Norwegian School of Economics
Bergen, 2020

The Power of Wind
– A Portfolio Approach

A Theoretical Study of Wind Power Characteristics in Norway

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Master thesis, MSc in Economics and Business Administration,

Business Analysis and Performance Management, and

Energy, Natural Resources and the Environment

NORWEGIAN SCHOOL OF ECONOMICS

Abstract

In this thesis, we analyse how geographical diversification and a portfolio approach lowers the variability in wind power production. Understanding variance of wind power production will increase system reliability. Evaluating the covariance of power production in different parts of Norway will become relevant as the share of variable renewable energy increases in the power energy mix. We use historical wind measures from the Norwegian coastline to evaluate how to minimise the variance of theoretical wind power production. The findings suggest that when utilising weekly aggregated wind data, the wind power correlation is low when the distance between two wind sites is approximately 900 km or more. We see that the correlation between wind power locations decreases as the distances increases regardless of the time interval studied. Portfolio theory states that assets' variance in a portfolio is not a problem if the assets do not covary. We argue that it is possible to handle wind power variability in the same way as stocks on the financial markets and that coordinating wind farms lowers the variability of wind power production. We present an optimal investment portfolio for onshore wind power production in Norway, utilising a Mean-Variance Portfolio (MVP). In the thesis, we have applied two different MVP approaches, first accounting for wind resources and second accounting for system demand. We find that how to best diversify wind locations differ depending on the optimisation problem. The empirical results reveal that geographical dispersion contributes to reducing variance in wind power production, associated with increased system reliability.

Keywords

Wind Power, Variance, Covariance, Efficient Frontier, Mean-Variance Portfolio, Bidding Zones, Reliability and Balance

Acknowledgement

First and foremost, we would like to thank our supervisor, Gunnar S. Eskeland, for being encouraging and constructive, and contributing with valuable input and insight throughout the period. Thanks to Jonas Andersson for being accessible and engaging in interesting discussions about the model. Finally, we would like to thank Kjeller Vindteknikk and Nord Pool for providing us with data and information, making this thesis possible.

Bergen, June 2020

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Table of Contents

List of Figures

List of Tables

1 Introduction

1.1 Motivation and Purpose

The Norwegian government has decided to reduce Norwegian greenhouse gas emissions with at least 50% by 2030 as a response to climate changes (Klima- og miljødepartementet, 2020). Thus, a key question is how Norway is supposed to meet this goal. If we replace most of today's fossil fuel with electric fuel, we get an estimated increase in electricity consumption of 30-50 TWh per year (Holmefjord & Kringstad, 2019). In 2018, 30-50 TWh equalled 27% of total Norwegian power production (SSB, 2019). Holmefjord and Kringstad (2019) state that if the fuel transition comes from renewable energy sources, greenhouse gas emissions in Norway will potentially halve. The possible reduction of greenhouse gas emissions sheds light on the importance of decarbonising the electricity sector by using renewable energy sources. However, the research on how to invest in renewables geographically to optimise the renewable resources in Norway is scarce.

Over the past years, wind power has developed rapidly due to high capacities and production costs that are becoming competitive with conventional energy sources (Milan, Wächter, & Peinke, 2013). The increased competitiveness of wind power, combined with excellent wind conditions, makes it attractive to build wind farms in Norway (Byrkjedal & Åkervik, 2009). Besides, the flexible Norwegian hydropower reservoirs allow energy to be stored at a low cost during periods of high wind power generation, avoiding periods of low power prices due to excess supply (Thema Consulting Group, 2019).

At the same time as the features mentioned above make wind power lucrative, wind energy suffers from a drawback in the fluctuational nature of its source (Milan, Wächter, & Peinke, 2013). In wind power production, this fluctuation is called intermittency, and are a combination of two factors: variability and predictability (Datta & Hansen, 2006). The variability emphasis that the wind does not blow at a constant speed and predictability refers to our lack of knowledge of the variability pattern in advance. The wind intermittency has implications on planning for the electricity system as well as the reliability of energy in a bigger picture.

Traditionally, the valuation of new investments in wind power farms has been done by assessing one site and its characteristics (Vindportalen, a, n.d.). However, the smoothing effect of diversification, meaning how the fluctuations of wind power move in different directions and create a stable flow, is not able to come into play if only considering one location. Additionally, stand-alone methods do not portray Norway as one energy system, leading to a challenge when optimising the power mix in the country.

The need to understand wind power intermittency and variability is crucial as the share of wind power in the power mix is increasing, making the power flow less flexible. According to portfolio theory, the variance is not a problem if the assets in the portfolio do not covary (Markowitz, 1952). Translating this to wind power production, we argue that it is possible to minimise wind power variability if coordinating wind farms in a portfolio. In the portfolios calculated in this thesis, we combine geographical areas of wind power, representing different assets.

This thesis will provide empirical evidence of the diversification effect of spreading wind farms along the Norwegian coast. Our study investigates how Norway can benefit from using a portfolio approach to reduce its intermittency problem and decrease the overall variability of wind power. We seek to answer whether a Mean-Variance Portfolio (MVP) can help to calculate the reliability of the grid, and with this be an essential method when analysing the optimal allocation of wind farms.

We begin our analysis by examining correlations between the wind farms. In this part, we find it evident that increased distance between wind farms will lessen the power correlation between the sites. The decreasing correlation with distance suggests that intermittency and variability problems are lowered as wind farms are placed a certain distance away from each other. When doing so, wind power fluctuations can smooth each other out and create a more stable flow to the energy system.

In the second part of the thesis, we conduct an MVP analysis. The MVP demonstrates that the overall variability of the combination of multiple wind farms decreases substantially compared to the variability of one single wind farm. Our results demonstrate that the optimal combination, when taking the trade-off between variability and power output, is to invest most of the wind energy in the northern and southern areas of Norway. Splitting the majority of wind power production in this way will make the overall wind power production in Norway more reliable, based on wind resources. In addition, the results reveal that Norway should invest least of the wind power production in the area around Trondheim.

As we add the electricity prices as a constraint in our analysis, representing the demand for electricity, we find an alteration in where to invest the resources compared to the model where we only examine the wind power produced. In this constrained approach, the area around Bergen comes out as the area with the largest share in the portfolio obtaining the minimum variance. Developing wind farms in this area will contribute to cover system demand for electricity.

To summarise, we find that the wind power variability decreases when considering the wind power market as one system by diversifying the wind farms geographically. The portfolio approach leaves the intermittency of wind power to be reduced in the larger system.

1.2 Research Question

This thesis investigates the following research question:

Can the Norwegian wind power production benefit from using a portfolio approach to reduce its intermittency problem and decrease the overall variability of wind power?

The rest of this thesis continues as follows. The second section contains the background of wind power and wind power in Norway. In the third section, we outline a review of the previous literature on the topic. In the fourth section, we describe our data. In section five, we present our empirical strategy, followed by our main findings and analysis in section six. The seventh section provides implications of the study and possible shortcomings of our results. Finally, we conclude in section eight.

2 Background

In this section, we will explain the basics of wind power before we illustrate today's wind power situation in Norway.

2.1 The Basics of Wind Power

2.1.1 The Underlying Physics of Wind Power

Wind is defined as a movement of air, caused by the uneven heating of the earth by the sun, creating differences in air pressure (National Geographic, n.d.). Air will always move from high-pressure areas to low-pressure areas, a movement that creates kinetic energy which can be utilised by wind turbines to generate power (Vindportalen, b, n.d.). The power extracted from wind, P(w), can be calculated from formula 2.1 (Narbel, Hansen & Lien, 2014).

$$P(w) = \frac{1}{2} \cdot C_p \cdot A \cdot \rho \cdot v^3 \qquad (2.1)$$

Where*:*

C_p = The power factor, i.e. the average power generated, divided by the rated peak power

A = Turbine areal (m^2)

ρ = Air density (kg/m^3)

v = Wind speed (m/s)

Formula 2.1 emphasises that the wind speed constitutes great importance regarding power production. In wind power production, wind speed represents a cubic growth. Thus, by doubling the wind speed, we observe an increase in power produced by eight times, making the wind speed the essential variable for wind power generation.

Wind turbines cannot capture all available energy in the wind. There are two fundamental limits to the efficiency of a wind turbine, limitations of absorbing wind energy and Betz law. The first limitation tells that that the wind will diverge into a larger wind flow behind the turbine, as illustrated in Figure 2.1 (Narbel, Hansen, & Lien, 2014). The wind flows through area A_1 with wind speed v_1, and after passing the rotor area A, the wind vanishes through area A_2 with wind speed v_2. Area A_2 is larger than area A_1 if the air density is approximately constant. v_1 has a higher wind speed than v_2, affecting wind turbines standing behind turbine A. Second, Betz law (Betz, 1966) tells that a wind turbine cannot absorb the energy of the wind in its entirety. Total absorption of energy would cause a standstill behind the turbine, prohibiting more wind from passing. Based on these limits, the theoretical maximum efficiency of a wind turbine is 59.3% (Afework, Hanania, Stenhouse, & Donev, 2018).

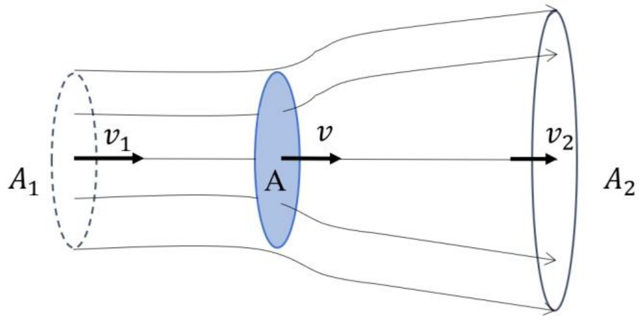

Figure 2.1 Wind speed and volume expansion before and after passing a wind turbine (A).

Efficiency losses will also occur when converting mechanical energy to electrical energy. In practice, wind turbines will never be able to extract all theoretically exploitable power from the wind. The best onshore wind turbines today deliver an energy efficiency of about 35% of the theoretical energy in the wind (Wind Europe, n.d.). Figure 2.2 illustrates the relationships of theoretical efficiency, theoretically usable efficiency, and practically usable efficiency.

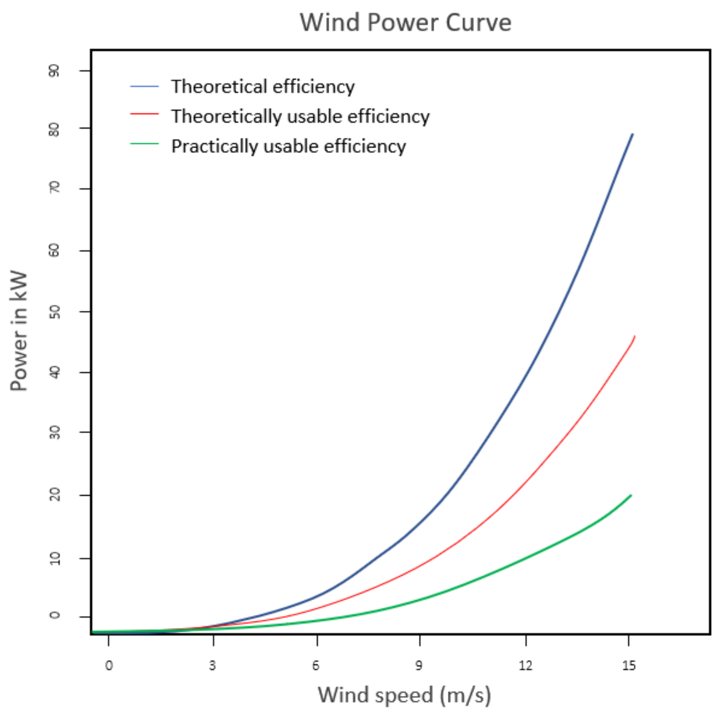

Figure 2.2 Theoretical efficiency, theoretically usable efficiency, and practically usable efficiency of wind

The Power Curve

Based on the underlying physics of wind power, every turbine model has an associated power curve, using different conversion factors to calculate power production. Thus, a change in wind speed of 1 m/s can represent various changes in production in different models. Different power curves also have varying production intervals. However, most of today's models have a cut-in speed at 3 m/s and a cut-out speed at 25 m/s, whereas the rated wind speed, i.e. the wind speed where the turbines can generate electricity at its maximum, usually peaks around 12-15 m/s (Johari, Leman, Ishak & Yusoff, 2019).

Figure 2.3 illustrates WindPRO, a multi-turbine power curve, where the average wind speed creates a basis for the production level at the wind site. The different lines in Figure 2.3 illustrates three different wind turbine models, installed at different sites, to maximise wind power production. As the WindPRO reveals, at rated wind speed, the turbine will not be able to utilise the kinetic energy at its entirely. The rated wind speed limit will prevent unnecessary strain and wear on the wind turbines. WindPRO turbines will automatically stop when the wind exceeds measures of 25 m/s, to prevent further damages on the turbines. As technology improves, the production interval will expand in both directions.

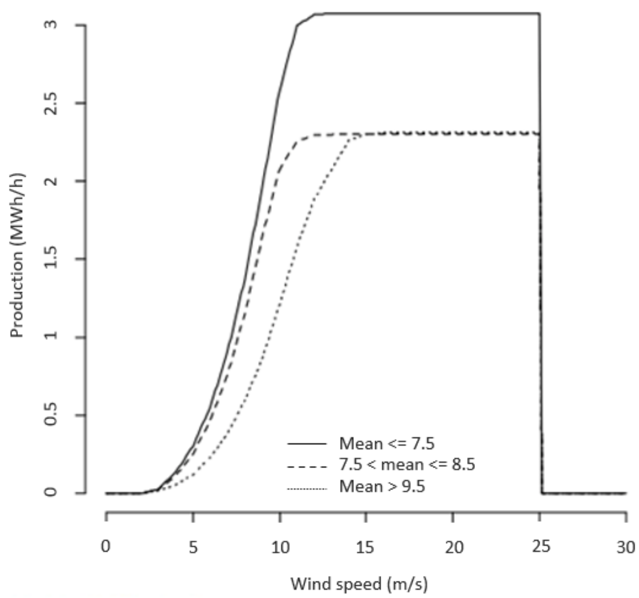

Figure 2.3 Multi-turbine Power curve. Wind power production at different wind speeds depending on average wind speed (Kjeller Vindteknikk, WindPRO).

2.1.2 The Wind Power Situation in Norway

Establishing wind power has previously not been prioritised in Norway, because of sufficient access to hydropower, as well as conflicts of interest related to the construction and development of wind farms (Moe, 2015). However, Norway has excellent wind resources and sufficient land area, making the country suitable for wind power production (Borsche, 2019). Modern utilisation of wind power started in Norway with Titran wind turbines in Sør-Trøndelag in 1986 (Hofstad, 2019). In 2019 Fosen Vind on the west coast of Trondheim, started operating (Statkraft, n.d.). Fosen Vind, comprising six wind farms, is today the largest onshore wind power project in Northern Europe, with a combined capacity of 1.057 GW.

Even though Norway has not had its primary focus on wind farm development, wind power production is increasing. In 2019, Norway had 36 wind farms with a total of 625 turbines, generating an accumulated capacity of 2.4 GW and an annual production of 5.5 TWh (Øverbø, 2020). The wind power production in 2019 was 43% higher compared to the production in 2018. The wind power production in 2019 corresponds to the electricity consumption of over 340,000 households and 4.1% of all power generated in Norway. Furthermore, there are 16 new wind farms under construction which are said to double today's wind power production (Energi Norge, 2019). Vindportalen (2019) expects that Norwegian wind farms will have an annual production of 16 TWh in 2021, meaning that wind power will account for approximately 10% of the total Norwegian power generation in the upcoming years.

The Process of Licencing Wind Farms in Norway

In Norway, a wind power project must receive a concession to obtain permission to build a wind farm. Intentionally, this concession will help the authorities regulate and control the wind power business to the best interest of society. To expose all externalities, the concession process for a wind farm today is extensive (Bjerkestrand, et al., 2020). Figure 2.4 presents an overview of the licencing process.

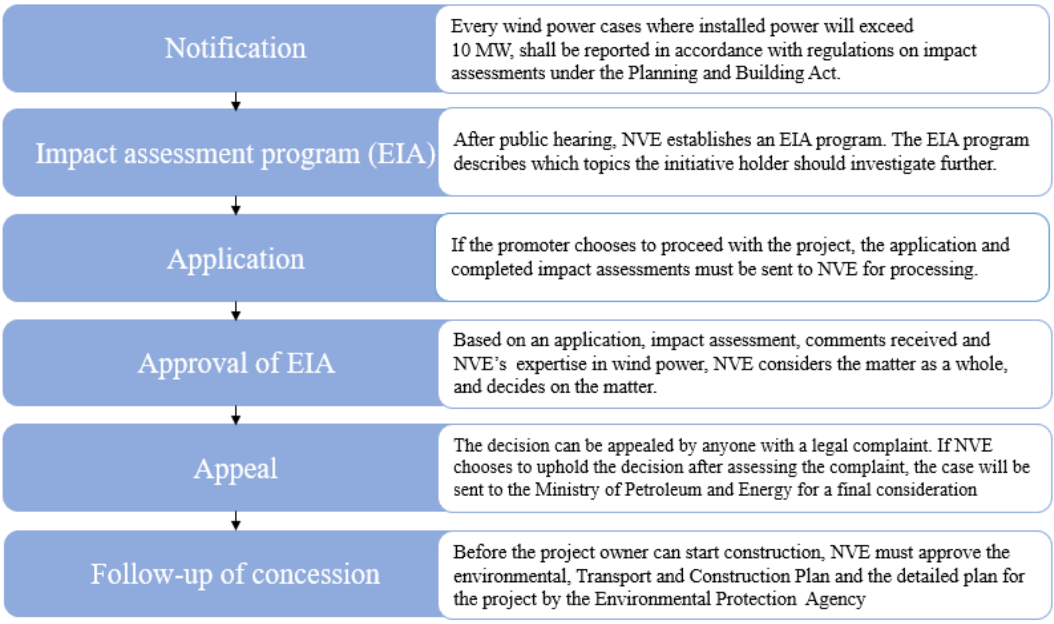

Figure 2.4 Overview of the licencing process of new wind farms in Norway (NVE, a, 2019).

