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The Use of Wind Speed Derivatives for a Norwegian Energy Producer

Bruk av vindhastighetsderivater for en norsk energiprodusent

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Preface

This master thesis completes our Master´s degree in Business Administration & Management with major in finance, at NTNU Business School in Trondheim.

The work with this thesis has been interesting, as well as challenging. Throughout the process, we have acquired knowledge about a topic that was relatively new to us. Studying weather derivatives has been an educating experience, and despite the difficulties, it has been a rewarding semester.

We would like to express our gratitude to our supervisor, Denis Becker at NTNU Business School, for great help when choosing the topic for our thesis. The process would not have been the same without his enthusiasm and professional guidance. We would also like to thank TrønderEnergi AS for contributing with data and information of importance for our thesis.

The contents in this master thesis are not necessarily endorsed by NTNU Business School, and any errors or omissions are the authors´ own.

Abstract

The objective of this thesis is to examine the effect hedging volumetric risk has on the operating income of a Norwegian energy producer, by using weather derivatives. The effect is evaluated based on changes in the volatility of operating income, as well as the profitability of the weather derivatives.

As there exists little prior research concerning wind derivatives, we choose to research this topic. The power industry is sensitive to fluctuations in weather conditions. Thus, we aim to find out if TrønderEnergi can hedge the downside risk in their production of wind power. The study concerns three of TrønderEnergi´s wind mill farms and three independent weather stations.

Due to weather derivatives not having a tradable asset as the underlying, methods used to price financial derivatives are not applicable. The most common underlying weather index is temperature, and consequently most pricing methods concerns temperature derivatives. Few have been applied on wind speed options.

In this thesis we will use some of the pricing methods that recur most often in previous literature. These are the historical burn analysis, the McIntyre method and the indifference pricing method. We will construct wind speed put options for the three wind mill farms and the three weather stations, for which we will apply these pricing methods.

The indifference pricing method provides prices for both the seller and the buyer. The average of the seller´s and the buyer´s indifference prices functions as put option prices. Due to the necessity of independent weather measurements, only purchasing put options for the weather stations is realistic. The findings demonstrate that purchasing wind speed put options in the period 2013 to 2017 would be profitable in all cases where prices were found, while the effect on volatility in operating income is ambiguous. Hence, wind speed put options may be a good tool to hedge volumetric risk in some cases.

Sammendrag

Formålet med denne oppgaven er å undersøke hvilken effekt sikring av volumetrisk risiko har på driftsresultatet til en norsk kraftprodusent, ved bruk av værderivater. Effekten er vurdert basert på endringer i volatiliteten i driftsresultatet, samt lønnsomheten av værderivatet.

Siden det er lite tidligere forskning om vindderivater, velger vi å undersøke dette temaet. Kraftindustrien er sensitiv for svingninger i værforhold. Dermed ønsker vi å finne ut om TrønderEnergi kan sikre seg mot nedsiderisko ved produksjon av vindkraft. Studien gjelder tre av TrønderEnergi sine vindmølleparker, samt tre uavhengige værstasjoner.

På grunn av at værderivater har underliggende som ikke er omsettelige, er ikke metoder som brukes til å prise finansielle derivater anvendelige. Den vanligste underliggende værindeksen er temperatur, og følgelig er de fleste prismetodene basert på temperaturderivater. Få metoder har blitt brukt på vindhastighetsopsjoner.

I denne avhandlingen vil vi bruke noen av de prisingsmetodene som går igjen oftest i tidligere litteratur. Dette er historical burn analysis, McIntyre-metoden og indifferensprisingsmetoden. Vi vil konstruere vindhastighetsopsjoner for de tre vindmølleparkene og de tre værstasjonene, som vi vil bruke disse prisingsmetodene på.

Indifferensprisingsmetoden gir priser for både selger og kjøper, og gjennomsnittet av selgerens og kjøperens priser fungerer som opsjonspriser. Da det er nødvendig med uavhengige værmålinger, er det kun realistisk å kjøpe opsjoner for værstasjonene. Resultatene viser at innkjøp av vindhastighetsopsjoner i perioden 2013 til 2017 ville vært lønnsomt i alle tilfeller hvor priser ble funnet, mens effekten på volatilitet i driftsresultatene er tvetydig. Derfor kan vindhastighetsopsjoner være et godt verktøy for å sikre seg mot volumrisiko i enkelte tilfeller.

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1 Introduction

Businesses around the world are exposed to increasingly uncertain weather conditions (Brockett, Wang & Yang, 2005). It is estimated that weather affects as much as 30 % of the economy and 70 % of companies in the U.S. (Alexandridis, 2013). Alaton, Djehiche & Stillberger (2002) present a list of industries that are, both directly and indirectly, affected by weather conditions. In this list they include, among others, energy producers, the leisure industry and the agricultural industry.

However, it is the energy sector that has the highest demand for weather risk management, and thus has caused this industry to develop (Alaton, Djehiche & Stillberger, 2002). A relatively recent type of financial tool has been developed to hedge weather risk, namely weather derivatives. According to Alexandridis (2013), organizations or individuals can use weather derivatives as a part of their risk management strategy to reduce risk associated with adverse or unexpected weather conditions.

The purpose of this thesis is to examine whether a Norwegian power producer can use weather derivatives to hedge volumetric risk and thus smooth their operating income. In this thesis we therefore analyze how TrønderEnergi´s revenues depend on weather, and how to hedge volumetric risk. Wind derivatives have received comparably little attention in the literature. We therefore look into different pricing methods for wind derivatives. Finally, we suggest how an energy producer can use wind derivatives to hedge against weather risk.

The sequence of this thesis is structured as follows: In section 2 we will discuss the use of weather derivatives, and the motivation of energy producers to hedge volumetric risk. The characteristics of weather derivatives are also presented here. Section 3 presents daily average wind speed data and financial data for three of TrønderEnergi´s wind mill farms and three related weather stations. Further, different AR(1) models, which explain the relationship between wind speed and operating income, are proposed and statistical analyses are conducted. In section 4 we discuss positive and negative traits of different pricing methods. In section 5 we calculate the prices of several wind speed put options for TrønderEnergi with three of the different pricing methods. The main focus is on the prices provided by the indifference pricing method, and basis risk is also discussed briefly here. Lastly, a conclusion is given in section 6.

2 Weather and Wind Derivatives

In the following section we introduce weather derivatives and their traits. Weather derivatives are financial contracts with payoffs depending on future weather, such as temperature, rainfall or wind speed (Härdle, 2017). Alaton, Djehiche & Stillberger (2002) state that weather derivatives usually are structured as futures, options or swaps based on underlying weather indices, and that temperature is the most common underlying variable.

