resources in the south than in the north.

Wind experiences a decrease in correlation over large distances to a greater extent than solar resources. This means that wind power is more applicable for spatial distribution of capacities in order to ensure a more stable aggregate output. Solar power does not experience large output variability over large distances and is therefore not as sensitive to spatial distribution.

The portfolio optimization shows that the allocation of wind and solar capacities in Europe can improve the aggregated performance, with higher average output and lower standard deviation. While the existing fleet has an allocation of about 59% and 41% solar PV, the optimal portfolios receive shares of about 82-86% wind power, using an hourly time resolution. Furthermore, the portfolio optimization favors the regions in Portugal and Greece, which both have windier summer months than the European average, making these two regions attractive areas for wind power in the context of compatibility with the rest of Europe.

Furthermore, the optimal aggregated share of wind and solar power changes at different time resolutions. The analysis shows that aggregate portfolios with lower time resolutions tend to favor higher shares of solar PV than portfolios with high time resolutions, moving from around 19% solar PV with hourly time resolution to about 50% solar PV with monthly time resolution. This indicates that decision-makers need to take time resolutions into account when attempting to find optimal allocations of wind and solar power capacities.

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10 Appendix

	AL02	AL03	AT11	AT12	AT13	AT21
1	0.30625	0.29360	0.34290	0.31025	0.25750	0.28900
2	0.30910	0.28255	0.32270	0.29255	0.24530	0.28425
3	0.30815	0.27055	0.30730	0.28865	0.23630	0.29420
4	0.30780	0.26700	0.29195	0.27810	0.22795	0.28940
5	0.29885	0.26950	0.27850	0.27160	0.23160	0.27985
6	0.28635	0.26980	0.26115	0.26310	0.21485	0.27490
7	0.27205	0.27810	0.25305	0.26305	0.21225	0.28865
8	0.23875	0.28595	0.24885	0.26500	0.20935	0.28470
9	0.20170	0.29905	0.24100	0.26005	0.20940	0.26205
10	0.19555	0.30470	0.24960	0.26480	0.21840	0.25735
11	0.20130	0.29540	0.26490	0.28135	0.23335	0.25545
12	0.20640	0.28935	0.27875	0.30540	0.24285	0.27495

Showing 1 to 12 of 8,760 entries, 335 total columns

Appendix 1: Table layout sample of 30-year average hourly capacity factors over the year for all regions. 330 regions, with five additional columns of metadata.

NUTS_ID	Market_Share	geometry
EL42	0.1479	list(list(c(27.88675, 27.74545, 27.7285, 27.88675, 2...
BG31	0.1065	list(list(c(22.99717, 23.40948, 23.63039, 24.11204, ...
UKI7	0.0355	list(list(c(-0.19142, -0.21597, -0.24633, -0.25302, ...
EL41	0.0296	list(list(c(26.98182, 26.83131, 26.61489, 26.60203, ...
NL11	0.0237	list(list(c(6.87491, 6.92093, 7.07489, 7.09271, 7.208...
ES30	0.0237	list(list(c(-3.06769, -3.16142, -3.35332, -3.69625, ...
FI1C	0.0237	list(list(c(30.14397, 29.16799, 28.83654, 28.75082, ...
UKG3	0.0237	list(list(c(-1.87254, -1.78805, -1.75327, -1.59546, ...

Appendix 2: Illustration of how geographic information is joined with optimization results.

	Return	Risk	SharpeRatio	Value_at_risk	row_number
1	0.2220012	0.07265734	3.055455	0.05297496	1
2	0.2395192	0.07300425	3.280894	0.06968593	2
3	0.2156031	0.07262178	2.968849	0.04665960	3
4	0.2299035	0.07227688	3.180872	0.06176232	4
5	0.2217459	0.07216414	3.072800	0.05386704	5
6	0.2248272	0.07275637	3.090138	0.05557061	6
7	0.2407175	0.08011377	3.004695	0.05434496	7
8	0.2537895	0.08100460	3.133026	0.06534466	8
9	0.2407925	0.07922532	3.039338	0.05648687	9
10	0.2387347	0.07205799	3.313092	0.07110278	10
11	0.2166351	0.07040980	3.076775	0.05283743	11
12	0.2201500	0.06858983	3.209659	0.06058615	12

Showing 1 to 13 of 2,000,000 entries, 5 total columns

Appendix 3: Illustration of raw results from the optimization model. Each row represents one iteration, with corresponding random weights for all regions. The best performing iterations are later matched with the associated weights, determined by row indexes.

	V1	V2	V3	V4	V5	V6	V7	V8	V9	V10
1	0.0098	0.0000	0.0000	0.0000	0.0195	0.0098	0.0049	0.0000	0.0000	0.0195
2	0.0000	0.0000	0.0051	0.0000	0.0000	0.0051	0.0000	0.0000	0.0051	0.0000
3	0.0000	0.0059	0.0000	0.0000	0.0000	0.0000	0.0059	0.0000	0.0000	0.0000
4	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
5	0.0000	0.0000	0.0000	0.0086	0.0000	0.0086	0.0000	0.0000	0.0000	0.0000
6	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0097
7	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
8	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0211	0.0000	0.0000	0.0000
9	0.0000	0.0000	0.0057	0.0000	0.0000	0.0000	0.0057	0.0000	0.0000	0.0000

Appendix 4: Sample of random weights. Each row consists of 330 columns, which each represents one region.

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