As a part of developing Norway as a renewable nation, The Norwegian Water Resources and Energy Directorate (NVE) was requested by the Ministry of Petroleum and Energy (OED) to make a national framework for wind power deployment, to create a knowledge base which was supposed to be used as a supplement to today's licencing process (Frieberg, 2019). However, this framework was shelved in 2019 by the government due to negative feedback from the municipalities. The municipalities perceived that the national framework was undemocratic and with a lack of local involvement (Bjerkestrand, et al., 2020). Even though the Norwegian government dismissed the national framework, it gives an idea of what factors the experts emphasise when planning for a deployment of wind farms in Norway. These factors include a review of how suitable the terrain is, e.g. through wind situation and topography, as well as technical-economic suitability, like the cost of production and transmission capacity (NVE, b, 2019).

2.2 The Nordic Power Market

Norway is part of the Nordic power market, trading power within Norway as well as cross-border. The Nordic power market has licensed Nord Pool's day-ahead as the spot marketplace for physical electricity, and this is where most of the power trading in the Nordics are done. The actors on the power market must notify sales and purchases within 24 hours before the operating hour (Nord Pool, a, n.d.). The power market represents a classical economic problem, wanting to maximise the difference between willingness to pay and cost related to production. If a power producer is operating on the Nordic day-ahead exchange, they become balance responsible. Meaning, the power producer must compensate for the deviation of expected power and actual power delivered, represented by financial penalties (Santos-Alamillos, Thomaidis, Usaola-García, Ruiz-Arias, & Pozo-Váquez, 2010).

2.2.1 The Norwegian Bidding Zones

The Norwegian power system is divided into five bidding zones. Bidding zones are defined as areas where congestion is infrequent, and electricity can easily be priced on an average cost basis (Alaywan, 1999). In Norway, the zonal pricing suggests fewer prices than there are physical connection points in the network, and a zone price aggregation based on available transmission capacity, demand, and supply (Bjørndal, Bjørndal, & Gribkovskaia, 2014).

The different Norwegian bidding zones cover large areas and consist of multiple connection points. Thus, zonal network constraints get lost in the price aggregation. Moreover, using zonal pricing as congestion management is a simplification, neglecting the physical characteristics of the power flow between the bidding zones (Bjørndal, Bjørndal, & Gribkovskaia, 2014). As the bidding zones disregard interzonal constraints, setting capacities on aggregated lines is complex. On the one hand, too restrictive capacity can result in the power system not being optimally used. On the other hand, if the transmission capacity is too encouraging, the market outcomes can end up with unattainable flows (Bjørndal, Bjørndal, & Gribkovskaia, 2014).

Since 2010, Norway has been divided into five bidding zones. However, between 2000 and 2010, several changes were made to the Norwegian zonal structure (Nord Pool, 2008), illustrated by the timeline in Figure 2.5. In Norway, Statnett has the overall responsibility of the electricity flow on the grid and determines how Norway is divided into bidding zones (Nord Pool, b, n.d.).

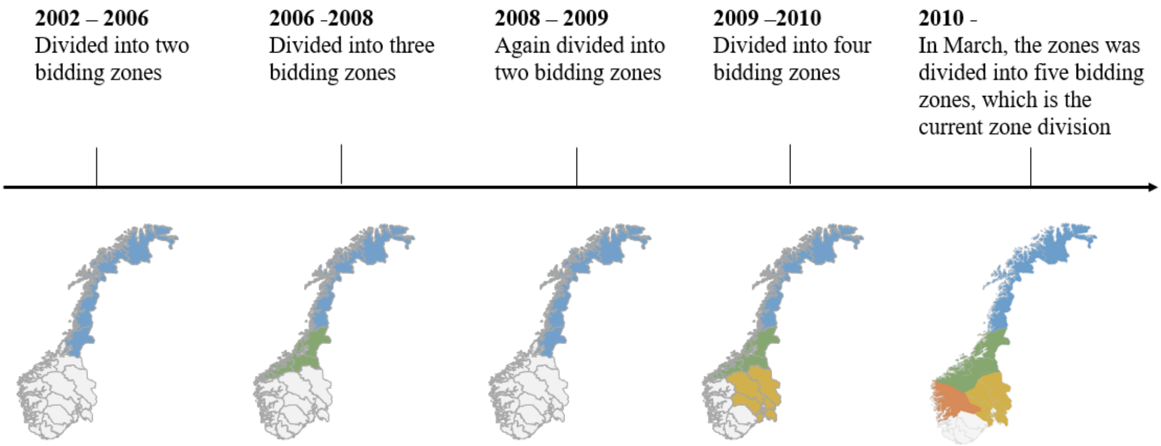

Figure 2.5 A timeline of Norwegian bidding zone divisions.

Increasing the number of bidding zones will increase the complexity of operating the grid and the trading of electricity. However, the electricity price will become more accurate, which will give a better indication of the power flow and potential congestions on the grid. When the power flow is congested, the prices between bidding zones will be unequal, and the price differences will represent the associated transmission cost between the bidding zones. This thesis will focus on the current practice with five bidding zones.

2.2.2 Power Purchase Agreements

In addition to the day-ahead market, Power Purchase Agreements (PPAs) are used for trading power. PPAs are bilateral agreements between a power producer and a corporate consumer of power (Næss-Schmidt, Lumby, & Münier, 2020). The agreements are a flexible way to reduce a variety of long-term risks for both parties, structured as future-contract, and signed several years ahead. As a result of extensive development of wind power, wind power producers are dominating signings of new PPAs (Eriksrud, et al., 2019).

Power producers use PPAs to secure investments by providing a stable income. Due to the wind farm’s substantial upfront investment and the wind resources variable nature (Narbel, Hansen & Lien, 2014), it will be beneficial for wind power producers to agree on PPAs. In addition, the wind farm investors require proof of a stable income stream, making these contracts lucrative. Most of the PPAs in Norway are physical contracts with fixed prices, securing the cashflow of wind farms in the valid contract period.

Wind farms have substantial difficulties predicting accurate power output (Papaefthymiou & Kuriwicka, 2009; Lee, Fields, & Lundquist, 2018; Davy, Woods, Russell, & Coppin, 2010). Hence, placing a bid on the Nordic electricity exchange will reflect a newsvendor problem, where the seller cannot with certainty predict the outcome of tomorrow’s production (DeMarle, 2019). Due to PPAs or other similar future-contracts, a wind power producer will not be balance responsible on the power market exchange. Consequently, there is no associated risk related to the bidding situation for a wind power producer after agreeing on a PPA, transferring the risk to the energy buyer in the agreement.

In this section, we have introduced the basics of wind power and the Norwegian power market. Next, we will introduce previous research and associated literature on the field.

3 Literature Review

In the following section, we will review studies that analyse topics of interest and discuss how our thesis contributes to the existing literature.

The characteristics of wind power have been of interest for several years and part of numerous research papers (Papaefthymiou & Kuriwicka, 2009; Lee, Fields, & Lundquist, 2018; Davy, Woods, Russell, & Coppin, 2010). As wind power contributes a larger share of electricity supply, the challenges related to wind power intermittency and variability have become increasingly prominent (Graabak & Korpås, 2016; Watson, 2013; Ren, Wan, Liu, Yu, & Söder, 2018; Holttinen, 2004). Research conducted in Denmark, Estonia, Finland, Sweden, and Germany illustrates a geographical smoothing effect, suggesting that the wind correlation between different locations decreases as the geographic distance increases (Davy, Woods, Russell, & Coppin, 2010; Ernst, 1999).

Further, various researches have used financial tools on power data to handle the variability (Hu, Harmsen, Crijns-Graus, & Worrell, 2019; Thomaidis, Santos-Almillos, Pozo-Vázquez, & Usalo-García, 2015; Naddami & Sanaa, 2018; Roques, Hiroux, & Saguan, 2010; Santos-Alamillos, Thomaidis, Usaola-García, Ruiz-Arias, & Pozo-Váquez, 2010). These papers are based on data from South Iberia, China, UK, Austria and Morocco, and point out that it is possible to make an optimal energy mix in order to lower the variability and make wind farm investments more secure by using an MVP. The papers state that the MVP’s makes it possible to illustrate the smoothing effect across specific geographical areas.

Our thesis is linked to Roques, Hiroux and Saguan’s (2010) research. Their paper investigates the effect of diversification of wind farms in Europe. The analysis is based on applying the MVP theory to data from Austria, Denmark, France, Germany and Spain, and the results suggest that it would be beneficial to coordinate wind locations across the countries. The geographical diversification of wind farms is said to reduce output variability. The research also finds that the optimal MVP depends on the transmission constraints taken into consideration.

In addition, our thesis relates to a paper by Koivisto, Cutuluis and Ekstrøm (2018). By looking at sun and wind data from different countries, they find that the optimal combination to double the expected annual variable renewable energy in Northern Europe, is offshore wind (30%), onshore wind (51%) and solar photovoltaic (19%). The paper highlights the importance of considering large geographical regions when planning future power and energy system with the goal to provide a stable renewable energy flow.

We contribute to the existing literature in various aspects. Firstly, to the best of our knowledge, this is the only study of its kind using MVP on wind data exclusively from Norway. Our approach to the variability problems of wind can further be used by Norway when deciding where to build wind farms. Secondly, we aim to amplify the reach of the literature by investigating how financial models can be used to examine the Norwegian power situation. Adequate wind conditions, a lot of land area (Borsche, 2019), and reliable water resources to stabilise the power prices, make Norway suited for wind power production (Thema Consulting Group, 2019). Norway is an elongated and narrow country. Still, we expect to find similar results on the effect of diversification of wind farm deployment as previous studies.

4 Data Description

In this section, we describe the data used to investigate the geographical smoothing effect of wind power in Norway and the system demand for electricity. Our data is drawn from two main sources, Kjeller Vindteknikk and Nord Pool.

4.1 Data on Wind Speed

Measures of wind speeds at specific locations are obtained from Kjeller Vindteknikk. The structure of the wind speed data is a time series, containing hourly measures of historical wind speeds from 01.01.2000 to 01.03.2013, at 70 different sites in Norway. The wind is measured at the height of 100 meters above ground level. From this data, we were able to extract the coordinates of the different locations and the associated bidding zones, illustrated in Figure 4.1. Hereafter, we will refer to the bidding zones as zones. Table 4.1 present the number of wind sites in each zone. Appendix A1 displays a complete map with place-names of the wind measurement locations.

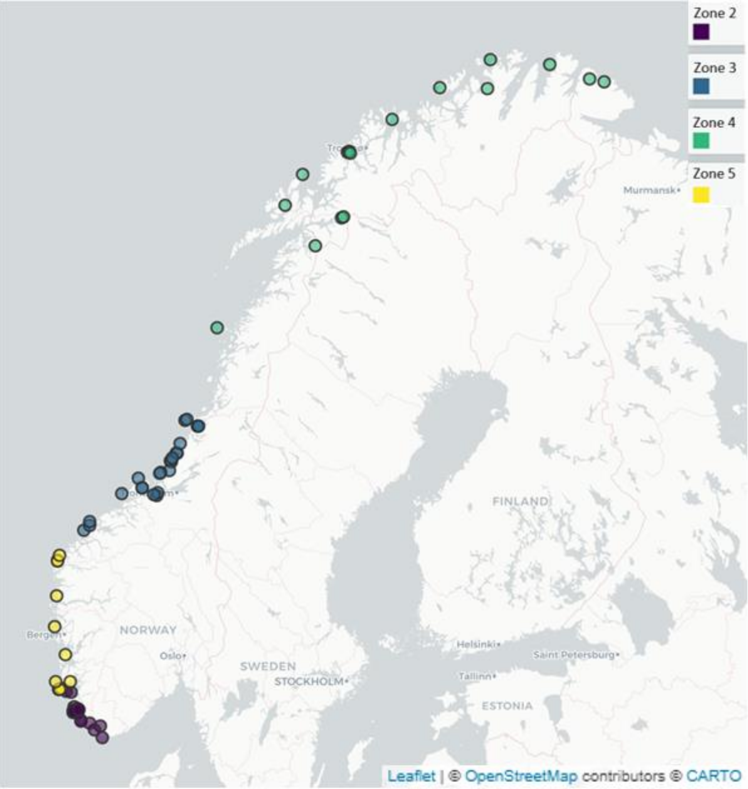

Figure 4.1 Wind measurements location divided into zones.

Table 4.1 Number of wind sites in the zones.

	Zone 2 *Kristiansand*	***Zone 3*** *Tromsø*	***Zone 4*** *Trondheim*	***Zone 5*** *Bergen*
Observations	17	25	16	12

We were able to transform the wind measured at the different sites into power produced per hour (MWh/h) using a multi-turbine power curve. We gained the power curve WindPRO from Kjeller Vindteknikk, reviewed in section 2.1.1 (Figure 2.3).

In this thesis, we utilise the transformed data for wind power (MWh/h) for further research. We acknowledge that not all wind speeds produce power and that the power produced at different wind speeds are non-linear. As production occurs in a specific wind speed interval, the transformed wind data reveal information of the intermittency and the variability a wind power producer experience. The transformed data enable us to calculate the correlation between the power produced at different locations and examine the covariance between the wind locations. Furthermore, the correlation and covariance calculations create a foundation for optimising deployments by utilising an Efficient Frontier, a model we will introduce in section 5.2.

4.2 Data on Day-ahead Prices

The data on day-ahead prices are obtained from Nord Pool. The structure of the data is a time series, consisting of daily observations of the spot electricity price, from 01.01.2000 to 01.03.2013. Further, when mentioning the electricity prices, we will refer to the prices set on the day-ahead market. From the price data, we extracted information from four bidding zones. Zone 1 is not included since we do not have wind measures from that zone. Figure 4.2 illustrates the price development in the different zones from the year 2000 and up to 2013.

Figure 4.2 Historical day-ahead prices. Zone 2: Kristiansand, Zone 3: Trondheim, Zone 4: Tromsø, Zone 5: Bergen.

4.3 Descriptive Statistics

To gain an understanding of central tendencies related to wind power production, we will, in this subsection, examine the statistical characteristics of wind power production.

We start by implementing adjustments to our data, allocating all the wind farms to their respective zones and calculate the zonal average energy production. As described in section 2.2.1, the zonal approach neglects interzonal constraints, where an aggregation within each zone is the basis for the electricity price. Since we are focusing on the current zone division, allocating the wind measures into the zones will demonstrate how the electricity market in Norway is structured today.

Figure 4.3 shows the average power production by zone. There are considerable and rapid variations in total generated power between 0-4 MWh/h during a short period. The variations appear random but are explained by varying wind conditions at different times. As a result, it is hard to predict the expected power production. Additionally, the variation of wind power production inflicts some challenges to the power system, which requires short-term balancing capacity (Skar, Jaehnert, Tomasgard, Midthun, & Fodstad, n.d.).

Our thesis finds that the average power production changes depending on the time of the year. As we see, the wind power production in Norway is lower during the summer months, June to August, than the winter months, December to February. The seasonal fluctuations are better illustrated when plotting the average wind power produced by month over 13 years, illustrated in Figure 4.4.

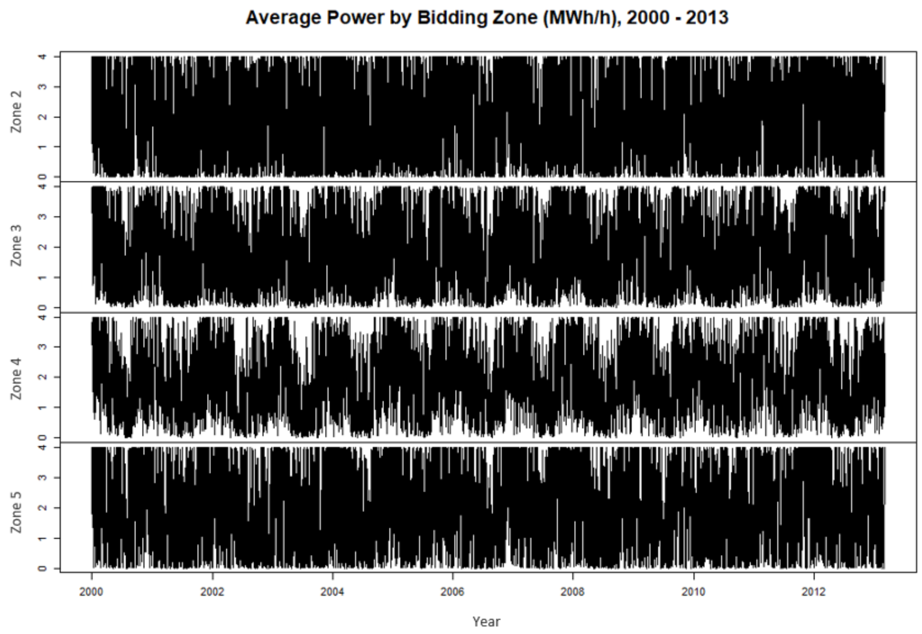

Figure 4.3 Average theoretical power produced in each zone over 13 years.