In this thesis, we construct several wind speed put options. According to Alaton, Djehiche & Stillberger, (2002) weather options have the following characteristics:

- The contract type (call or put)
- The contract period
- The underlying index (e.g. wind speed, rainfall, HDD)
- An official weather station from which the weather data are obtained
- The strike level
- The tick size

Options are common types of financial contracts and can be either a call or a put option. When a weather option contract is written, the buyer pays a premium to the seller. Then, depending on the type of contract, the buyer receives a payout if the weather index is above or below the predetermined strike level. Thus, the strike level determines whether the contract gives a payout or not. In addition to the strike level, the payout is also dependent on the tick size. The tick size defines the amount of money the buyer will receive for each unit the weather index is above or below the strike level (Alaton, Djehiche & Stillberger, 2002).

The contract must also define the underlying weather index. This index could be rainfall, snowfall, wind speed or any other weather phenomenon. Compared to regular financial options, the underlying is the main difference between the two. As mentioned, temperature is the most common underlying variable for weather derivatives (Alaton, Djehiche & Stillberger, 2002). Between October 1997 and April 2001, more than 98 % of all weather derivatives were temperature related (Brockett, Wang & Yang, 2005). Contracts related to rainfall represented 0.9 %, while snow represented 0.5 %, and wind represented as little as 0.2 % of all weather derivatives.

Lastly, the weather contract must define a certain period in which the underlying index is calculated. The length of this period can vary. However, since weather forecasts only predict weather for approximately a week ahead, weather options tend to have at least a month until maturity (Alexandridis, 2013). The weather station at which the weather index is measured must be an independent third party. As the payout of the contract is based on the data delivered from this third party, their reliability and whether they are open to tampering and fraud or not, should be considered (Berlage, 2013).

When using weather records from an independent weather station as the underlying in a weather derivative, basis risk will in most cases occur. Basis risk represents risk due to the distance between the area the hedger wishes to cover and the location the contract is written on (Brockett, Wang & Yang, 2005). It may be that the weather is slightly different in two areas, even though they are relatively close and correlated. Thus, the hedger must bear the basis risk. To minimize basis risk, the weather data should be recorded at or as close as possible to the location one wishes to cover (Berlage, 2013).

By looking at wind speeds measured directly at TrønderEnergi´s wind mill farms, we exclude the basis risk entirely. However, this leads to the issue of the measurements not being independent. For a counterparty to be willing to enter into a weather contract, there must be an independent third party providing the measurements so that they are reliable. Therefore, we have also retrieved wind measurements from three different weather stations located nearby each wind mill farm. By comparing weather derivatives written on both locations for each wind mill farm, the magnitude of basis risk can be examined. Hence, we can gain insight into the difference between contracts with and without basis risk.

During the last decades, wind power has become an important source of renewable energy (Benth, Benth, 2012). Several power companies, such as TrønderEnergi, use wind mill farms in their production. Naturally, these wind mill farms are exposed to risk related to wind conditions (Caporin, 2012). Wind sensitive companies, especially energy producers, can use wind derivatives to hedge volumetric risk (Cao & Wei, 2004).

The wind power production is dependent on the speed, duration and direction of the wind. All modern wind turbines have advanced control systems which rotates the blades to fully exploit the wind intensity (Norwea, 2012). Hence, wind speed is the most relevant measure of weather exposure in practice. To reduce this risk, companies can use insurance contracts or wind derivatives. These types of derivatives are standardized products, which is only dependent on the daily average wind speed (Alexandridis, 2013).

As mentioned, wind derivatives are not commonly used financial instruments. According to Alexandridis (2013), the slow growth in this particular market is due to difficulties in modelling wind accurately, in addition to the problems related to valuing related contracts. A reliable framework for valuation is missing, and therefore financial institutions are somewhat unwilling to quote prices on wind derivatives.

2.1 Weather Derivatives and Their Historical Development

The first official deal concerning weather derivatives was created in 1997 between Koch Energy and Enron (Cao, Li & Wei, 2003). The market for weather derivatives expanded fast after this deal, and individually negotiated contracts started to be traded over-the-counter (OTC) (Alaton, Djehiche & Stillberger, 2002). The companies in the energy sector were the main driving force behind the growth in the OTC market. This growth led to the expansion of organized markets, such as the Chicago Mercantile Exchange (Cao, Li & Wei, 2003), which introduced its first futures and option contracts on temperature in 1999 (Benth, Benth, 2012).

The market for weather derivatives is relatively widespread in the U.S. (Alaton, Djehiche & Stillberger, 2002), and the world´s largest weather derivatives exchange is the Chicago Mercantile Exchange (Thind, 2014). Compared to the U.S. market, the market in Europe has had a slower growth. One reason for this can be the early deregulation of the energy market in the U.S. However, Alaton, Djehiche & Stillberger, (2002) see a growth potential in the European market.

According to the Ministry of Finance (2017), there is a growing need for weather derivatives in the power industry. Such contracts have emerged during the past few years due to the fact that strong incentive programs have reduced the price risk, while increased the volumetric risk. Therefore, the volatility in production of both wind and solar energy has created a greater need for hedging volumetric risk. The market for weather derivatives is expected to expand, also outside the power industry. Financial actors such as insurance companies may also have interest in this market (Ministry of Finance, 2017).

2.2 Advantages and Challenges of Weather Derivatives

A problem for businesses is coping with uncontrollable risks, and weather is one of the most significant uncontrollable risk factors (Sharma, 2007). In sectors like agriculture and power, conventional risk hedging instruments are insufficient to tackle this unpredictable risk. The introduction of weather derivatives means that unpredictable risk no longer equals unmanageable risk. The awareness of this weather risk management possibility has increased among actors like shareholders, analysts, lenders and rating agencies (Berlage, 2013). Companies are not expected to control the weather, but they are now expected to manage weather risk. Blaming poor performance on weather is no longer sufficient and is less and less accepted by stakeholders.

Weather derivatives can be purchased to hedge smaller deviations in weather, while insurance is traditionally used to cover damages caused by catastrophic events (Bossley, 1999). The purchaser of insurance must demonstrate an actual damage or loss to be covered, whereas the payout from a derivative automatically depends on the actual weather outcome. As insurance policies are affected by asymmetric information and loss adjustment issues, weather derivatives can be considered more attractive as tools to manage weather risk (Sharma, 2007).

Many researchers point out that moral hazard and adverse selection are sever problems concerning insurance policies (Sharma, 2007). Moral hazard is when a person with insurance increase their risk exposure to obtain a higher payoff from their insurance policy after buying insurance. Adverse selection describes a situation where the insured person possesses a larger amount of information and knowledge about the actual risk exposure than the insurance issuer. This implies that the insured party has a greater ability to evaluate the fairness of the terms and conditions. As the payout given by weather derivatives is determined by an unbiased weather report, weather derivatives can be seen as favorable since problems with both moral hazard and adverse selection is not present.

Weather derivatives may be beneficial for several reasons. Leggio (2007) mentions five reasons for hedging weather risk, including smoothing revenues, covering excess costs, reimbursing lost opportunity costs, stimulating sales and diversifying investment portfolios. According to Brockett et al. (2009), weather derivatives appear to have a low correlation with other financial instruments which make them fitting as diversification tools. High correlation between the different wind mill farms may indicate poor diversification within the company and may also point to the need for some sort of insurance against low wind speed and production.

In spite of weather derivatives being flexible with limitless applications (Leggio, 2007), the use of weather derivatives is not particularly common, especially outside the U.S. (Alaton, Djehiche & Stillberger, 2002). This may be due to the fact that these instruments are relatively new, and the knowledge and awareness of them is still limited (Leggio, 2007).

When pricing financial derivatives, the underlying is usually a tradable asset. (Brockett et al., 2006). The market for weather derivatives is an incomplete market, which means that the underlying in these contracts is weather, which is not a tradable asset. Thus, traditional pricing methods are not suitable when pricing weather derivatives (Hamisultane, 2008). Quotations of liquid contracts suffice as bases when obtaining “fair” prices for the weather derivatives. However, an obstacle is the lack of liquidity in most of the quoted prices. Thus, the foundation for valuating weather derivatives based on such prices is limited.

2.3 Wind Derivatives and Their Use in the Energy Sector

Like other types of renewable energy, such as hydro and solar power, the cost structure of wind power is characterized by high investment costs and low operating costs. When the construction of a wind mill farm is finished, the farm can produce at low costs since the wind is free. Nevertheless, wind power needs a relatively high price for delivered energy, which can be achieved through high power prices or subsidies.

Compared to most countries in Europe, Norway has a more complicated terrain and extreme climate. In addition, the distances between roads and power lines are longer and the Norwegian salary level is generally higher. This leads to a more expensive infrastructure in Norway compared to the rest of Europe (Norwea, 2012). The extreme weather also contributes to larger maintenance costs and more expensive construction. The benefit of producing in Norway is that the extreme weather gives higher production, and renting land is less costly due to large uncultivated areas.

The main drivers of operating costs in wind power production are related to operating and maintenance of the turbines (Norwea, 2012). These maintenance costs will usually increase as the turbines gets older. This evolution of operating costs shows that weather derivatives can be an attractive tool to smooth the results by hedging against low production. We know that the costs will increase, and it is important to secure future income independent of weather conditions.

The income of a wind mill farm comes from selling the electric power delivered by the turbines. In addition, as of 2012, Norwegian renewable energy producers are receiving an electricity certificate per MWh delivered (Norwea, 2012). Both the electricity price and the price of the certificates are determined in a market based on supply and demand. The hourly price is called the spot price, which is the price a producer receives for selling electricity or certificates. The spot price varies continuously, but with financial instruments the spot price can be fixed up to several years ahead (Norwea, 2012). By hedging the spot price, one will reduce the risk related to the price through predictable income.

However, income is a result of both production and price. Whereas 95 % of the power supply in Norway comes from hydropower, only 1 % comes from wind power (Huisman, Michels, Westgaard, 2014). Hydropower producers´ storability gives them the opportunity to decide when to produce hydropower. This is a decision between producing now, or later at a possibly higher spot price. Wind power producers do not have any storage possibilities. As wind power production contributes little to the total power supply, it is natural to assume that production of wind power affects the spot price to a very small extent. If this is the case, hedging volumetric risk in addition to price risk, may be a favorable solution for wind power producers.

Today, wind power producers in Norway are dependent on subsidies to be profitable. In the meantime, it is being systematically worked towards reaching the so-called “grid parity”. This is the point at which the wind power producers can deliver electricity at the market price without the need for subsidies. As of 01.01.2022, new Norwegian wind mill farms will no longer receive these electrical certificates (Vindportalen, 2019). Thus, wind derivatives can be effective tools to stabilize the transition to a situation without subsidies and also contribute to a more stable income.

3 Data and Statistical Analysis

In this section, the data material is presented, and several statistical analyses are conducted. TrønderEnergi has supplied wind speed data, as well as production data, from three of their wind mill farms, namely Valsneset, Bessakerfjellet and Ytre Vikna. TrønderEnergi is a large energy company, which does not only produce wind power, but also produces hydropower (TrønderEnergi, 2019). As of May 2019, they have 18 hydropower plants, and only 5 wind mill farms. Because of this, we have not been able to retrieve financial data concerning the individual wind mill farms. We have solved this by calculating operating income using historical production data and spot prices from Nordpool.

By using wind data from TrønderEnergi´s actual locations, we will get more exact estimates and eliminate basis risk completely. However, for a seller to be willing to enter into a weather contract, we need more reliable wind data from a trusted, independent third party (Berlage, 2013). Therefore, we have also retrieved wind speed data from three weather stations located nearby each wind mill farm from the Norwegian Metrological Institute.

3.1 Wind data

In the following, the daily average wind speed data is presented. This includes correlations between the wind mill farms, as well as correlations between the wind mill farms and their related weather stations. Descriptive statistics for the wind mill farms and the weather stations are also included.

We received hourly measurements of ten minutes from TrønderEnergi. This is the same type of wind data we retrieved from the Norwegian Metrological Institute. In accordance with Alexandridis (2013), we use daily average wind speed in our analysis. We have measurements of wind speed from 01.01.2009 to 31.12.2018 and production from 01.01.2009 to 31.12.2017. However, as historical spot prices from Nordpool only go back to 2013, our analysis covers the years 2013 to 2017. The descriptive statistics for each wind mill farm and weather station also describe this period.

In the data received from TrønderEnergi, there are several missing values and abnormalities. First of all, Bessakerfjellet has some cases of negative production. All of these cases occur on days with low wind speed and may be due to the turbines using power when starting up. Therefore, we did not remove any of these values from our dataset, as there is a reasonable explanation for them.

Secondly, Ytre Vikna has days with missing values for wind speed. This may be due to maintenance, measuring errors or loss of data. We have chosen to remove these values for both wind speed and production. Alexandridis (2013) suggests replacing missing values with the average of the seven days before and after the missing data. However, some of the cases in which values are missing are up to 59 days in a row. Therefore, we have chosen to leave them as missing values and remove production for the same day.

Lastly, we found some abnormal measurements for all of the wind mill farms. These were cases of very high production on days with low or zero wind speed. We have chosen to remove all of these cases with production above 20 MWh. Reasons for these abnormal measurements can be failures at weather stations or maintenance of measurement equipment. Keeping all of these data points could lead to erroneous correlations and models but removing all of them could lead to a narrow data basis. Therefore, we chose a production limit of 20 MWh in these cases.

Correlations between the different wind mill farms are presented in the table below.

Table 1: Correlation Between TrønderEnergi´s Wind Mill Farms

	Correlation
Valsneset – Bessakerfjellet	0.92
Valsneset – Ytre Vikna	0.81
Bessakerfjellet – Ytre Vikna	0.82

Table 1 shows very high positive correlation between all of the wind mill farms. This indicates poor diversification in TrønderEnergi´s wind production and that there may be a need to hedge the volumetric risk.