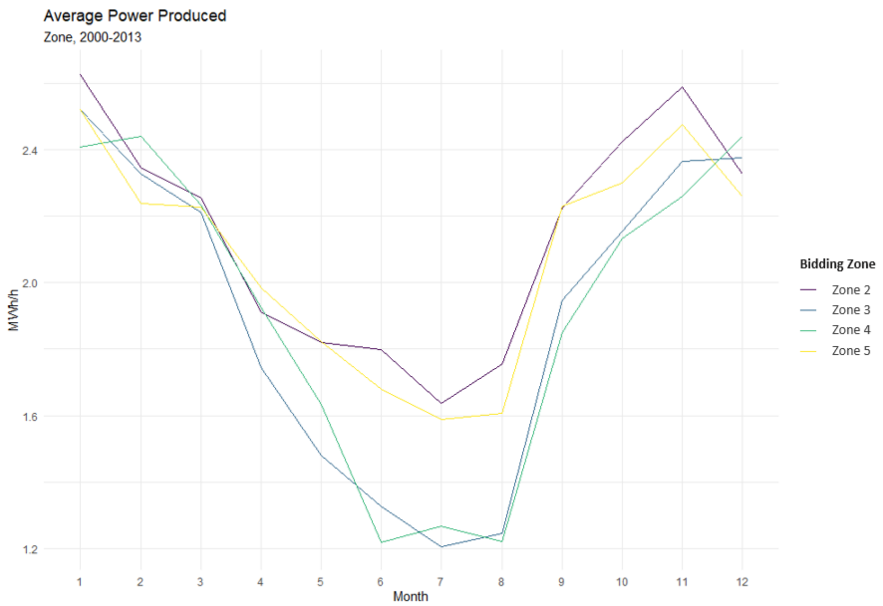

Figure 4.4 Zonal average power produced per month.

The mean power production depends on which time frame used in the analysis. Accounting for all data, the mean throughout the years is 2.001 MWh/h. When only considering summer months the mean decreases with 29%, with an average of 1.430 MWh/h. For winter months, the mean increases by 20.5%, with an average of 2.411 MWh/h (Table 4.2). Summarised, the hourly production varies with 69% when comparing summer months and winter months. The standard deviation for all the sites has an average of 1.604 MWh/h and ranges from 1.508 MWh/h to 1.715 MWh/h.

Table 4.2 Average hourly power production statistics (MWh/h).

	Min	*Max*	*Mean*	*Median*	*% change from year to season*
Year	0	4	2.001	1.7332	
Summer	0	4	1.430	0.788	↓ 29 %
Winter	0	4	2.411	2.976	↑ 20.5 %

As a result of the uneven heating of the earth by the sun, as well as earth rotation, the earth has global wind systems. In Norway, the prevailing wind direction is southwest via west to the northwest (Vindportalen, c, n.d.). However, since wind is air moving from high-pressure areas to low-pressure areas, the wind can come from all directions. Besides, the local wind is largely influenced by the local topographic condition that affects both the direction and the wind speed. Hence, wind conditions vary widely between locations in Norway and are consequently independent. In addition, measurements of wind speed are continuous random variables, varying over all time frames (Zhang, 2015). The wind power output is a translation of the wind speeds, and therefore we argue that our data measurements are independent and random.

Our output data initially have a multimodal distribution due to the characteristics of the power curve (Appendix A2). However, to utilise portfolio theory, the data needs to have a normal distribution (Cautero, 2019). To meet the normal distribution assumption, we have applied the central limit theorem, stating that the sum of independent random variables that are not normally distributed, tends toward a normal distribution when added together (Montgomery & Runger, 2003). When applying this theorem, we have aggregated the output data to consist of weekly averages. Therefore, the data we have used consists of about 13 years, with an average of 53 weeks, giving us a total of 699 observations. When doing this modification, we see that the zonal data are close to normally distributed, and the model assumptions will hold (Figure 4.5 and Figure 4.6).

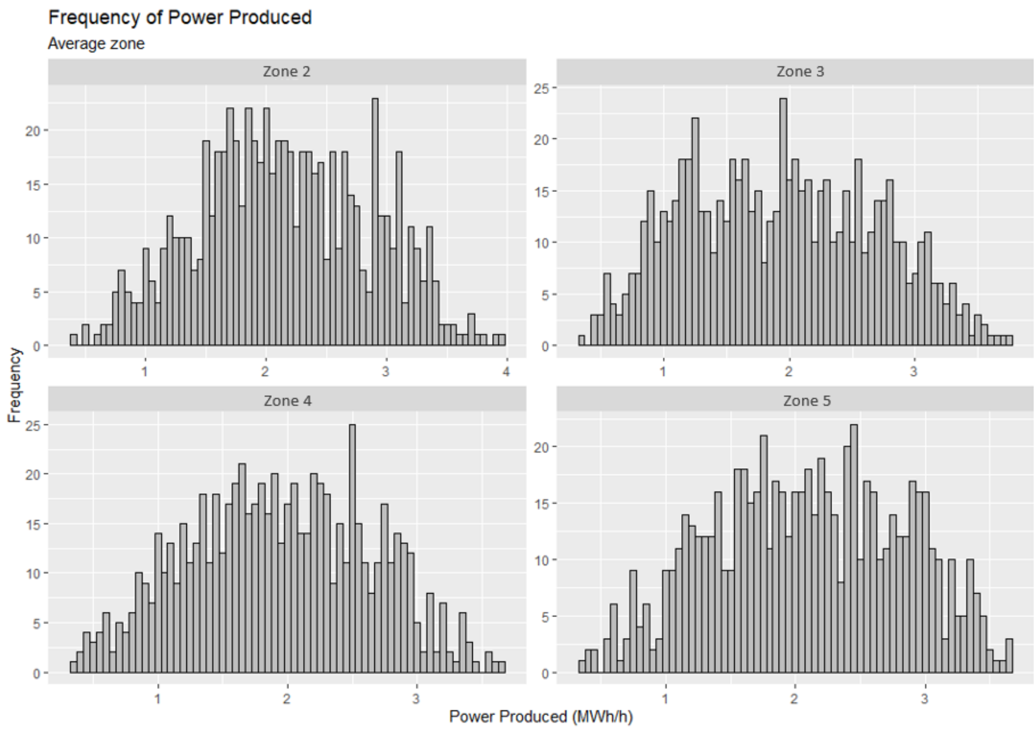

Figure 4.5 Histograms on weekly average aggregated power output data.

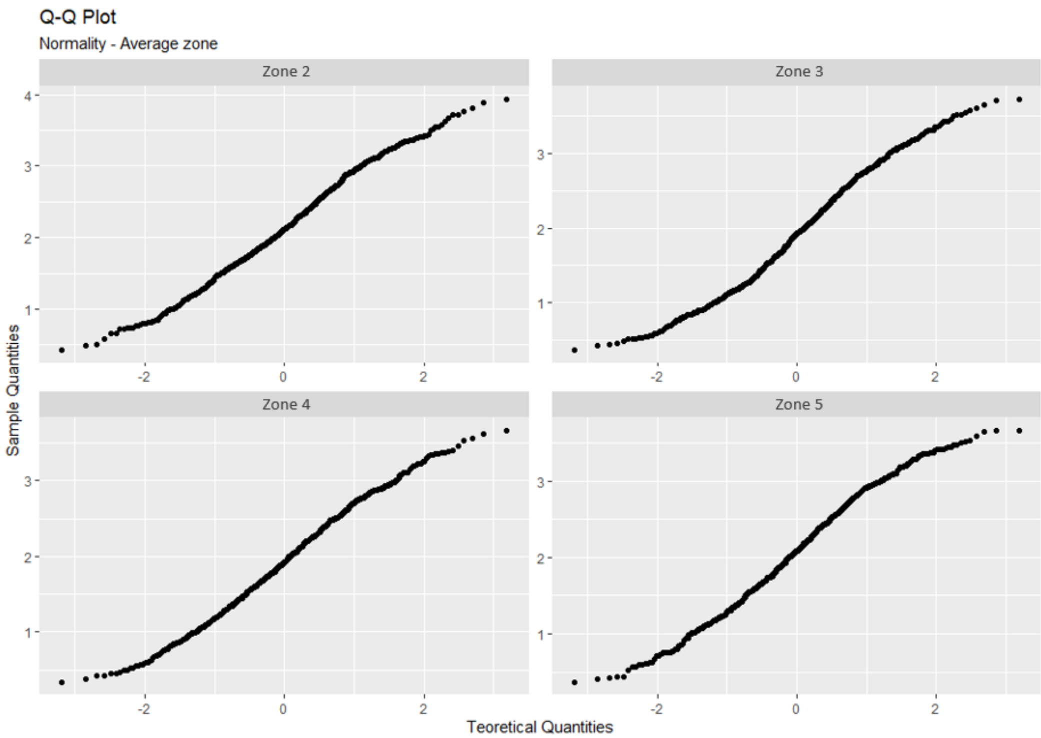

Figure 4.6 Normality plots for weekly average aggregated power output data.

In this section, we have described our data and presented the modifications we have implemented to the dataset. In the following, we will explain the models we use to explore the geographical smoothing effect in the Norwegian wind power production.

5 Empirical Approach

The goal of this thesis is to explore how the spread of wind farm locations in Norway affects the production of energy regarding variability. To examine this question, we will apply tools from financial discipline. The theories presented in this section are parts of a vast amount of literature both on financial tools and studies of renewable energy, as previously described in the literature review. We apply what we perceive as the most relevant models to answer our research question. In this section, we present the theory behind covariance and portfolios.

5.1 Covariance and Correlation

To answer our research question, we utilise a covariance model. This model enables us to explore the statistical characteristics of wind power, setting the background for how the wind farms power production behave together and how to lower the variability when we connect wind energy in a larger system. The covariance formula is presented in 5.1 (Pollard, 1997), where x and y represent different variables, in our case, different wind locations.

$$cov(X,Y) = \sum_{i=1}^{N} \frac{(x_i-\bar{x})(y_i-\bar{y})}{N} \tag{5.1}$$

Where:

x_i = the value of the X-variable for item *i*

y_i = the value of the Y-variable for item *i*

$\bar{x}$ = the mean of the X-variable

$\bar{y}$ = the mean of the Y-variable

N = the number of data points

Covariance measures the total variation of two random variables from their expected values. A positive covariance indicates that the two variables tend to move in the same direction. In contrast, a negative covariance reveals that the two variables tend to move in the opposite direction. However, covariance does not indicate the strength of the relationship between the variables.

To look at the strength of the relationship between the variables, we use Pearson's correlation coefficient. The correlation value is a scaled measure of covariance. Formula 5.2 expresses the concept of correlation (Kent State University, 2020).

$$\rho(X,Y) = \frac{Cov(X,Y)}{\sigma_X \sigma_Y} \tag{5.2}$$

Where:

$\rho(X,Y)$ = the correlation between the variables X and Y

$Cov(X,Y)$ = the covariance between the variables X and Y

σ_X = the standard deviation of the X-variable

σ_Y = the standard deviation of the Y-variable

How to evaluate the correlation relationship depends on the output value. If the correlation is one, the movements of the two variables coincide. If the correlation is negative one, the two variables move in a different direction at the same point of time. At the value zero, the two variables are uncorrelated, and the volatility does not follow the same pattern. Furthermore, the interpretation of the correlation coefficient differs substantially between research fields, and there are no specific guidelines for the interpretation of the correlation strength (Akoglu, 2018). However, according to Evans (1996), low correlation is below 0.4, moderate correlation is between 0.4 and 0.6, whereas high correlation is over 0.6, which is the interpretation we will apply in this thesis.

To use the covariance and correlation formulas, the data need to 1) be continuous, 2) have values for all the variables, 3) have a linear relationship between the variables, 4) be independent cases, 5) have bivariate normality, 6) be a random sample of data from a population, and 7) have no outliers (Kent State University, 2020). As we have done the aggregation of wind power data on a weekly average, our data fulfils all the requirements mentioned. In addition, we have argued that the wind power data is independent and random. Hence, we can use the data when calculating covariance and correlation. We use the correlation calculation to examine the geographical smoothing effect. The covariance calculation is the basis for portfolio theory, which we will elaborate in the following subsection.

5.2 Portfolio Theory

Markowitz introduced in 1952 the Efficient Frontier, a financial tool to help investors compose an investment portfolio with the best returns given a certain amount of risk. Different combinations of securities produce different levels of return. We can calculate whether a portfolio measures up to the Efficient Frontier using a graph where the level of standard deviation represents the x-axis, and the investment returns represent the y-axis, see Figure 5.1. It is impossible to build a risk-free portfolio, due, in part, to the stock market's inherent risk (Cautero, 2019). However, potential returns can balance a portfolio or an investment's risk.

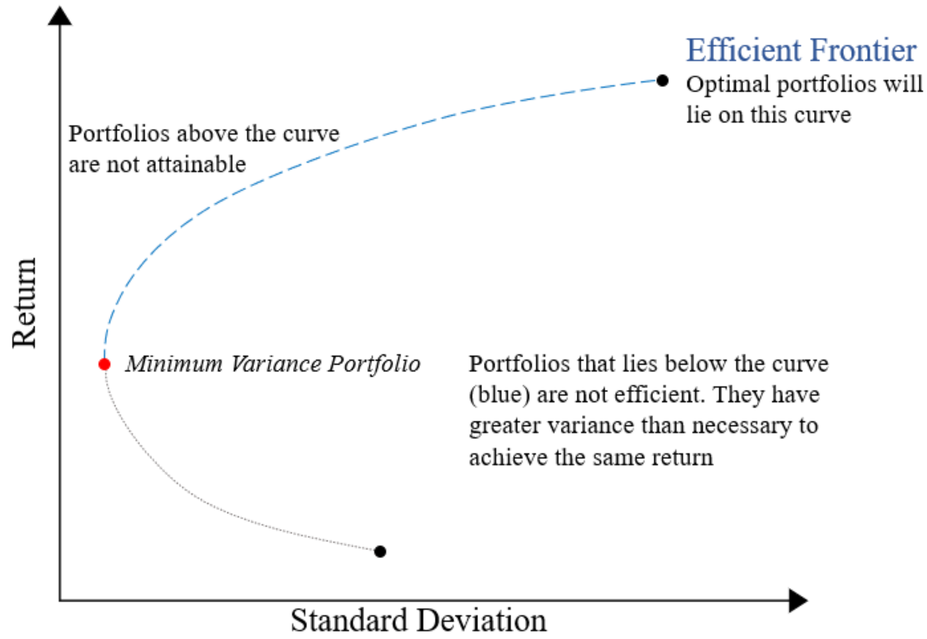

Figure 5.1 Mean-Variance Portfolio with associated Efficient Frontier and Minimum Variance Portfolio.

At the Efficient Frontier, the optimal portfolio refers to a Pareto optimal trade-off between risk and return. It is possible to make a various number of optimal portfolios with varying levels of return, each containing the least amount of risk achievable from the assets included. Portfolios that do not lie within a north-western coordinate at the Efficient Frontier are considered as sub-optimal because the rate of return is not high enough to justify the risk measured as standard deviation (Malik, 2019). In this thesis, we will focus on the minimum variance portfolio on the Efficient Frontier, hereafter referred to as Minimum Variance

(MV). The MV represents a portfolio where the expected return cannot be improved without increasing expected portfolio risk.

One of the critical concepts of Efficient Frontier is that different types of investments often move in opposite directions. The key to reducing the risk is to invest in a diversified portfolio, hence, to invest in different asset classes. A portfolio with a certain level of risk and secured stocks can become less risky when adding higher-risk investments, and at the same time give higher returns (Stevens, 2001).

In Markowitz's portfolio theory, the Minimum Variance MVP can be written as formula 5.3 (Würtz, Setz, Chalabi, Chen & Ellis, 2015):

$$\min_{w} w^T \hat{\Sigma} w \qquad (5.3)$$

Where:

$\hat{\Sigma}$ = the estimate of the covariance of the assets

w= the individual investment subject of the different assets in the portfolio.

$w^{T}1 = 1$ means that all capital is invested

$\bar{r}$ = the target return expressed by $w^T \hat{u} = \bar{r}$ where $\hat{\mu}$ is the mean of the assets

The main goal is to minimise the variance-covariance $\sigma^2 = w^T \Sigma w_1$, where the solution to the portfolio model is formula 5.4:

$$w^* = \hat{\mu} w_0^* + w_1^* \qquad (5.4)$$

Where:

$$w_0^* = \frac{1}{\Delta}\left(B\hat{\Sigma}^{-1}\hat{\mu} - C\hat{\Sigma}^{-1}1\right)$$

$$w_1^* = \frac{1}{\Delta}\left(C\hat{\Sigma}^{-1}\hat{\mu} - A\hat{\Sigma}^{-1}1\right)$$

$$\Delta = AB - C^2$$

With:

$$A = \hat{\mu}^T \hat{\Sigma}^{-1} \hat{\mu}$$

$$B = 1^T \hat{\Sigma}^{-1} \hat{\mu}$$

$$c = 1^T \hat{\Sigma}^{-1} \hat{\mu}$$

Minimum Variance MVP represents the point with the lowest risk on the efficient frontier. The set of weights in this portfolio is expressed in formula 5.5.

$$w_* = \frac{\Sigma^{-1}1}{1^T\Sigma^{-1}1} \tag{5.5}$$

When making the Efficient Frontier, we can calculate risk and return. If we have *N* assets *i*, with a corresponding return, r_i, standard deviation and the correlation between the assets in proportion X_i, and the expected return of the portfolio, *p*, is presented in formula 5.6 (Roques, Hiroux, & Saguan, 2010). The portfolio's standard deviation is presented in formula 5.7.

$$E(r_p) = \sum_{i=1}^{N} x_i E(r_i) \tag{5.6}$$

$$\sigma_p = \sqrt{\sum_{i=1}^{N} x_i^2 \sigma_i^2 + \sum_{i=1}^{N} \sum_{j=1}^{N} x_i x_j \rho_{ij} \sigma_i \sigma_j} \tag{5.7}$$

The Efficient Frontier theory assumes that assets' returns follow a normal distribution, which is not always realistic (Cautero, 2019). In addition, the theory assumes that investors are rational and typically avoid risk and that the investors alternatively can deposit cash at a risk-free interest rate in the bank.

5.2.1 Mean-Variance Portfolio in the Case of Power

In this thesis, we are applying financial models on wind power production. The power market is guided by similar optimisation objects as we see in finance, specifically when maximising return and minimising risk (Cunha & Ferreia, 2014). In addition, previous researches have demonstrated that it is possible to apply a portfolio approach on power output (Arnesano, Carlucci & Laforgia, 2012; Adams & Jamasb, 2016; Francés, Marín-Quemada & González, 2013).

We believe that portfolio models are a useful tool when evaluating variance related to wind power production. The statistical characteristics of the wind are exogenous. Besides, a low correlation between power produced and electricity prices (Appendix A3), suggests that the Norwegian wind power produced is not large enough to affect the electricity price. Furthermore, our aggregated data is close to normally distributed, making the power output behaving similar to stock revenue (Amaral, Plerou, Gopikrishnan, Meyer, & Stanley, 2000).

Using the portfolio logic, we treat wind locations as assets that are possible to interchange with varying combinations. When applying the Efficient Frontier to wind power, we can conduct an analysis showing how to diversify the placement of wind farms to get the optimised balance between return, e.g. power output, and output variation measured as standard deviation. Our hypothesis is that when using the MVP, we can smooth the variance to a given level of power output.

It is possible to calculate numerous portfolios with wind power, using different approaches to the optimisation problem. The different approaches, e.g. minimising transmission cost or maximising power produced, will have several optimal solutions for wind power output level with an associated variation. We will use the same approach as Roques, Hiroux and Saguan (2010), utilising portfolio theory, and more specifically an MVP, to optimise the expected power output and minimise standard deviation. When using this approach, we assume that the value of a stable flow of wind power is higher than the value of short periods with high wind power production. Further, we will evaluate the situation where diversification is decided based on system demand in different zones.

In this section, we have described the models we will utilise to answer our research question as well as argued for why we can use these models for this purpose. In the following, we will apply the models to our data and analyse the results.

6 Empirical Analysis

In this section, we test the effect of distance between wind farms on variability. The analysis consists of four parts. First, we calculate the theoretical capacity factor of wind power production, examining where Norway has suitable wind conditions. Second, we determine the zonal wind power production correlation and see whether the correlation changes with distance. Third, we run the MVP for wind power production, followed by the MVP accounting for system demand. Wherein, the MVP calculation displays the optimal deployment strategy of wind power in Norway. Finally, we summarise our results.

6.1 Capacity Factor

Location characteristics are said to be one of the main factors when determining the economics of wind power (Narbel, Hansen & Lien, 2014). As seen in formula 2.2, Wind speed is an essential feature regarding power output from a wind farm. By calculating the capacity factor, we find the quality of the wind resource at the individual sites. The capacity factor of a wind farm is the ratio between its actual power output over a period, and its potential power output when operating at full capacity (Hofstad, 2013). Formula 6.1 describes the calculations of the capacity factor.

$$Capacity\ factor = \frac{Actual\ produced\ effect}{Total\ installed\ effect} \tag{6.1}$$

Figure 6.1 illustrates the overall high wind quality and availability of wind along the Norwegian coastline, given perfect power production within the interval of the power curve (3 m/s - 25 m/s). These capacity factors are based on theoretical perfect power production, making them artificially high compared to what is expected. For our dataset, the capacity factor varies between 35% to 60%, which can be expressed as 3,066 to 5,256 full load hours per year. The overall average capacity factor for our data are 50%, amounting for 4,380 full load hours per year. Whereas, in 2019, the actual capacity factor for wind power in Norway was estimated to be 33.5% (NVE, b, 2020), expressed as 2,936 full load hours per year.

We observe some variations in minimum and maximum capacity factors between the different zones, as described in Table 6.1. Furthermore, zone 3, around Trondheim, is the area with the highest observed capacity factor, but with the lowest zonal average (47.4%). Zone 2, the area around Kristiansand, has the highest zonal average of 53.5%.

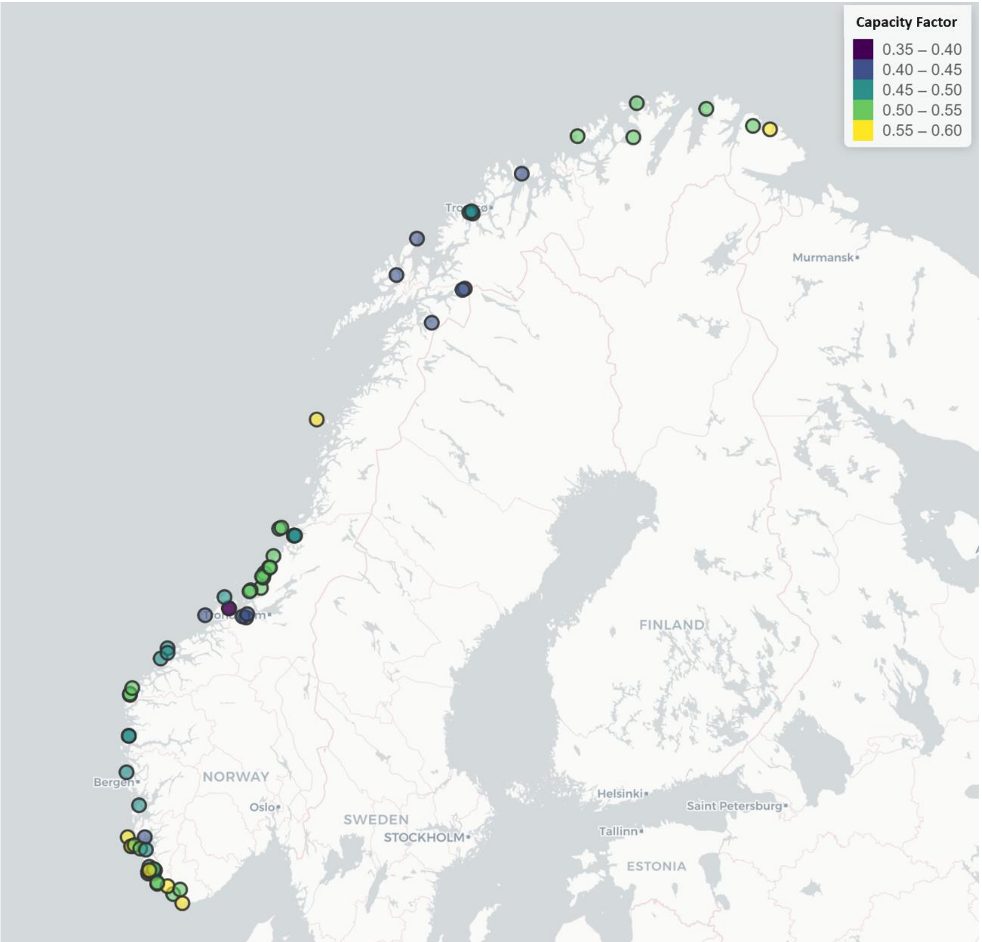

Figure 6.1 Theoretical wind capacity factor in Norway based on 13 years.

Table 6.1 Maximum and minimum capacity factor within zones and the zonal average

	Zone 2	*Zone 3*	*Zone 4*	*Zone 5*
Maximum Capacity Factor	Fjeldskår 59.4%	Ytre Vikna 59.9%	Vardøya 57.2%	Hywind 57%
Minimum Capacity Factor	Askjesundet 45.8%	Hitra 36.6%	Nygårdsfjellet 41.9%	Tysvær 41.4%
Zonal Average Capacity Factor	53.5%	47.4%	48.2%	51.5%

By assessing the capacity factor of wind power production, our study confirms that the Norwegian coastline, in general, has suitable wind conditions. The high capacity factor can be used as an argument for building wind farms along the entire coastline. As the capacity factor is generally high, we will in the following part, consider the correlations between different wind locations to examine how to best diversify the wind farms when taking the variability of wind into account.

6.2 Distance and Power Correlation

In this subsection, we investigate whether wind power production benefits from geographical dispersion, analysing the correlation across zones and individual sites. For correlation calculations, we use the formula stated in the previous section (5.1.1). If we take zone 2 and zone 4 as examples, we calculate wind power correlation between the two locations as seen in the formulas 6.2 and 6.3. The distance between these two sites can be up to 1,800 km, so a low correlation between these two zones indicates the concept of geographical smoothing.

Covariance between zone 2 and zone 4:

$$\sum_{i=1}^{n} \frac{(Zone\ 2_i - \overline{Zone\ 2})(Zone\ 4_i - \overline{Zone\ 4})}{Observations} = 0.16 \tag{6.2}$$

Correlation between zone 2 and zone 4:

$$\sum_{i=1}^{n} \frac{Cov(Zone\ 2, Zone\ 4)}{\sigma_{Zone\ 2}\sigma_{Zone\ 4}} = 0.283 \tag{6.3}$$

The correlation matrix shown in Table 6.2, implies that the correlation between power production from two wind farms reduces as the distance between them increases. Our result is supported by research done in other countries (Roques, Hiroux, & Saguan, 2010; Milligan & Factor, 1999; Holttine, 2004). In practice, the result means that the power generated in Northern Norway correlates the least with the power generated in Southern Norway, better illustrated by the map in Figure 6.2, where zone 2 is the starting point. Low correlation between wind farms results in less variable total power production (Holttine, 2004). When applying this knowledge, it will be beneficial to build wind farms in zone 2 and zone 4, as these areas have the lowest correlation in Norway.

Table 6.2 Correlation between zonal power production with correlation level description.

	Zone 2	*Zone 3*	*Zone 4*	*Zone 5*
Zone 2	1	Moderate	Low	High
Zone 3	0.469	1	High	High
Zone 4	0.283	0.650	1	Moderate
Zone 5	0.718	0.677	0.431	1

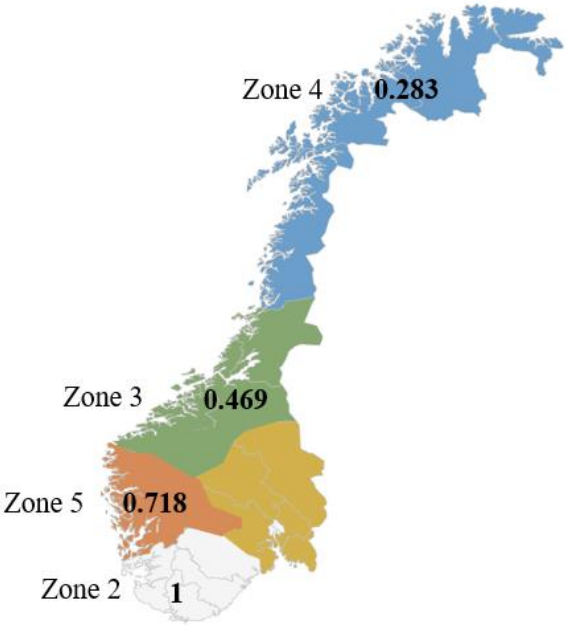

Figure 6.2 Power production correlation map, with zone 2 as the reference point.

To further evaluate the correlation in more detail, we utilise individual wind sites data. Thus, the correlation will be different compared to the zonal average data, where a smoothing effect within the zone will come into play. We calculate the correlation between each location and with all the other locations. To see how distance affects correlation, we plot these variables against each other, as shown in Figure 6.3. By examining correlation and distance, we observe that the correlations reach a low correlation (0.4) at approximately 900 km in the distance between the wind sites. In contrast, we find a moderate correlation coefficient (0.4 to 0.6) between wind farms with distances of 300 km to 900 km.

The point around 500 km (Figure 6.3) raises an additional question. What makes the correlation diverge from the regression line? The deviation from the line indicates that distance explains some of the diversification, but not in its entirety. In our calculations, we do not account for Norwegian topography. When taking this approach, we treat the same distance in the same way, independent of factors affecting the wind speeds such as mountains or weather systems. 1,800 km is the maximum distance between two points on the Norwegian mainland (Thornæs, 2020). Therefore, location pairs with a distance of 500 km are more frequent than location pairs with 1,800 km, being a reasonable explanation for the irregularities around 500 km.

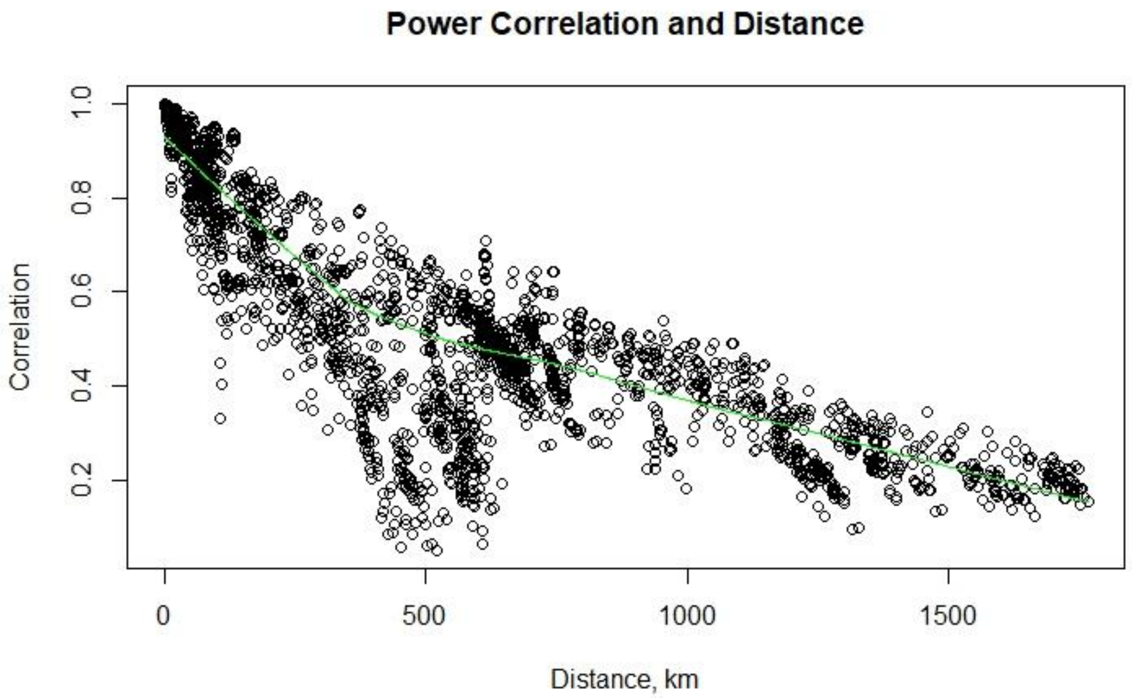

Figure 6.3 Power production correlation and distance pairs.

The areas north and south of Stad (Appendix A4) are often used as a reference point when talking about the weather in Norway, as Stad represents a border between weather systems (Rommetveit, 2010). We plot the correlation between power production and the distance for zone 2 and zone 5 (Figure 6.4), representing the area south of Stad, and the same for zone 3 and zone 4 (Figure 6.5), representing the area north of Stad. While south of Stad follows a similar pattern as Figure 6.3, north of Stad do not have the same clear pattern as previously found, which can be a factor in explaining the irregularities of a 500 km distance. Another feature worth noticing is that south of Stad has a correlation that is decreasing faster than when considering the whole of Norway. In this area, we receive a low correlation when the distance between the wind farms is approximately 275 km or more.