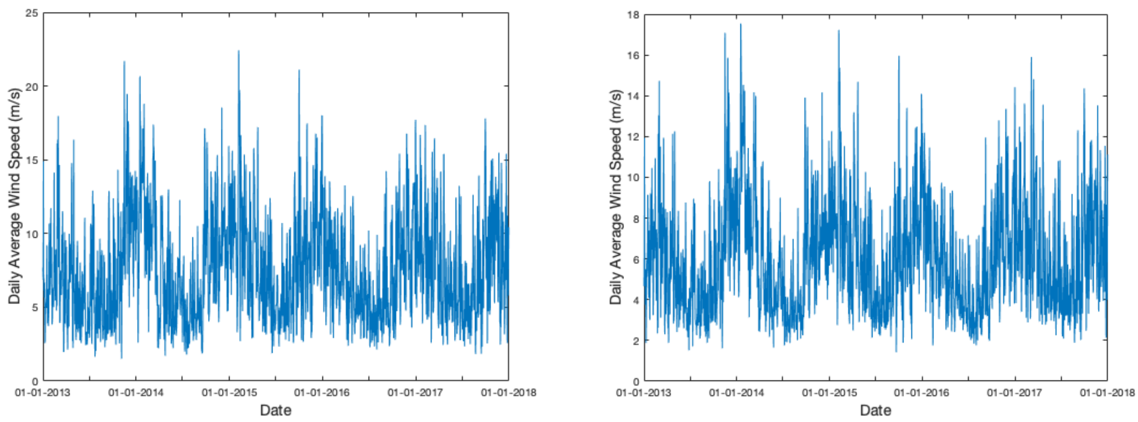
3.1.1 Valsneset

Valsneset wind mill farm is situated in Bjugn, Trøndelag and consists of five turbines. The farm has been operating since November 2006 and was officially opened 01.06.2007. The closest weather station is Ørland III, which is located approximately 12.6 km from Valsneset. The correlation between the wind speed measurements from these two locations is 0.95. The table below presents descriptive statistics for daily average wind speed (DAWS) for Valsneset and Ørland III from the period 2013 to 2017.

Table 2: Valsneset and Ørland III: Descriptive Statistics for DAWS 2013 – 2017

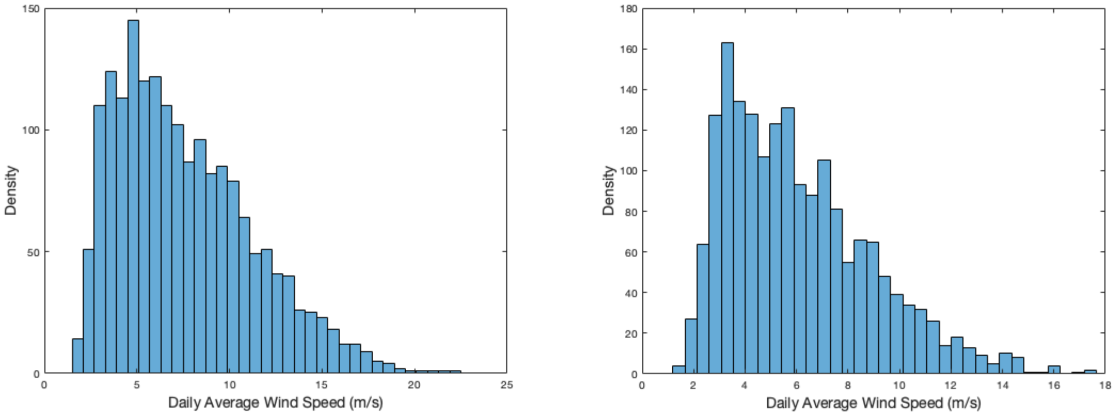
Variable	Mean	Std.dev	Min	Max	N
DAWS Valsneset	7.61	3.68	1.51	22.42	1 826
DAWS Ørland III	6.08	2.83	1.42	17.54	1 826

Figure 1: Daily Average Wind Speed for Valsneset (a) and Ørland III (b)



(a) (b)

Figure 2: Histograms of Daily Average Wind Speed for Valsneset (a) and Ørland III (b)



(a) (b)

Table 2 contains descriptive statistics for daily average wind speed at Valsneset and Ørland III. The mean represents the average of the daily measurements of wind speed. The diagrams in figure 1 presents the daily average wind speed of Valsneset and Ørland III for the years 2013 to 2017. Tendencies to seasonal fluctuations are observed in the line diagrams. From the histograms in figure 2, both kurtosis and skewness are observed as positive. It is also observed that the daily average wind speed is not normally or symmetrically distributed.

For both Valsneset and Ørland III, the wind speed measurements range from 1.51 to 22.42 m/s and from 1.42 to 17.54 m/s, respectively. Further, table 2 shows that Valsneset has got a higher mean, standard deviation and min-max values than Ørland III. In correspondence with the very high positive correlation, the differences between the two are very small.

3.1.2 Bessakerfjellet

Bessakerfjellet wind mill farm is located in Roan, Trøndelag and consists of 25 turbines, which makes it the third largest wind mill farm in Norway. The construction was completed in the autumn of 2008. The closest weather station is Buholmråsa fyr, which is located approximately 20.5 km from Bessakerfjellet. The correlation between the wind speed measurements from these locations is 0.89.

Table 3: Bessakerfjellet and Buholmråsa Fyr: Descriptive Statistics for DAWS 2013 – 2017

Variable	Mean	Std.dev	Min	Max	N
DAWS Bessakerfjellet	8.12	4.11	1.23	23.77	1 826
DAWS Buholmråsa fyr	7.44	3.53	1.47	21.44	1 826

Table 3 contains descriptive statistics for wind speed at Bessakerfjellet and Buholmråsa fyr. As we can see from table 3, the measurements range from 1.23 to 23.77 m/s with a mean of 8.12 m/s for Bessakerfjellet. The daily average wind speed measured at Buholmråsa fyr has a mean of 7.44 m/s and ranges from 1.47 to 21.44 m/s. It is observed that Bessakerfjellet has got higher mean, standard deviation and maximal value than Buholmråsa fyr. The minimum value is higher for Buholmråsa fyr than for Bessakerfjellet. However, the differences are not especially large. This is reflected in the high positive correlation between the two.

3.1.3 Ytre Vikna

The construction of Ytre Vikna wind mill farm was completed in October 2012. The wind mill farm is located in Vikna, Trøndelag and consists of 17 turbines (Multiconsult, 2019). We have measurements of wind speed from 01.10.2015 to 31.12.2018 from this wind mill farm. Hence, the descriptive statistics for this wind mill farm and related wind mill farm will be from the period 01.10.2015 to 31.12.2017. The closest weather station is Nordøyan fyr, which is located approximately 16 km from Ytre Vikna. The correlation between the wind speed measurements at these locations is 0.85.