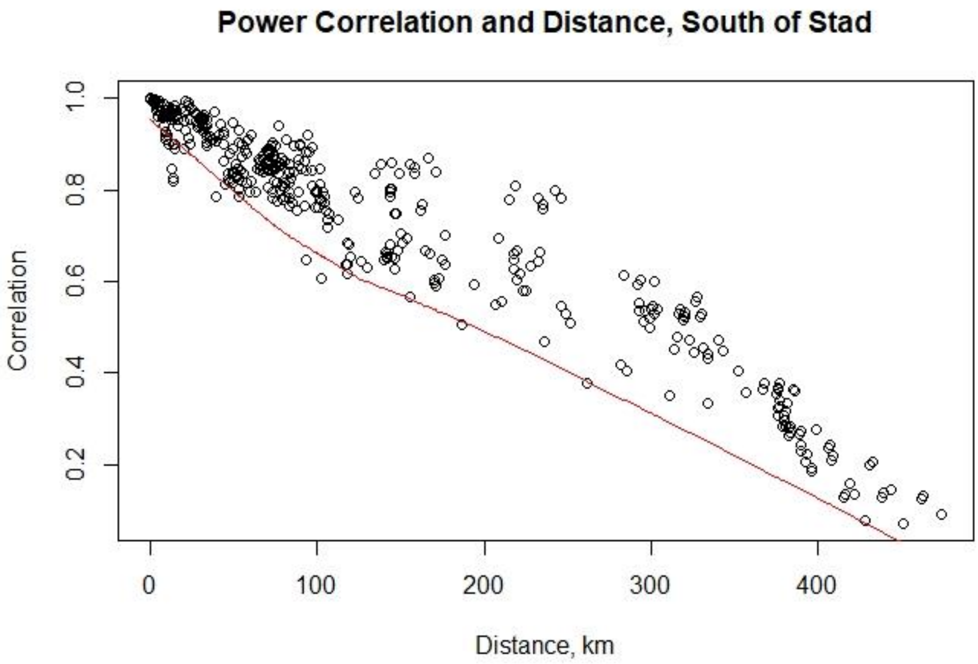

Figure 6.4 Power production correlation and distance south of Stad.

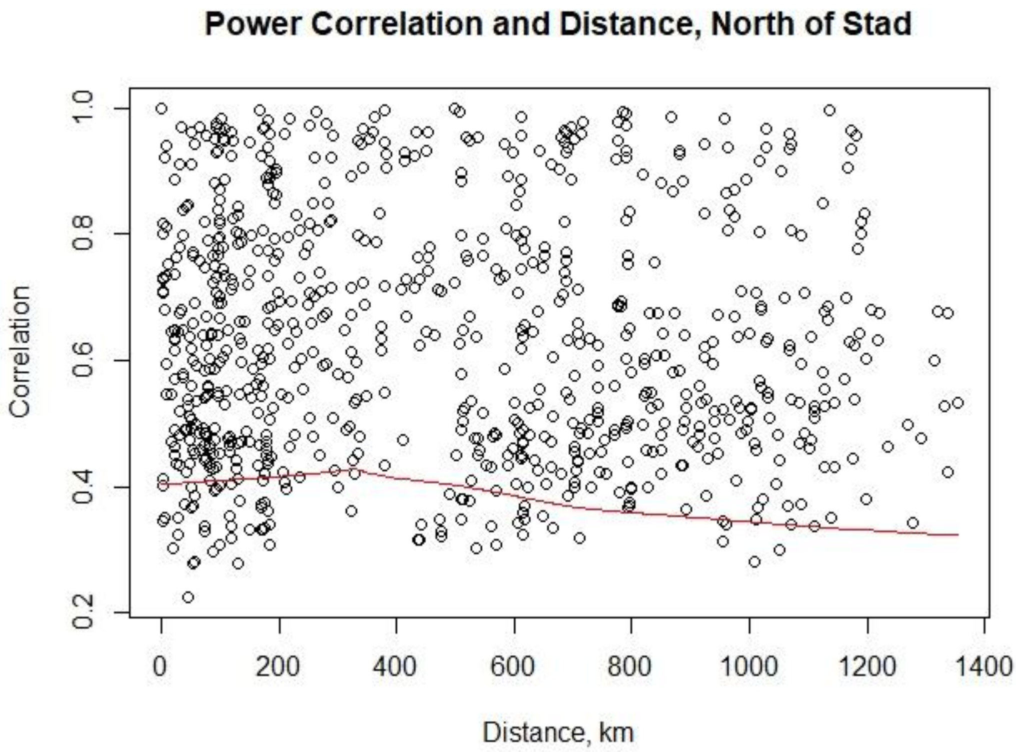

Figure 6.5 Power production correlation and distance north of Stad.

Wind speed varies across time frames, and this variation affects the power system. When studying time averages based on one, two and three weeks, we see that the regression lines follow the same pattern regardless of time (Figure 6.6). The power production gets smoothed out when composing power production based on an average of more than one week, making the power production over different areas more similar and the correlation higher.

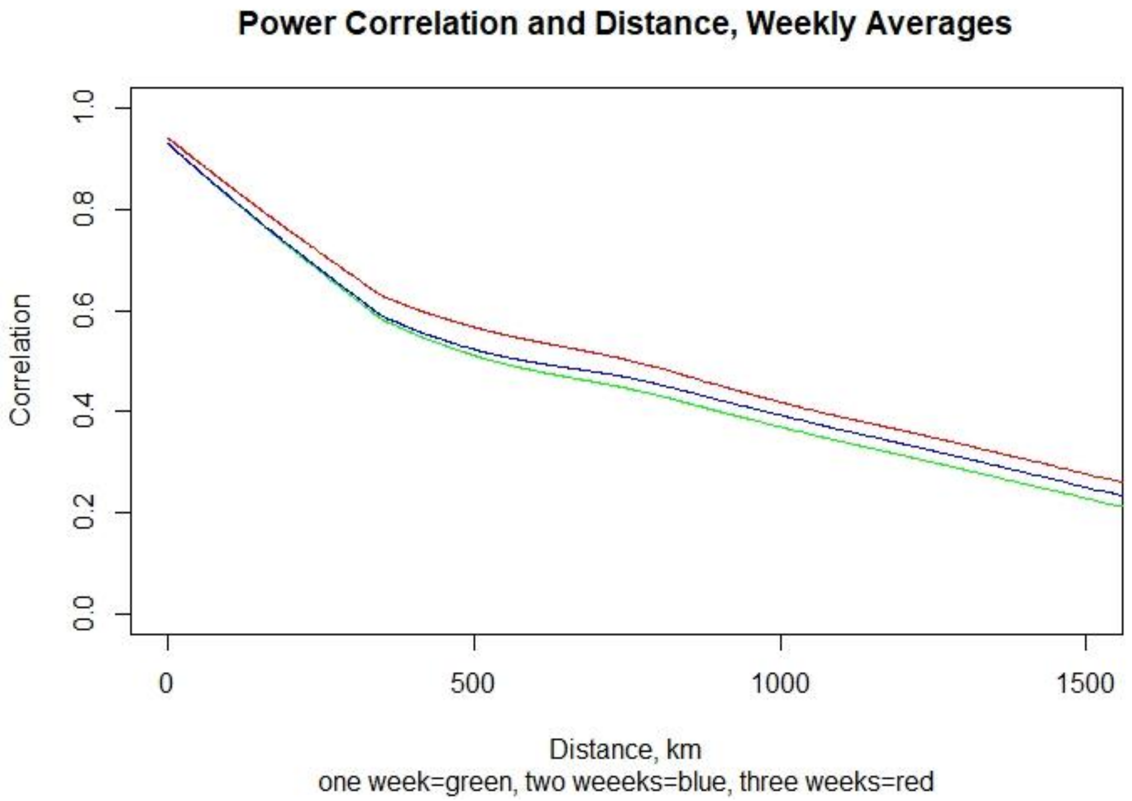

Figure 6.6 Power production correlation and distance pairs based on different time frames.

Seasonal cycles and annual variations are essential for long-term studies and system planning. We see that the power production correlations between wind sites are similar, regardless of season, see Figure 6.7. This means that even though the wind speeds vary over the seasons, and that higher wind speed is more frequent in the wintertime (Appendix A5), the wind power correlations between the different sites stay more or less the same. In Figure 6.8, we see that the correlation between weekly average wind power production at different wind sites in January, April, July and October, are similar the first 300 km. After 300 km, the correlation lines diverge, but they still have declining trends.

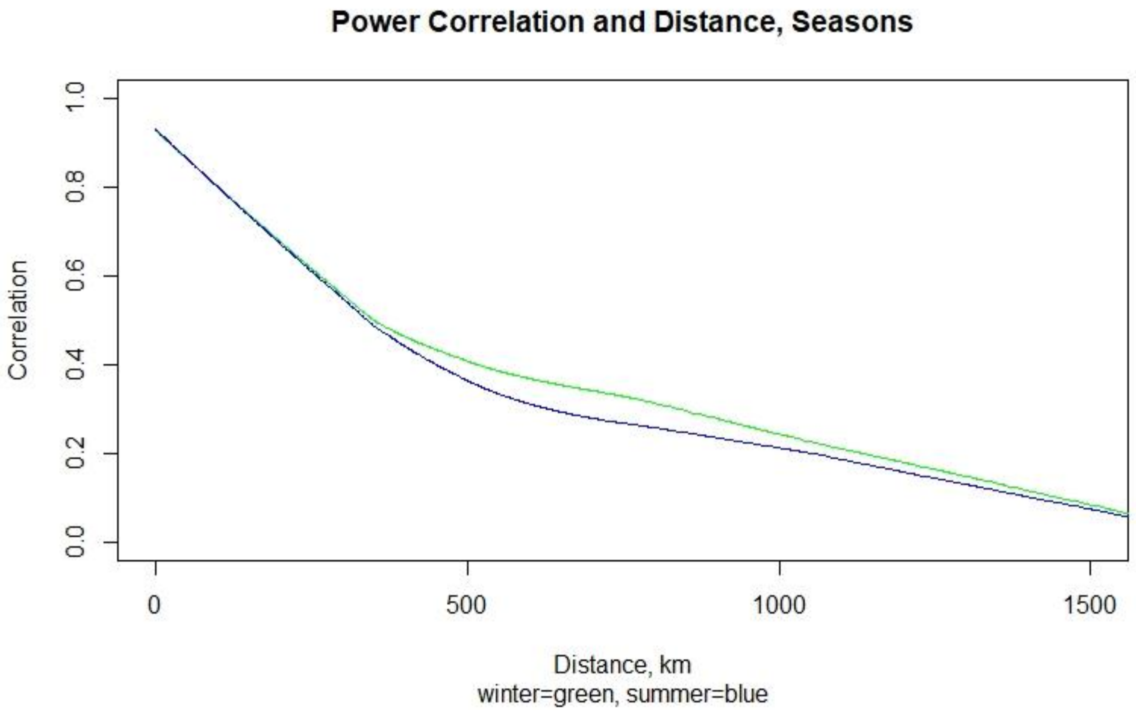

Figure 6.7 Power production correlation and distance pairs based on season.

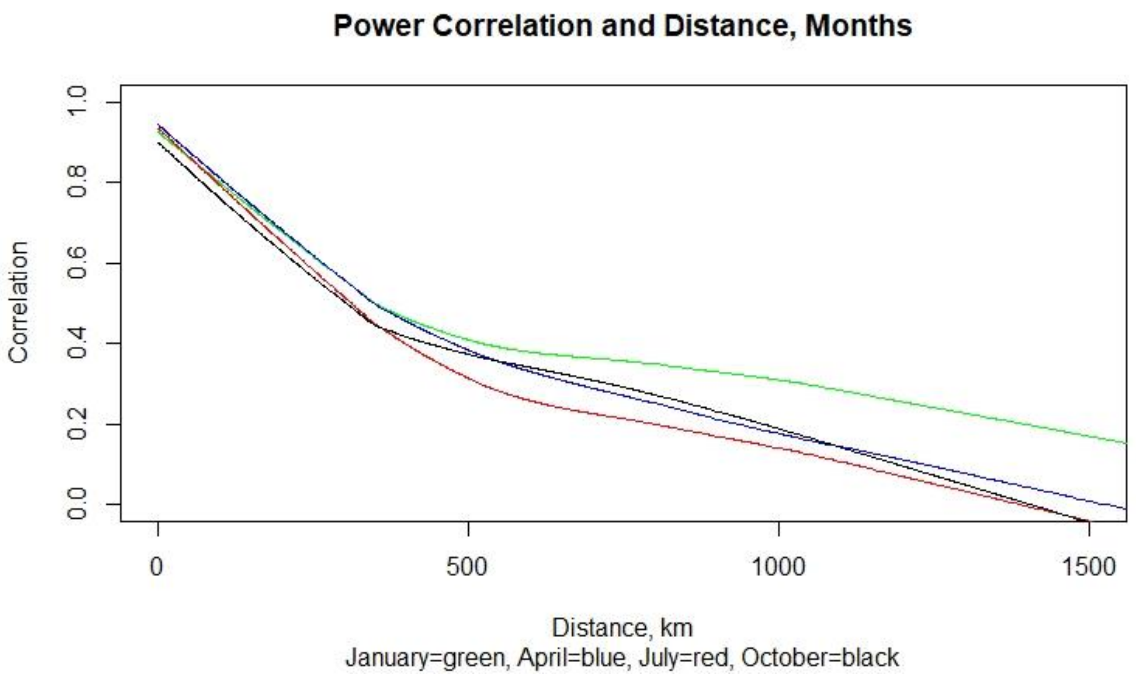

Figure 6.8 Power production correlation and distance pairs based on months

To demonstrate the phenomenon of correlation and distance more visually, we use three different reference points from our dataset and examine how the weekly correlation between the reference point correlates with the other locations in the dataset. Figure 6.9 illustrates correlations from the different reference points. We choose Fjeldskår, Ytre Vikna, and Hamnefjell as reference points, as they are located in different zones and represent different parts of Norway. Each of these reference points illustrates that building wind farms along the entire coastline is unnecessary to benefit from the reduced correlation in wind power production.

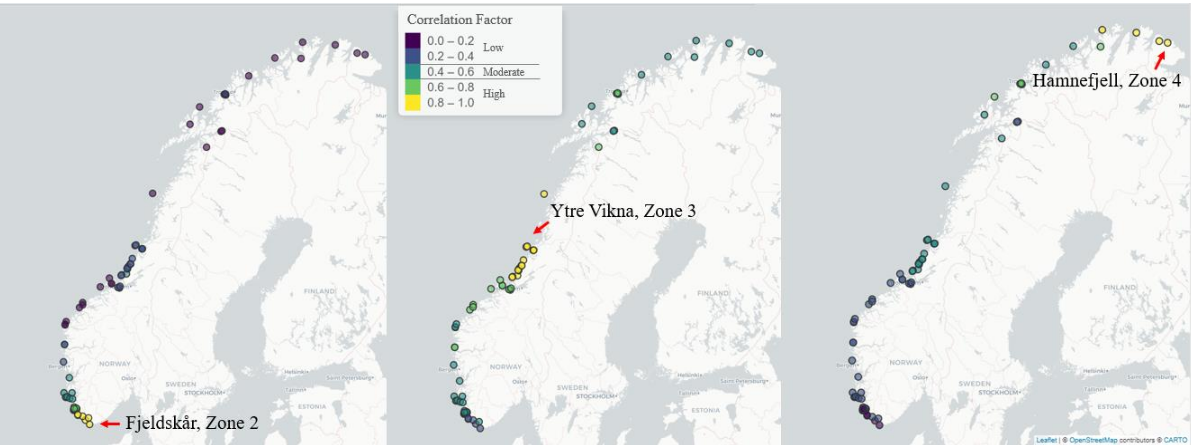

Figure 6.9 Correlation with reference points and the rest of the wind farms. From left to right: Fjeldskår, Ytre Vikna, Hamnefjell.

6.3 Unconstrained Approach

From the observation of power production variation, together with the results from the correlation between the different wind sites, a portfolio approach will show how to best combine the wind sites in terms of variability and covariance. We start by making a portfolio with a combination of the different zones, denoted as the unconstrained approach. In the unconstrained approach, we account for the wind resources, assuming adequate transmission capacity.

In our thesis, we use the different wind sites as the average power production within each zone in our calculations. The unconstrained Efficient Frontier has an expected return and standard deviation, as displayed in formula 6.4 and 6.5.

$$E(r_p) = X_{no2}E(r_{no2}) + X_{no3}E(r_{no3}) + X_{no4}E(r_{no4}) + X_{no5}E(r_{no5}) \tag{6.4}$$

$$\sigma_p = \sqrt{X_{no2}^2\sigma_{no2}^2 + \ldots + X_{no5}^2\sigma_{no5}^2 + X_{no2}X_{no3}\rho_{no2no3}\sigma_{no2}\sigma_{no3} + \ldots + X_{no4}X_{no5}\rho_{no4no5}\sigma_{no4}\sigma_{no5}} \tag{6.5}$$

Based on the portfolio formulas described in section 5.2, as well as formula 6.4 and 6.5, we can draw the Efficient Frontier. The y-axis represents the power output in MWh/h, and the x-axis represents variability, measured by the standard deviation (Figure 6.10). The colourful dots represent the individual zones, and the black dots are the Efficient Frontier, consisting of different portfolio combinations that are optimal. The red dot displays the MV, the point we will focus on in this thesis, as it represents the Minimum Variance portfolio.

The portfolio plot in Figure 6.10 expresses that investing in one wind site gives a much higher variance than a combination of wind sites. The Efficient Frontier allows us to maximise wind power output for a given level of variance, or equivalently, minimise the variance for a given wind power output. Reducing the variation in wind power production will create a stable and reliable source of electricity. Being able to diversify variability in energy production will play an essential role when the demand for electricity increases, as this lowers the variation, hence gives a more stable energy flow.

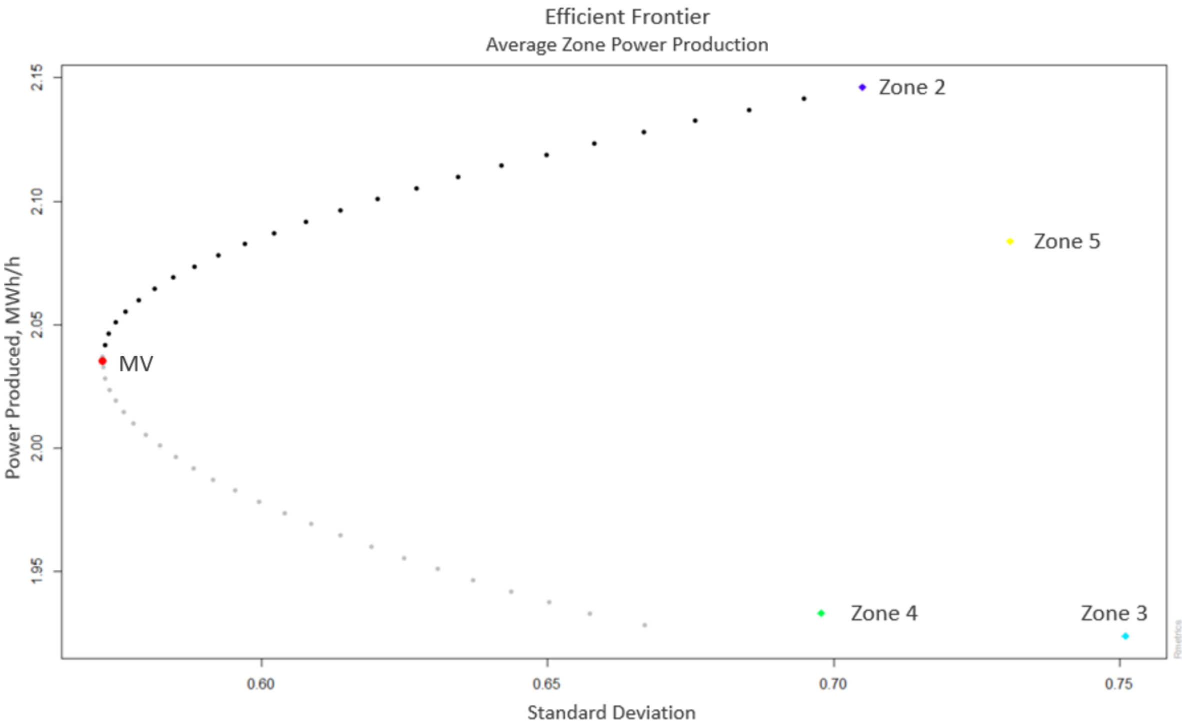

Figure 6.10 Efficient Frontier with average zone power production over 13 years.

In Table 6.3, we break down the Efficient Frontier into standard deviation and power produced. When comparing zone 2 with the MV, the power output is 5% higher. However, the standard deviation decreases with 20%, going from zone 2 to the MV. This illustrates that MV is a trade-off between variance and power output. MV has the lowest standard deviation, and reasonable power output, being the Pareto optimal mix of the wind sites.

Table 6.3 Standard deviation and power produced (MWh/h) for individual zones and the minimum variance point of the Mean-Variance Portfolio.

	Zone 2	*Zone 3*	*Zone 4*	*Zone 5*	*MV*
Standard Deviation	0.71	0.75	0.70	0.73	0.57
Power Produced	2.14	1.92	1.93	2.08	2.04

When considering the MV, we assess how the investment should be allocated between the four zones to minimise the variance in wind power production. Investing the largest portion in zone 4, and the least in zone 3 will minimise that variance, as shown in Figure 6.11 below. The results support our previous findings that the northern and the southern parts of Norway have the lowest correlation. We have also found that both areas have adequate wind resources.

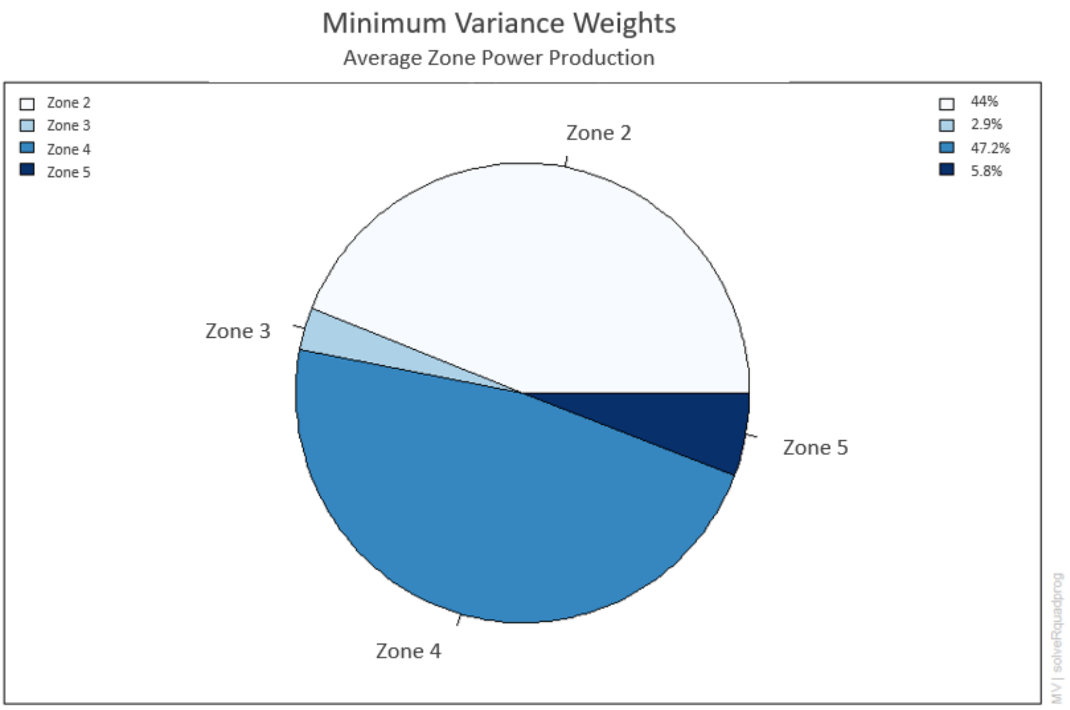

Figure 6.11 The weights between the different zones in the zone average Minimum Variance point of the Mean-Variance Portfolio.

6.4 Constrained Approach

In this subsection, we will use another portfolio approach. Whereas we in the unconstrained approach (subsection 6.3) solely evaluated the wind resources, we will, in the following, evaluate a constrained approach, accounting for the value of electricity. We assume that the zonal electricity price from the Nordic power exchange reflects the system demand for electricity. Adding electricity prices in the MVP model will create an additional consideration when optimising wind farm deployment relative to the unconstrained approach. Investigating wind power deployment and system demand will provide guidelines on where power is scarce, i.e. where the wind power has high value.

This Efficient Frontier for the unconstrained approach has an expected return and standard deviation, as displayed in formula 6.6 and 6.7. Figure 6.12 displays the constrained Efficient Frontier. In the graph, the y-axis represents the hourly value of theoretical power production, hereafter referred to as hourly value, and the x-axis represents the variance in hourly value.

$$E(r'_p) = X'_{no2}E(r'_{no2}) + X'_{no3}E(r'_{no3}) + X'_{no4}E(r'_{no4}) + X'_{no5}E(r'_{no5}) \tag{6.6}$$

$$\sigma'_p = \sqrt{X'^2_{no2}\sigma'^2_{no2} + .. + X'^2_{no5}\sigma'^2_{no5} + X'_{no2}X'_{no3}\rho'_{no2no3}\sigma'_{no2}\sigma'_{no3} + .. + X'_{no4}X'_{no5}\rho'_{no4no5}\sigma'_{no4}\sigma'_{no5}} \tag{6.7}$$

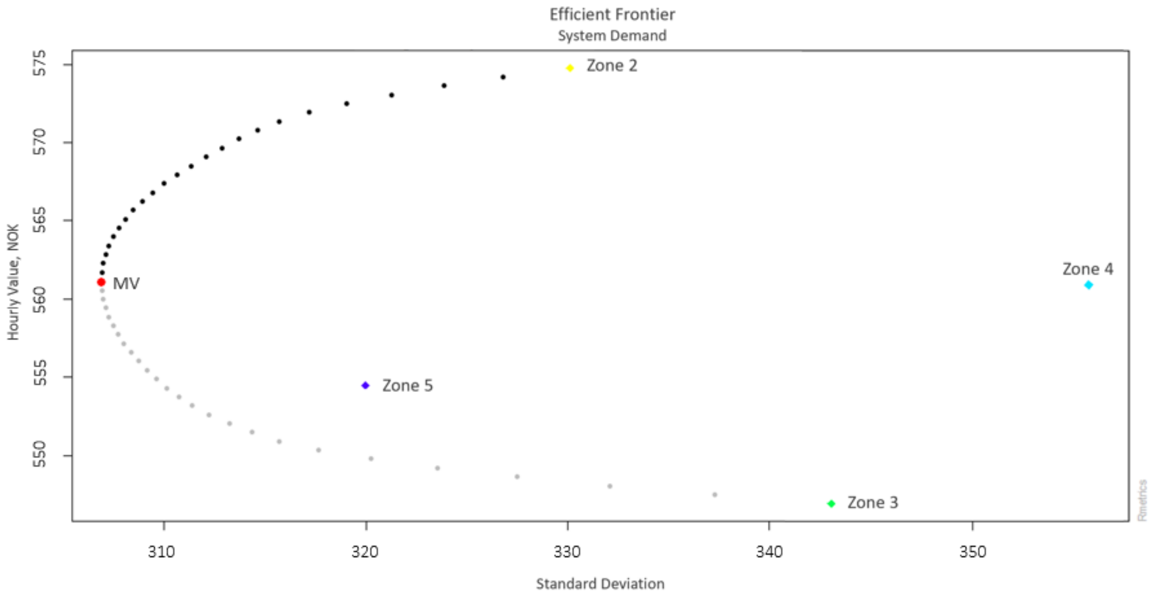

Figure 6.12 Efficient Frontier with average hourly value data over 13 years.

In Table 6.4, we break down the Efficient Frontier into standard deviation and hourly value of the power produced. Zone 2 represents the area with the highest hourly value of power production. However, we see that the standard deviation is 7.6% higher than the MV. Furthermore, zone 5 is the area with the lowest standard deviation, compared to the MV, the standard deviation is 4.3% higher, and the hourly value decreases with 1.11%.

Table 6.4 Standard deviation and power produced for zones individually and for minimum variance Mean-Variance Portfolio (average NOK per hour).

	Zone 2	*Zone 3*	*Zone 4*	*Zone 5*	*MV*
Standard Deviation	330.13	343.10	356.63	319.98	306.88
Hourly Value	574.76	546.92	560.85	554.47	561.10

Figure 6.13 displays the share of the individual zones in the MV when accounting for system demand. In the constrained approach, the largest share should be invested in zone 5 to minimise the variance. As seen in Table 6.4, zone 3 has both high standard deviation and low hourly value being the reason for the low share of deployment this zone has in the MV.

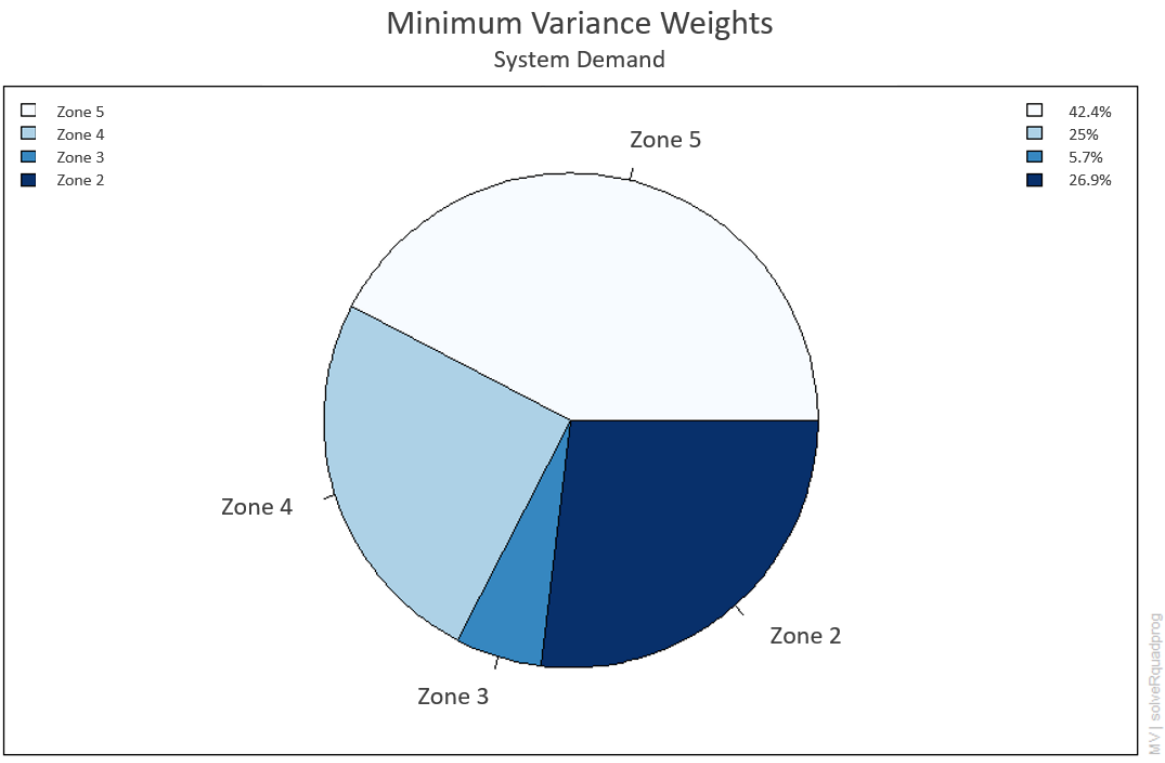

Figure 6.13 The weights between the different zones in the Minimum Variance point of the Mean-Variance Portfolio when accounting for system demand.

6.5 Summary of Results

To summarise, our empirical results provide evidence that a geographical smoothing effect exists. We have found that the correlation between wind power locations decreases as the distance increases, regardless of the time interval studied. Taking this into account, it is possible to lower the overall variance in wind power production, obtaining a stable and reliable flow of wind power, when coordinating the deployment of wind farms.

We have found that even though the wind conditions are adequate along the whole coast of Norway, the MVP model displays that we should carefully assess where to build wind farms. The unconstrained MVP displays how to minimise the variance, only accounting for wind resources, whereas the constrained MVP include system demand as a factor when minimising the variance. Further, our results show that the share of ideal wind power production in each zone depends on the approach applied. When maximising wind power production based on system demand, Norway should deploy the largest share of wind farms in zone 5. In contrast, the optimal share of wind farms in zone 5 is small when maximising the wind resources, as demonstrated in Table 6.5.

Table 6.5 Share of the individual zones in the minimum variance point of the Mean-Variance Portfolios with the unconstrained and constrained approach.

MVP	*Zone 2*	*Zone 3*	*Zone 4*	*Zone 5*
Unconstrained	44%	2.9%	47.2%	5.8%
Constrained	26.9%	5.7%	25%	42.4%

In Figure 6.14, we use the weights from the constrained approach to see how this solution will fit into the Efficient Frontier of the unconstrained approach. Not surprisingly, the weights from the constrained approach when used on the unconstrained dataset, $MV_{Constrained}$, comes out as a sub-optimal option for the unconstrained approach, placed beneath the Efficient Frontier. From Figure 6.14, we see that the variance of $MV_{Constrained}$ is higher than necessary to achieve the specific return. If combining the zones optimally according to the unconstrained Efficient Frontier, we can achieve the same variance as in $MV_{Constrained}$ and at the same time increase the power output by 1.76%.

Even though Figure 6.14 shows that the constrained approach is not optimal compared to the unconstrained approach, we see that the differences when putting the constrained weights in the unconstrained data is moderate. Our main goal is to evaluate the effect of variance when combining the different zones, and we find that the difference in standard deviation between $MV_{constrained}$ and $MV_{unconstrained}$ is 5%. However, the impact of a 5% difference in variance regarding the power system, is a topic for another study.

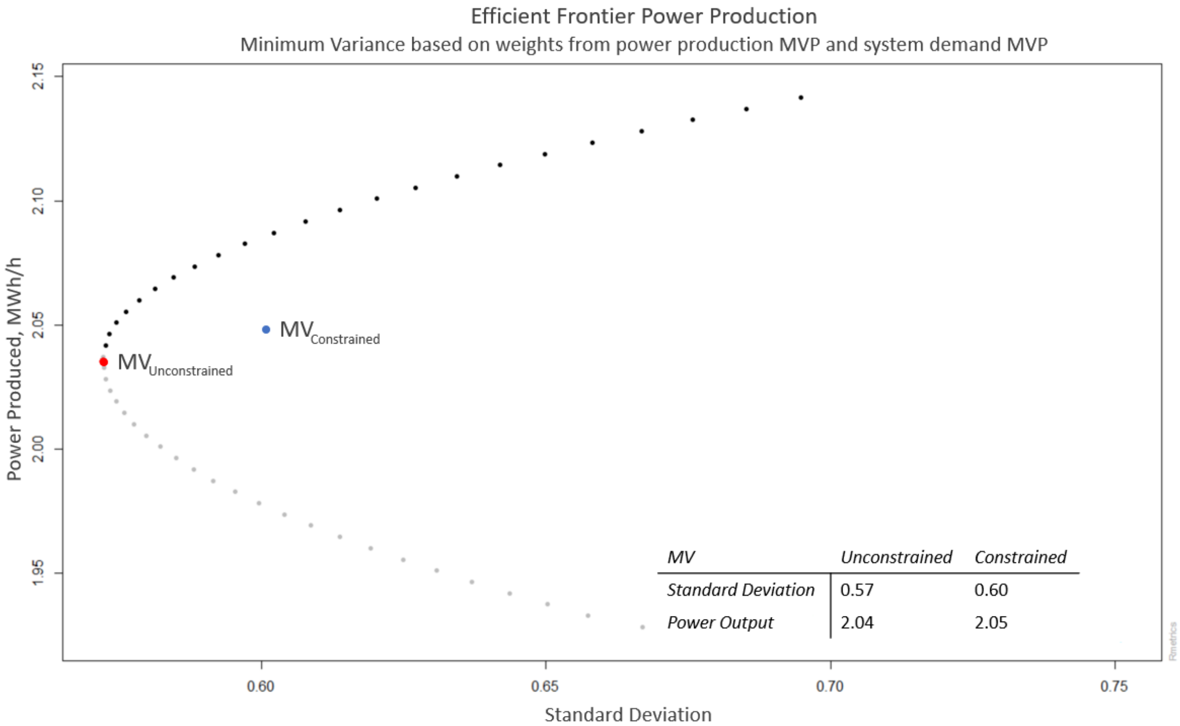

Figure 6.14 Constrained and unconstrained MV weights placed in the Efficient Frontier of the unconstrained approach.