Table 4: Ytre Vikna and Nordøyan Fyr: Descriptive Statistics for DAWS 2015 – 2017

Variable	Mean	Std.dev	Min	Max	N
DAWS Ytre Vikna	7.96	3.35	1.11	19.05	762
DAWS Nordøyan fyr	8.98	3.95	1.01	21.38	815

From table 4 we observe that Nordøyan fyr has a wider range in daily average wind speed, with a lower minimum value and a higher maximum value than Ytre Vikna. Nordøyan fyr also has a higher mean and standard deviation. The number of observations are uneven for the two locations, as there are several missing values for Ytre Vikna.

3.2 Financial data

In the following section, an explanation of the calculations concerning operating income is given, and descriptive statistics for operating income are presented. Our focus is to examine if and in what scale operating income is affected by the wind speed. Thus, we calculate the operating revenue, as well as depreciation and operating expenses. We assume that revenue is a result of the amount of electricity sold and the daily spot price. The revenue is estimated by multiplying daily production by daily spot price for each wind mill farm.

Daily electricity spot prices from 2013 to 2017 are retrieved from Nordpool. Prices from earlier years are not available, therefore, there are only five years of financial data for Valsneset and Bessakerfjellet. However, the wind speed measurements from Ytre Vikna begin on 01.10.2015, making this the wind mill farm with the least available data.

When calculating operating income, depreciation and operating expenses are deducted from operating revenues. Although depreciation is not dependent on production, we choose to include this cost item in the calculation of operating income. One can argue that depreciation is unnecessary to include when hedging volumetric risk, as it can be interpreted as a fixed cost. Excluding this cost in the calculations of operating income could be an interesting approach to hedging with weather derivatives. However, depreciation is a part of the definition of operating income, and we choose to include it.

According to Norwea (2012), the wind turbine constitutes approximately 70 – 75 % of the total investment costs. In our analysis, we choose to set the investment costs of the turbines to 70 %. Total investment costs for Valsneset and Bessakerfjellet are retrieved from TrønderEnergi´s websites, and were 110 million NOK and 500 million NOK, respectively. Sufficient information concerning investments costs for Ytre Vikna is not available. Thus, investment costs per wind mill at both Valsneset and Bessakerfjellet are calculated, and the average between the two is multiplied by the number of wind mills at Ytre Vikna. This results in total investment costs of 375 million NOK for Ytre Vikna.

It is common to estimate a wind mill farm´s life to 20 – 25 years (Norwea, 2012). Yearly depreciation is calculated linearly with an expected lifetime of 25 years. Although degressive depreciation might have been preferable, sufficient information for the necessary calculations is not available. Daily linear depreciation for Valsneset, Bessakerfjellet and Ytre Vikna is estimated to 8 439, 38 357 and 27 386 NOK, respectively.

Norwea (2012) states that operating expenses usually lie between 120 and 180 NOK per MWh. We choose to set this rate to 135 NOK per MWh. This rate is set equal for all three wind mill farms and is multiplied by daily production to calculate daily operating expenses. We choose this rate to be below the average, due to the linear depreciation calculation. The daily depreciations are relatively high, and we choose a somewhat low rate for operating expenses to compensate for this.

Table 5: Descriptive Statistics for Daily Operating Income

Variable	Mean	Std.dev	Min	Max	N
OI Valsneset	1 956.77	11 219.35	– 16 563.28	46 835.40	1 826
OI Bessakerfjellet	15 506.97	57 103.83	– 90 792.78	303 013.80	1 826
OI Ytre Vikna	7 963.98	38 181.05	–63 646.32	197 231.50	762

Table 5 contains descriptive data for daily operating income for each of the wind mill farms. As we can see there is a large span from the minimum value to the maximum value for all of them. Further, there are great differences between the means of the individual wind mill farms. Bessakerfjellet, which is the largest wind mill farm of the three, naturally has the highest mean for operating income, and also the highest standard deviation. Meanwhile, Valsneset has the fewest wind mills, and consequently it has the lowest mean, and also the lowest standard deviation.

3.3 Statistical Analysis of Price and Production

In what follows, we will shortly discuss the interrelation between the production and the energy prices. As mentioned above, wind power producers´ contribution to the total power supply is limited compared to hydropower producers. Therefore, we examine the correlations between production at each wind mill farm and the spot price. The table below presents correlations between daily spot price and daily production at each wind mill farm, as well as between the daily spot price and the total daily production.

Table 6: Correlation Between Daily Spot Price and Daily Production

	Correlation
Valsneset	0.07
Bessakerfjellet	0.08
Ytre Vikna	0.08
Total	0.04

From table 6, we observe a very low correlation between daily spot price and daily production at each wind mill farm and also the total production from all three. This indicates that supply of wind power has little effect on the spot price. This is in accordance with our expectations and implies that hedging volumetric risk may be beneficial.

3.4 Statistical Analysis of Operating Income and Wind Speed

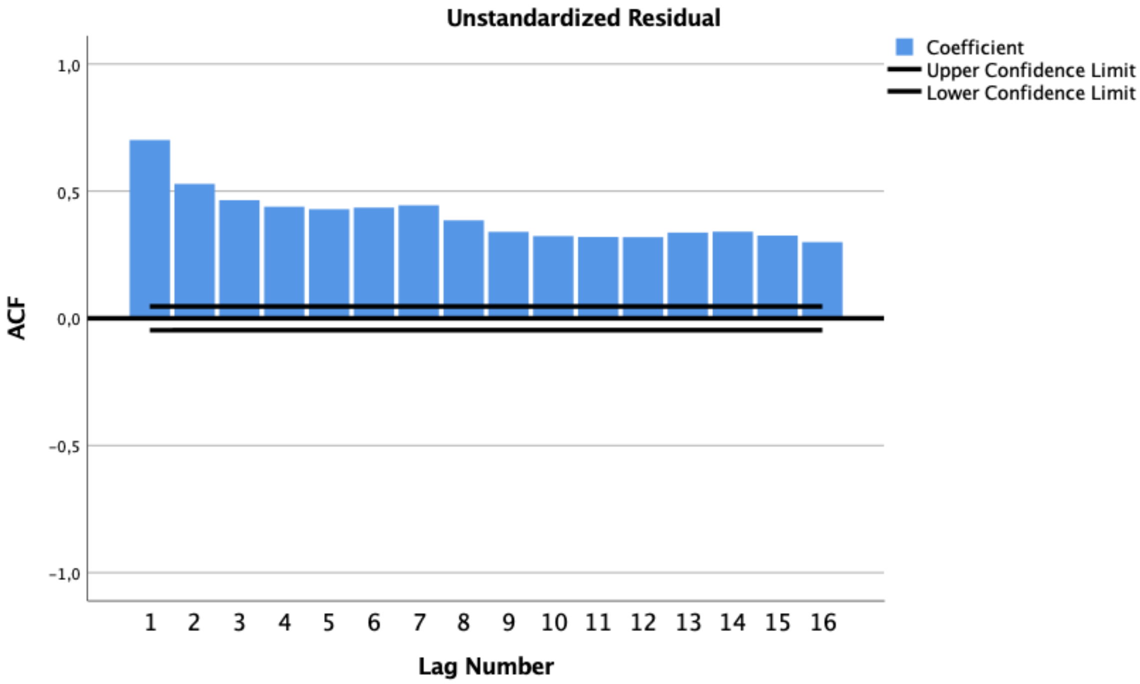
In the following segment, statistical analyses of the relationship between operating income and wind speed are conducted. In our analysis, four different models have been proposed to explain the relationship between operating income and daily average wind speed. Because the analysis is focused on several different wind mill farms and weather stations, our discussion concerning the choice of model will deal with Valsneset. AR(1) models for the rest of the locations can be found in appendix A.1.

Firstly, by using the ordinary least squares (OLS) method, a linear regression model is proposed:

$$OI = -16\,271.10 + 2\,395.67 * DAWS$$

where OI is the dependent variable and represents daily operating income, and DAWS is the independent variable and represents daily average wind speed. This model has an R^2 of 0.62. The linear model shows that a change of one m/s in wind speed will increase operating income with 2 396 NOK.

Figure 3: Valsneset: Correlogram for Unstandardized Residuals for Model 1



From the correlogram in figure 3, significant autocorrelation is observed. This problem does not disappear when lagging the dependent variable. As no autocorrelation is a Gauss-Markov assumption for time series regression (Wooldridge, 2016), this model does not provide BLUE estimates. This is also the case for the two other wind mill farms and all of the weather stations. Thus, this model is in violation of the assumptions of OLS. Further, we therefore apply AR(1) models in our analysis.

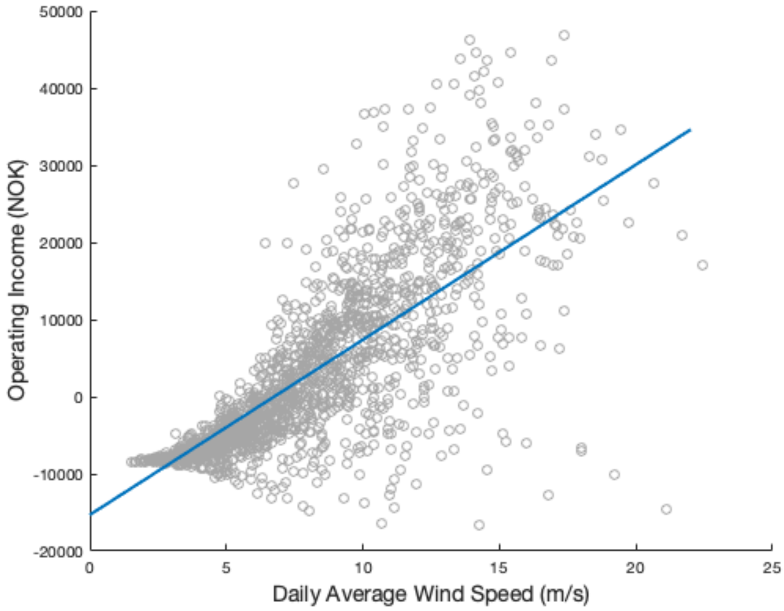
By using AR(1), a new linear model is proposed:

$$OI = -15\,307.52 + 2\,269.32 * DAWS \tag{1}$$

This model has an R^2 of 0.81, implying that it has a very high degree of explanation. This means that 81 % of the variance in daily operating income can be explained by daily average wind speed. The linear model shows that a change in wind speed of one m/s will increase operating income with 2 269 NOK. Further, we observe that Valsneset and Bessakerfjellet have higher values of R^2 than their corresponding independent weather stations, Ørland III and Buholmråsa fyr, respectively. However, Ytre Vikna has a lower R^2 than Nordøyan fyr. This model has a Root Mean Square Error (RMSE) of 4 931.65 and a Bayesian information criterion (BIC) of

17.02. These values should be as low as possible. The linear model, as well as the scatter plot of data points, are illustrated by figure 4.

Figure 4: Valsneset: Linear Model



From figure 4, we observe that the data points are clustered around the linear line to some degree. However, a certain amount of observations are not located in accordance with the linear line. This indicates that another model may provide a better explanation of the relationship between operating income and wind speed.

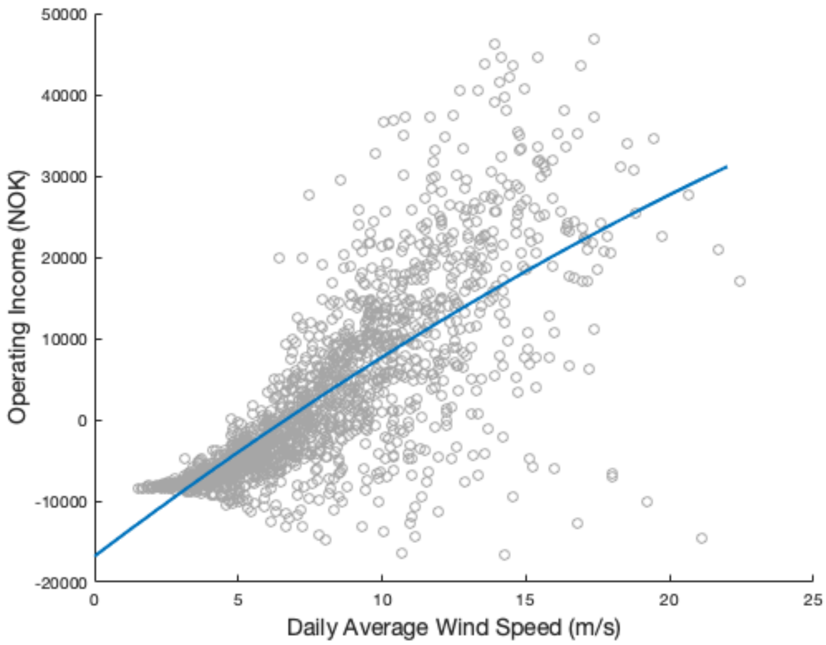
To examine if another model fits our data better, we suggest a quadratic model. Wind mills will cease to produce power when the wind speed exceeds a certain level. As operating income is affected by production volume and the spot price, it is natural to assume a decreasing effect of wind speed on operating income. The quadratic model can be written as:

$$OI = -16\,805.06 + 2\,678.19 * DAWS - 22.65 * DAWS^2$$

This model yields an R^2 of 0.81, which is the same as for the linear model. Also for this model, Valsneset and Bessakerfjellet have a higher R^2 than their related weather stations, and Ytre Vikna has a lower R^2 than Nordøyan fyr. This model has lower values for both RMSE and BIC than the linear model, which also is the case for Buholmråsa, Valsneset and Ørland III. For Ytre

Vikna and Nordøyan fyr, these values are higher for the quadratic model. This model is illustrated in figure 5, along with the scatter plot.