What approach to apply should be aligned with the national strategy of wind power production. On the one hand, adding the constraint which reflects the system demand will reveal where the wind power production will have the highest hourly value. On the other hand, it will result in a sub-optimal deployment of wind farms, if the aim is to optimise the wind resources. The system demand for power is predicted to change in the future (Spilde, Lien, Ericson, & Magnussen, 2018). Therefore, we argue that an optimisation based on the wind resource solely will be the most efficient as today's electricity demand does not reflect tomorrow's demand.

7 Discussion

In the following section, we discuss the implications of our study, shortcomings on the datasets and limitations imposed on our study as a result of the modelling chosen. Finally, we discuss further research.

7.1 Implications of the Study

The main goal of this thesis was to investigate whether the Norwegian wind power production can benefit from using a portfolio approach to reduce its intermittency problem and decrease the overall variability of wind power.

Our empirical results show that distance is an important factor for the correlation between wind farms. Previous research done on the topic, find that this is not unique for Norway. We further analyse how to best diversify the deployment of wind farms to minimise the variance, utilising portfolio theory. Our findings from these analysis emphases that a portfolio approach illustrate how to combine wind farms to lower the overall variability of wind power.

Even though other research, presented in the literature review, has touched the same topic as our thesis, we differentiate when it comes to how we apply the models. Our study is the first using wind data exclusively from Norway to analyse the question of how portfolio theory can help mitigate the weekly aggregated variance of wind power production. Using weekly average will provide a picture of how Norway should handle long-term planning for wind power. Additionally, we have used a system demand approach. This approach demonstrates how to best deploy the wind power to maximise the value of wind power in Norway.

Our thesis contributes to the existing literature by presenting a nation-based study on how to optimise the deployment of wind farms in Norway. We utilise a portfolio approach to determine where to place wind farms, demonstrating the benefits of using financial tools in energy policy. The Norwegian government can use the MVP approach as a supplement when deriving a wind farm deployment strategy. The deployment process of wind farms used today lack the capability to take intermittency and correlation of wind power production into account.

Evaluating correlation and covariance between wind locations will give insight into how the overall wind power production variance can be reduced. In general, the power market has a lack of tools to mitigate uncertainty (Adams & Jamasb, 2016), making our study relevant. The MVP approach can be of economic importance due to its ability to optimise the trade-off between variability and power output, regarding both optimising the wind resource and the system demand. An MVP approach can make power production more reliable, and the planning for transmission easier.

7.2 Limitations of the Datasets

7.2.1 Wind Measures

The wind data was measured in the period from 2000 to 2013. Therefore, it is possible that the data is outdated and hence, do not reflect today's wind speeds. However, the wind is exogenous. Therefore, our use of seasonal naive predictions is presumably still representative. Nevertheless, because of climate changes, the wind speed might be affected along the coast of Norway. Whether this will have a positive or negative impact on our study is unknown. However, we must keep in mind that climate changes can affect the optimal location of wind power production based on how the wind is blowing in the future (Tobin et al., 2015).

Furthermore, we could extract information about different sites at specific locations along the coast from the dataset. The density of sites for wind measurement varies, and some of the sites have test locations nearby. This might result in biased figures if the statistics are too similar, smoothing the zonal average. In addition, our approaches assume that the potential area for wind farm development is equal and feasible in each area, an assumption that is not necessarily true. For instance, the different zones might have different topography and demography, affecting where it is possible to build wind farms. However, all the zones cover relatively large areas with wilderness, and possibilities to build wind farms.

Our research is built on theoretical power production based on historical wind measures by using the WindPRO multi-turbine power curve. Hence, the power data does not represent the actual wind power production in this timespan. The power produced appears artificially high and does not consider other issues like maintenance and unpredictable downtime of wind turbine that prevent production accordingly.

7.2.2 Day-ahead Prices

The zones in Norway have changed multiple times, creating some errors in the electricity price dataset when using today's division of five zones. Applying five zones for the period analysed will create some artificial zones, consisting of a duplication of another zone's electricity prices. The duplication of the zonal prices will then claim an unconstrained flow of electricity between areas, which is not necessarily true.

Further, using the electricity prices from 2000 to 2013 might reflect a different demand for electricity than what we experience today, and in the future. Increased electricity demand over the last couple of years due to the electrification of the transporting sector, households, and industry (Sletten et al., 2018), change the way we consume electricity. Therefore, the information about the system's need extracted from the price dataset might be outdated. Thus, using more recent electricity prices will reflect the increased demand for electricity and reflect today's transmission situation. However, using price data from the same period as the wind data reveals the specific weather conditions that occurred at the time, the price data was measured, demonstrating how wind power and prices correlate.

7.3 Limitation of the Modelling

A drawback when using MVP theory on wind data is the challenge related to the original multimodal distribution. A multimodal distribution indicates that standard deviation is not a suitable measurement of variance, making the model presented in this thesis unfavourable. To handle this problem, we aggregated data on a weekly basis leading to a trade-off between short time intermittency and weekly variations. The weekly aggregations make the correlations higher compared to the correlations of shorter time intervals. Therefore, our approach does not handle the complications of short-time fluctuations, but rather take the weekly lack of power into account.

In section 6.2, we examined how the correlation between wind sites depends on distance, stating that geographical dispersion leads to a lower correlation. In our modelling, we assumed that wind power outputs are individual data points. However, weather operates in systems, making it possible that the weather systems' characteristics and topography can be the reason for the reduction in correlation, and not the distance itself.

We have not explored the Norwegian transmission network in detail. We have assumed that the electricity price reflects the system demand, yet, the electricity price aggregation is more complex, including transmission cost and marginal loss tariff (Statnett, 2019). In the on-peak hours, the electricity price reflects demand, and in off-peak hours the electricity price is equal to the variable cost of power production (Léautier, 2018). However, the correlations between bidding zones are high (Appendix A6), indicating sufficient transmission capacity. In the long-run perspective, transmission capacity can be viewed as flexible, making it possible to adjust to the transmission in accordance with the power flow requirements.

7.4 Further Research

This study is limited to wind power in Norway, but the power system in the country is not. Norway is connected to a larger power system, the Nordic power exchange, trading power with the Nordic, Baltic, Central Western European and UK markets (Nord Pool, c, n.d.). Therefore, it would be interesting to investigate the resource endowment in each of these European countries and use a portfolio approach to optimise the deployment of renewable energy sources across borders.

In our study, we have focused on a single renewable energy source, wind power. However, including multiple power sources in the portfolio will provide a more realistic picture of the energy mix. Hence, it could help us determine what energy source to invest in and where to invest geographically based on variability and power output.

Furthermore, we have aggregated the data to weekly observations to fulfil the model assumptions. However, this smooths out the production spikes and does not capture short time intermittency. As Drake & Hubacek (2007) states, using time intervals of 5-10 minutes would be better fitting to capture a precise picture of the shot-time intermittency problem when it comes to the wind power variability. Therefore, it would be interesting to look at data with such characteristics.

We have used standard deviation as a measure of variance, stating that reducing the absolute variance in the portfolio will contribute to providing a reliable and balanced supply of power. However, we suggest that further research should investigate other measures to uncover challenges related to wind power production, such as Value at Risk and Conditional Value at Risk. These risk measures investigate the power distribution tails, revealing the potential losses related to the fluctuation of power production.

8 Concluding Remarks

This thesis introduces a model obtained from the finance discipline to investigate the benefits of diversifying wind farms to reduce variation in the production of wind power. To find evidence in favour of, or against a geographical diversification, we use a portfolio approach. We demonstrate how to use the theory of Mean-Variance Portfolio (MVP) to optimise where to build wind farms in Norway. For this, we transform historical wind data from 2000 to 2013 from 70 wind sites in Norway to theoretical power production.

Our thesis implies that we can benefit from geographical dispersion, as the correlation decreases with an increasing distance. We see the same effect of distance on correlation regardless of time. When studying the correlation between wind sites based on average weekly power production, we find that low correlation occurs when the distance between two wind sites reaches 900 km. The correlation increases when going from the average power production of one week to average power production of two and three weeks. When calculating average power production over longer time intervals, the production spikes even out, making the power production across the country obtain a higher correlation coefficient.

We demonstrate how to use an MVP approach to minimise the variance of weekly average power production, which in terms will contribute to mitigate wind power fluctuations efficiently. The importance of providing a stable and efficient power flow will increase as the share of wind power in Norway's energy mix increases. Knowing that variation will create problems for the electricity market as a result of uncertainty and unstable supply, it will be beneficial to produce wind power with reduced variation.

In this study, we introduce a new approach when using MVP on power, accounting for system demand. Applying this alternative approach gives an indication of where power in Norway is scarce and where power has high value. This perspective is better fitted for meeting the need for electricity than when only focusing on wind resources.

Our results show how the ideal wind location portfolios differ depending on whether the focus is on optimising wind power output or optimising power depending on system demand. We find that when solely looking at power production, aiming for a minimum variance, optimising the wind resource, most of the wind farms should be located in the northern and southern parts of Norway. This is unexpected when knowing that Norway has adequate wind resources along the entire coast. However, when accounting for system demand, the area around Bergen has the largest share in the minimum variance solution. When optimising the wind resource, the share of deployment in the area around Bergen amounts for 5.8%, while the deployment share amount for 42.4% when accounting for system demand. The considerable shift in share regarding wind power deployment in the different optimal solutions is surprising and reveals that the value of power in Bergen is high.

Interestingly, our results indicate that the area around Trondheim should have the smallest share of deployment, both when optimising wind resources and when accounting for system demand to lower the total variability of wind power. This result is noteworthy when knowing that this area has the largest wind farm system in Northern Europe today.

Even though our thesis is narrowed, we demonstrate how the financial approach can give insights that are relevant for the wind power politics and how intermittency and correlation can be of importance when deciding on where to construct wind farms. We have shown how different approaches give different optimal solutions. However, we recommend that what approach Norway should apply when planning for wind power deployment, depends on the overall national strategy of wind power production.

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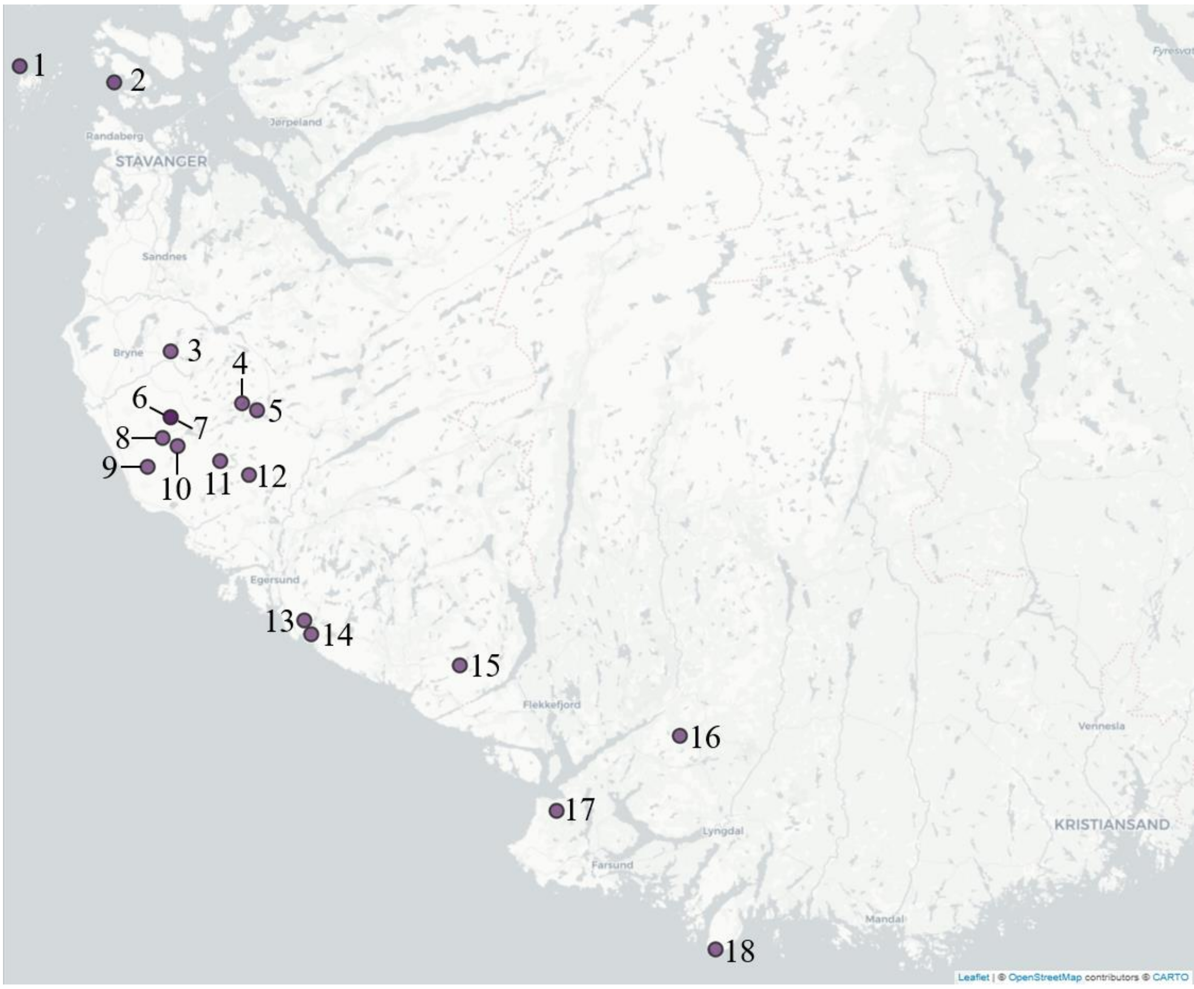
Appendices

A1 Place-names for the Wind Location

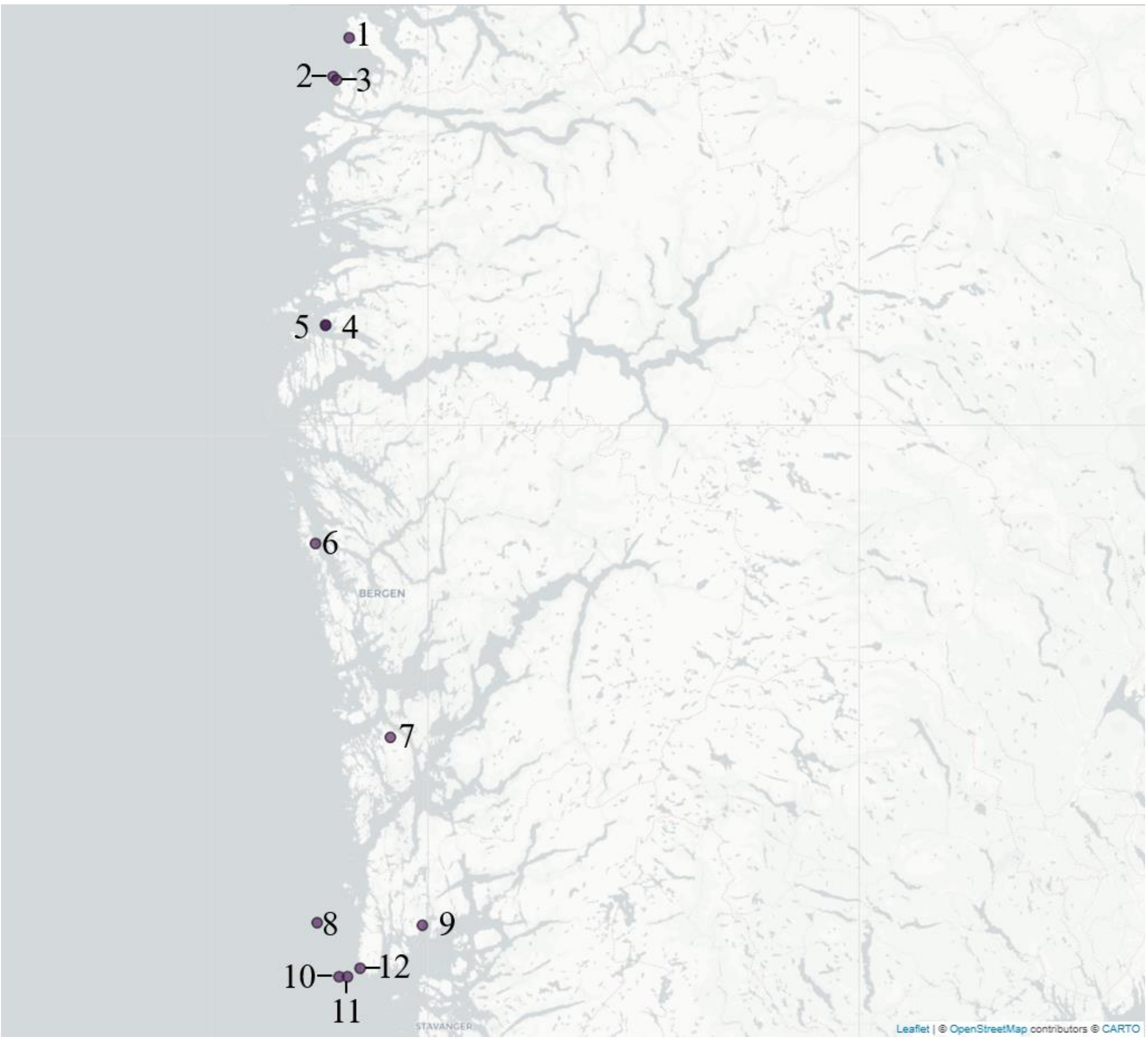
Zone 2



A1.1 Wind locations with name in zone 2.