Figure 5: Valsneset: Quadratic Model



From figure 5, we observe a slightly decreasing effect of daily average wind speed on daily operating income. According to a report from Norwea (2012), production will stagnate when wind speed reaches 11 – 13 m/s and be constant until approximately 25 m/s. Therefore, we expect the curve to flatten a bit around 11 – 13 m/s. As the figure shows, the curve does not flatten to a noteworthy degree, due to the properties of the model.

From the scatter plot, it seems that a different model than the first two, may be more suitable for the data. Therefore, our last proposed model is a third-degree polynomial model that can be written as follows:

$$OI = -\,6\,156.84 - 1\,749.29 * DAWS + 489.84 * DAWS^2 - 17.13 * DAWS^3$$

This model has an R^2 of 0.83, which is slightly higher than for the two previous AR(1) models. However, the difference is very small, and all three models have very high degrees of explanation. This model also has the same pattern for R^2 for the wind mill farms and the weather stations. From graph 6 we observe that the regression line has a kind of S-shape.

Figure 6: Valsneset: Polynomial Model

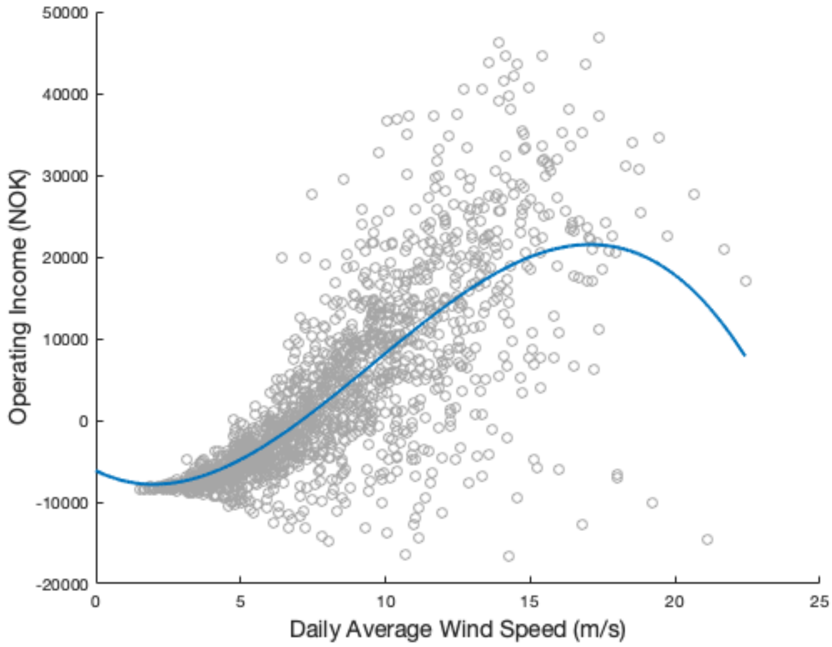


Figure 6 illustrates the polynomial model and the scatter plot. We observe that the pattern of this curve has a better fit to our expectations and the scatter plot. Compared to the other models, this model provides a more realistic picture of the relationship between operating income and wind speed. The polynomial model has a somewhat higher R^2 than the other models. It also has the lowest values of RMSE and BIC among the three models. This is also the case for the other two wind mill farms and all of the weather stations. Hence, this model has the best fit to our data.

Table 7: Model Summary Valsneset

Models	R^2	RMSE	BIC
OI = – 15 307.52 + 2 269.32 * DAWS	0.81	4 931.65	17.02
OI = – 16 805.06 + 2 678.19 * DAWS – 22.65 * DAWS^2	0.81	4 918.27	17.02
OI = – 6 156.84 – 1 749.29 * DAWS + 489.84 * DAWS^2 – 17.13*WS^3	0.83	4 602.51	16.89

Table 7 summarizes the different AR(1) models for Valsneset. Even though the polynomial model has the best fit to our data, it is important not to just choose the best fitting model, but a model that is applicable in pricing. Alexandridis (2013) argues that a common wind derivative has a constant tick size, and that wind options have linear payouts. Therefore, we use the linear model for each location when choosing tick sizes.

4 Pricing Methods

In the following section, different pricing methods are presented. Advantages and disadvantages of the methods are discussed, and two of the methods are derived thoroughly. We consider five different pricing methods that have previously been used on different kinds of weather derivatives, which may be fitting when pricing wind derivatives.

When pricing financial derivatives, one usually applies pricing methods that are based on the assumption of no arbitrage (Brockett et al., 2006). A very common pricing method is the Black-Scholes model which assumes that the payout of the option is dependent on an asset with a market price (McIntyre, 1999). McIntyre (1999) claims that a simple model based on Black-Scholes can be suitable and give exact answers to pricing degree-day options. However, this method relies on restricting and unrealistic assumptions. Therefore, this kind of method may not be suitable for pricing weather derivatives because the market for weather derivatives is an incomplete market. That is, the underlying in these contracts is weather, which is not a tradable asset. (Brockett et al., 2006). However, McIntyre (1999) and Leggio (2007) argues that it may be suitable when pricing options on heating degree days and precipitation, respectively.

When choosing pricing methods, we will consider methods that have been proposed in earlier literature. Since there does not exist a lot of research on wind derivatives, we have also considered methods applied on other underlying variables, such as degree-days. This is the most common underlying variable (Alaton, Djehiche & Stillberger, 2002), and consequently there are more literature available for temperature derivatives.

4.1 The Actuarial Pricing Method

The actuarial pricing method uses past weather data to estimate the probability of future outcomes (Putnam, 2000). The objective is to simulate weather outcomes by using historical weather data. The method assumes that through independently repeating an experience many times, we obtain a more valid estimate of the expectation of the phenomenon that have been observed (Hamisultane, 2008). This is called the law of large numbers.

The actuarial method is widely used in different industries, such as health and life insurance and property (Cao, Li & Wei, 2003), and is also a common method used in practice when pricing weather derivatives (Brockett et al., 2006). However, due to the actuarial method being developed in a framework that does not account for financial markets, it is not very appropriate when pricing weather derivatives. According to Cao, Li & Wei (2003), this method is only favorable in cases with extreme weather conditions, since they do not occur in a certain pattern. Since we have observed seasonality in our data, this model is not suitable for our analysis.

4.2 The Historical Burn Analysis

Alexandridis (2013) argues that the historical burn analysis serves as a benchmark when pricing weather derivatives. The historical burn analysis is a method which assumes that on average the past reflects the future (Cao, Li & Wei, 2003). Following this method, you will see how the contract would have performed in the past and use the average of the realized payoffs as an estimate for the contract value. Historical burn analysis may be the easiest method to implement. According to Cao, Li & Wei (2003), this makes the method likely to cause large estimate errors.