1	Norbø	11	Gravdal
2	Askjesundet	12	Eikeland Steinsland
3	Åsen	13	Eigersund
4	Makaknuten	14	Svaheia
5	Stigafjellet	15	Tellenes
6	Høg Jæren I	16	Kvinsheia
7	Høg Jæren II	17	Lista
8	Røymyra	18	Fjeldskår
9	Friestad		
10	Skinansfjellet		

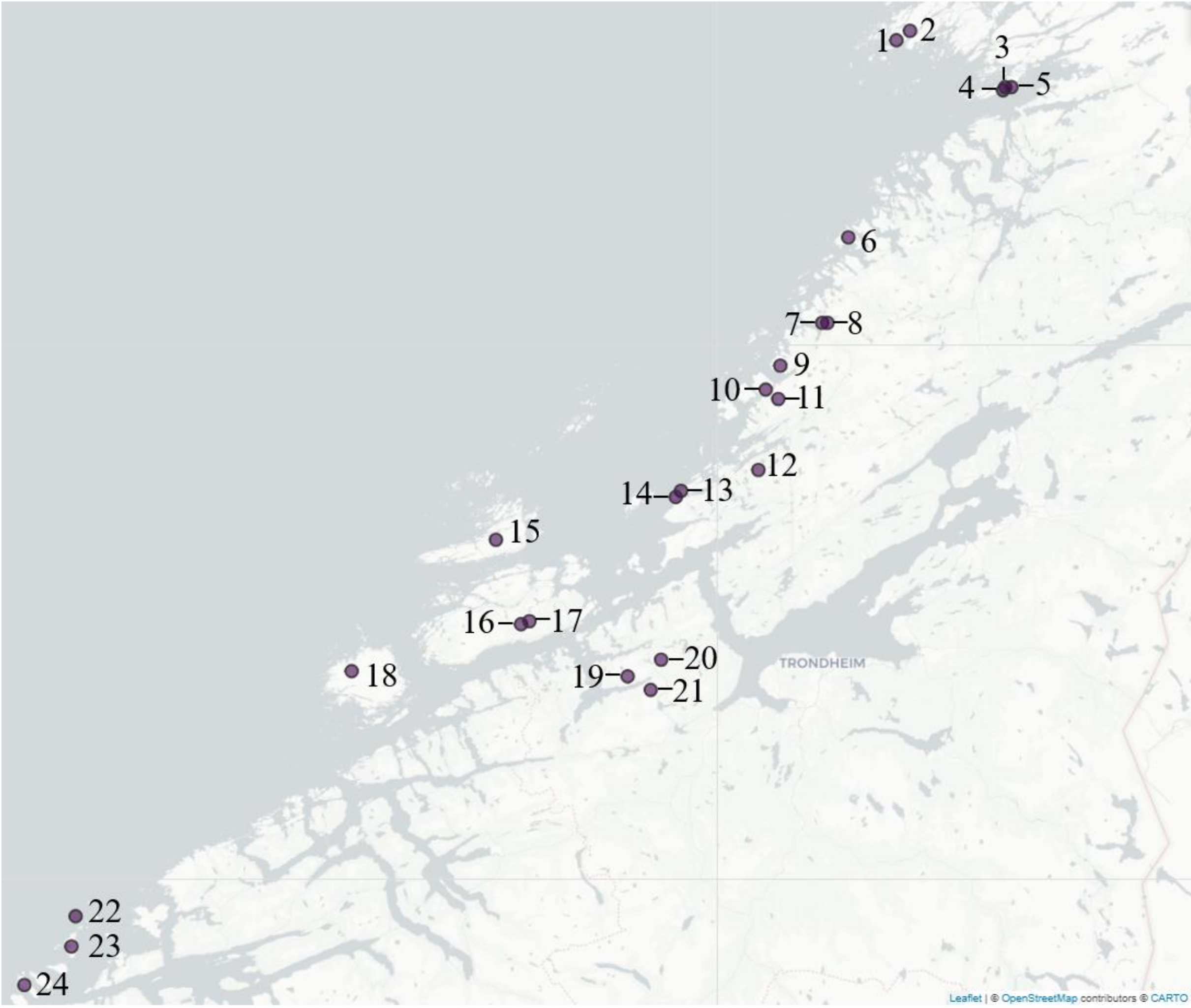
Zone 5



A1.2 Wind locations with name in zone 5.

1	Stadt	11	SWAY Karmøy
2	Mehuken I	12	Sandvesanden
3	Mehuken II		
4	Luteland testanlegg I		
5	Luteland testanlegg II		
6	SWAY Kollsnes		
7	Midtfjellet		
8	Utsira		
9	Tysvær		
10	Hywind		

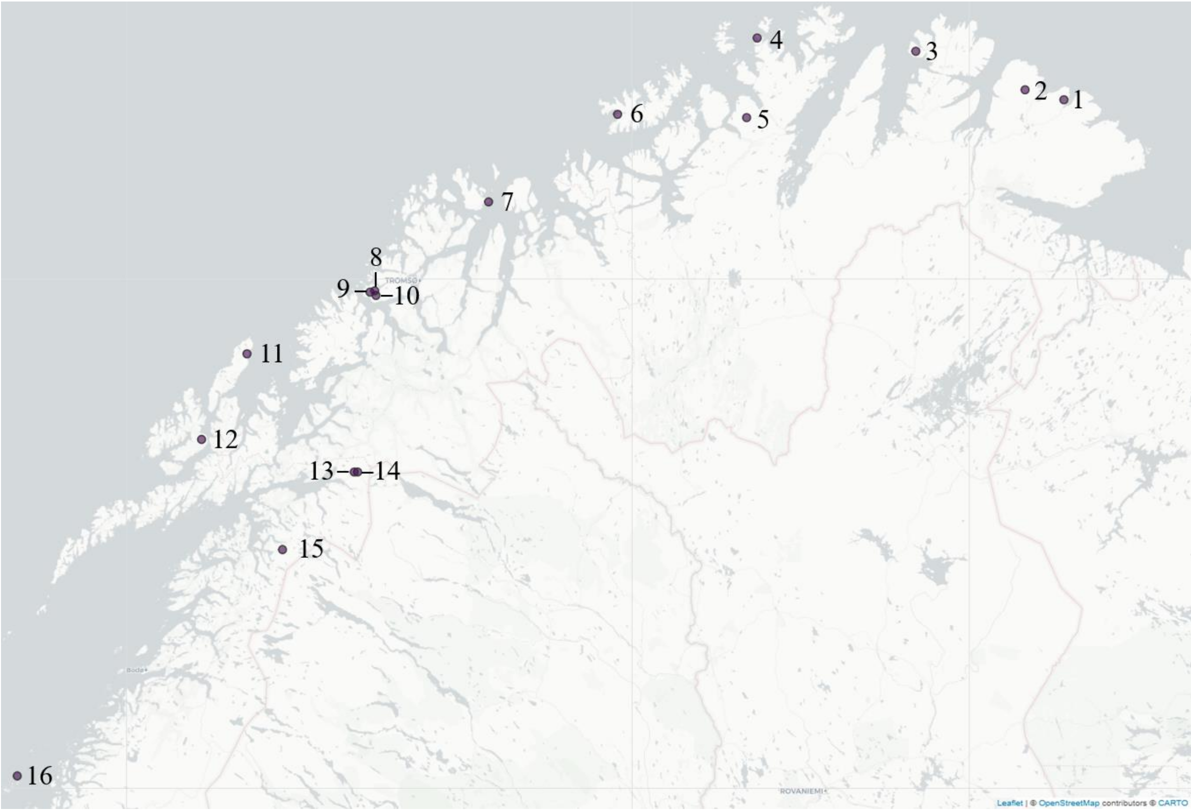
Zone 3



A1.3 Wind locations with name in zone 3.

1	Ytre Vikna trinn I
2	Ytre Vikna trinn II
3	Hundhammerfjellet
4	Hundhammerfjellet demo I
5	Hundhammerfjellet demo II
6	Sørmarkfjellet
7	Bessakerfjellet I
8	Bessakerfjellet
9	Roan
10	Harbakfjellet
11	Kvenndalsfjellet
12	Storheia
13	Valsneset
14	Valsneset testsenter
15	Frøya
16	Hitra I
17	Hitra II
18	Smøla
19	Svarthammaren
20	Remmafjellet
21	Geitfjellet
22	Havsul
23	Harøy
24	Haramsfjellet

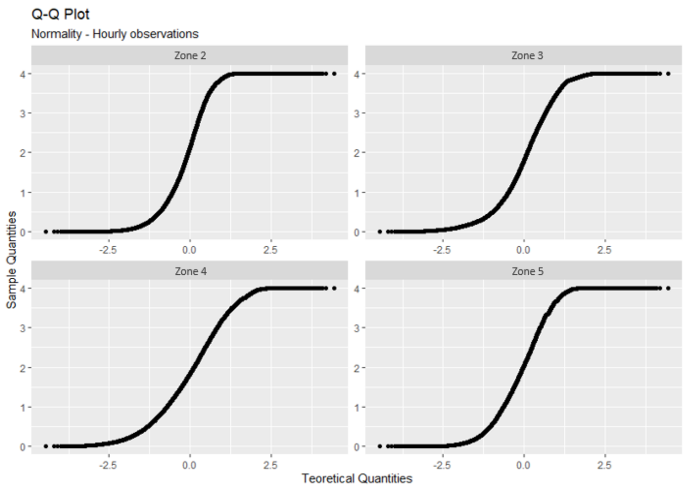
Zone 4



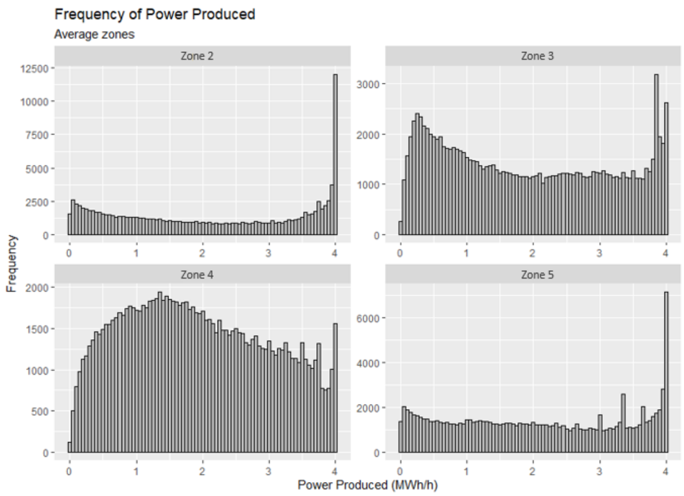
A1.4 Wind locations with name in zone 4.

1	Hamnefjell
2	Rakkocearro
3	Kjollefjord
4	Havøygavlen
5	Falesrassa
6	Dønnesfjord
7	Fakken
8	Raudfjell
9	Kvitfjell
10	Sandhaugen
11	Andmyran
12	Anstadblaheia
13	Nygårdsfjellet trinn I
14	Nygårdsfjellet trinn II
15	Sørfjorden
16	Vardøya

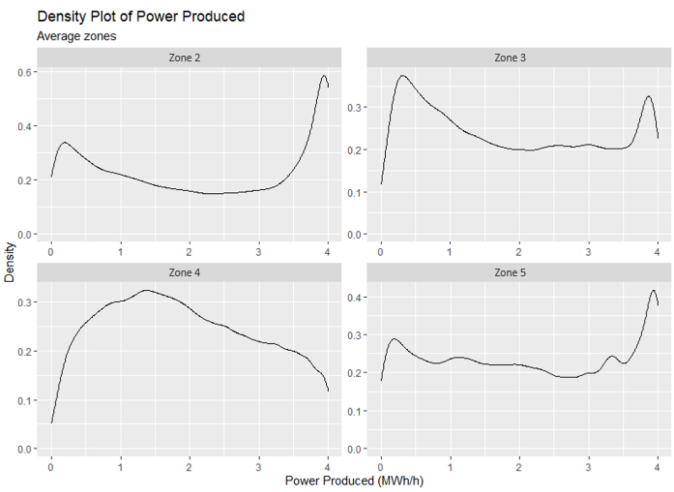
A2 The Originale Distribution of the Wind Speed data



A2.1 Normality plots for hourly power output data.



A2.2 Histograms on hourly power output data.



A2.3 Density plots on hourly power output data.

A3 Correlation Between Power Produced and Zonal Prices

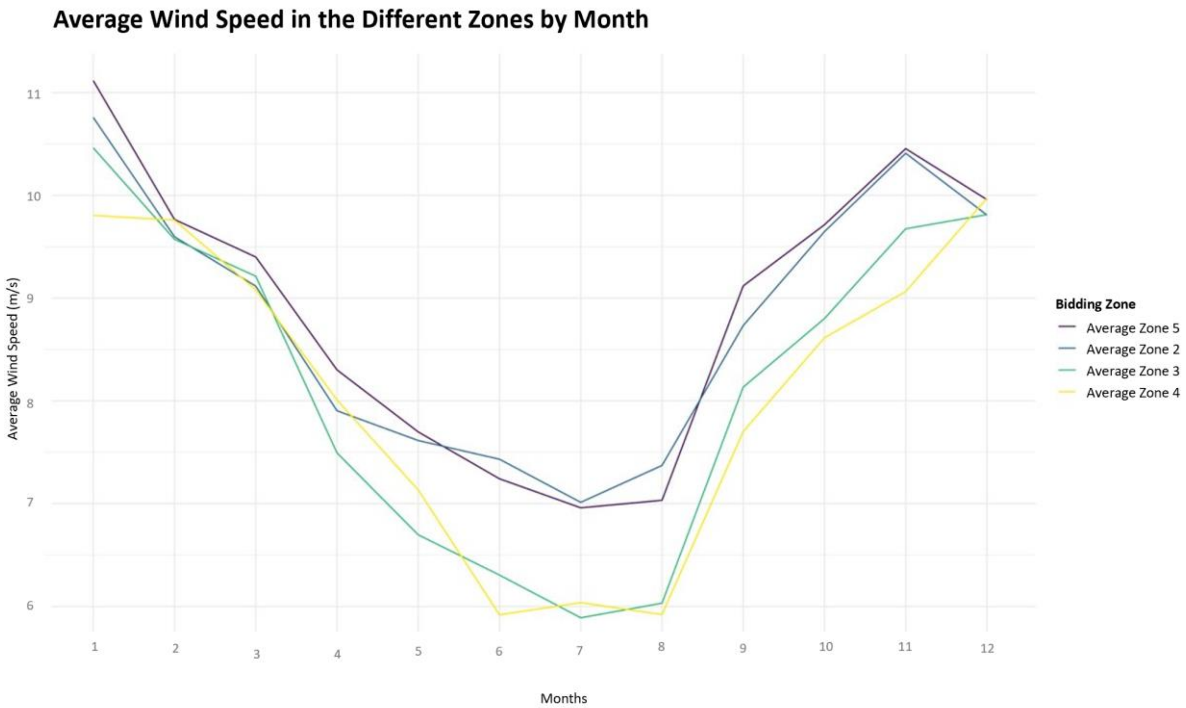
A3.1 Correlation between power price and power production based on the whole year.

	Price zone 5	*Price zone 2*	*Price zone 3*	*Price zone 4*
Power zone 2	0.001	0.002	-0.012	-0.013
Power zone 3	0.048	0.048	0.008	0.004
Power zone 4	0.107	0.104	0.066	0.062
Power zone 5	-0.029	-0.027	-0.055	-0.055

A4 Location of Stad

A4.1 The location of Stad, a border between weather systems in Norway.

A5 Average Wind Speed in the Different Zone by Month



A5.1 Average wind speed in the different zones by month.

A6 Correlation between zonal prices

A6.1 Correlation between zonal prices.

	Zone 2	*Zone 3*	*Zone 4*	*Zone 5*
Zone 2	1	High	High	High
Zone 3	0.827	1	High	High
Zone 4	0.828	0.996	1	High
Zone 5	0.997	0.83	0.831	1