The assumption that the past distribution reflects the future distribution is not very realistic. Benth & Benth (2012) refer to issues concerning the use of historical burn analysis on derivatives with aggregated values as the underlying. This leads to a significant reduction in data points, which can give very few non-zero payoff data. This may result in an inaccurate and uncertain price estimate. However, our time series contain a sufficient amount of non-zero payoff data and we choose to apply this method in our analysis.

When estimating a price by using the historical burn analysis, one calculates the average of the historical payoffs (Cao, Li & Wei, 2003). This average is considered the fair value of the weather derivative and serves as a benchmark price.

4.3 The Monte Carlo Approach

The concept behind the Monte Carlo approach is to create many simulations of the weather outcome and to calculate the payoff for each simulation (Putnam, 2000). These simulations generate random numbers (Nelken, 2000). The advantage of this method is that there is no limit to the number of simulations, which is the case of the actuarial pricing method. However, this procedure is complicated, and it is necessary for the user to fully understand the simulations. Lack of understanding may lead to pricing errors (Putnam, 2000).

Nelken (2000) argues that this method can be applied when pricing weather derivatives. Hamisultane (2008), however, states that this method may lead to unreliable prices due to illiquidity in already quoted prices. Our dataset is quite large, and numerous simulations would be complicated and time consuming. Therefore, we will not use this method in our pricing of weather derivatives.

4.4 The McIntyre Pricing Method

Although there have been several arguments against using Black-Scholes when pricing weather derivatives, McIntyre (1999) claims that his interpretation of Black-Scholes is sufficient for valuing these derivatives. The model assumes a normal distribution and is relatively simple to compute when compared to numerical methods, such as the Monte Carlo approach. Even though our dataset does not fit the assumption of normal distribution, we choose to calculate prices for the weather derivatives by using this model. The motive behind this is that the model is quite simple to compute and provides comparable prices. The model presented by McIntyre provides the price of a weather derivative W, and is given by:

$$W = \varphi(m-k) \cdot N\left(\frac{\varphi(m-k)}{\sigma}\right) + \sigma^2 \cdot P(k) \qquad (2)$$

where $\varphi = \pm 1$ for a call and a put, respectively. m is the mean of the weather phenomenon (Leggio, 2007), while k is the strike level and σ^2 represents the volatility. $N(\cdot)$ is the cumulative standard normal distribution, while P is the probability density function for a standard normal random variable.

We can write $P(k)$ as follows:

$$P(k) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(k-m)^2}{2\sigma^2}} \tag{3}$$

The volatility in equation (3) stems from historical data, whereas the expected volatility of the price-maker is termed implied. This means that the implied volatility is subjective and dependent on the price-maker´s expectations concerning future trends and forecasts, as well as his or her position. Higher volatility implies greater risk and thus, a higher derivative price. Together with the implied mean, implied volatility represents the risk, and ergo the purchase price of the derivative.

4.5 The Indifference Pricing Method

Brockett et al. (2006) and Xu, Odening, & Mußhoff (2007) have presented the indifference pricing method, and our derivation of the indifference pricing formula is based on these two articles. The indifference pricing method is based on the principle of equivalent utility (Brockett et al., 2006). This approach deals with risk preferences and gives the indifference prices based on the expected utility arguments. When using this method, the investor´s objective is to maximize expected utility of his or her wealth.

To maximize an investor´s wealth, we need to model the investor´s risk preferences (Xu, Odening, & Mußhoff, 2007). This is usually expressed with an exponential utility function which is used to derive the indifference pricing formula. The utility function is expressed as:

$$U(X) = 1 - e^{-\gamma \cdot X} \tag{4}$$

where γ is the absolute risk aversion parameter, which is greater than zero. X represents the investor´s wealth. We assume an economic actor to have a positive utility of wealth. Therefore,

we insert the number 1 in front of the negative exponential function presented by Xu, Odening, & Mußhoff (2007).
In the following we assume two market participants, a seller and a buyer, and a two-date economy. In order to maximize their wealth at time T, both market participants optimize their investments at time t = 0. A two-date economy implies that no adjustment or trading is allowed between these two points. We will examine the decision-making process of both the seller and the buyer.

The seller´s initial wealth is denoted by x_s, at time t = 0. He has to consider the amount, α_s, of capital to invest in a risky portfolio, in addition to selling k_s shares of a weather derivative at the price $F_s(I)$. The return of the capital market investment is denoted by r_s. The remaining wealth is invested in a risk-free asset, with return r_f. If selling shares of weather contracts is not an option, the wealth of the seller will be:

$$X_s^{wo} = (x_s - \alpha_s) \cdot \left(1 + r_f\right) + \alpha_s \cdot (1 + r_s) \tag{5}$$

If selling the weather derivative is possible, the wealth of the seller is:

$$X_s^{w} = (x_s - \alpha_s + k_s \cdot F_s) \cdot \left(1 + r_f\right) + \alpha_s \cdot (1 + r_s) - k_s \cdot W_T \tag{6}$$

where W_T is the payoff related to the predetermined weather index. For simplicity, we hereby refer to (1 + r_f) and (1 + r_s,) as q_f and q_s, respectively. The payoff of the weather derivative depends on the tick size L, and is calculated as follows:

$$W_T = max(0, K - I_T) \cdot L \tag{7}$$

where K and I_T represent the strike level and the weather index at time t = T, respectively. Equation (7) represents a put option, where the buyer receives a payout if the weather index is below the strike level.

The decision-making process of the buyer is similar to the one of the seller. The difference is that the buyer spends an amount of capital, α_b, on a risky production activity. This activity is to some degree dependent on weather conditions. In addition, the buyer has the opportunity to purchase k_b units of a weather derivative. As for the seller, the remaining wealth of the buyer, is invested in a risk-free asset. The return on production is denoted by r_b. The initial wealth of the buyer is denoted x_b, and also here, $(1 + r_b)$ we refer to as q_b. The terminal wealth of the buyer without investing in the weather derivative is:

$$X_b^{wo} = (x_b - \alpha_b) \cdot q_f + \alpha_b \cdot q_b \tag{8}$$

Including the opportunity to purchase the weather derivative, the wealth of the buyer is:

$$X_b^w = (x_b - \alpha_b - k_b \cdot F_b) \cdot q_f + \alpha_b \cdot q_b + k_b \cdot W_T \tag{9}$$

Further, we derive the indifference price of the seller and the buyer in accordance with this framework. The seller´s optimal amount invested in the risky asset, α_s, is found in the intersection where the seller is indifferent between including the weather derivative in his portfolio or not. This is given by:

$$sup_{\alpha_s} E[U(X_s^w)] = sup_{\alpha_s} E[U(X_s^{wo})] \tag{10}$$

The next step in the process of Xu, Odening, & Mußhoff, (2007) is to approximate the certainty equivalent (CE) of the indifference price by using Pratt´s Theorem. Further, they replace the expected utility in equation (4) with the CE in order to get a closed form solution of the indifferent price. The CE can be written as follows:

$$CE = E(X) - \frac{\gamma}{2} \cdot \sigma^2(X) \tag{11}$$

where $E(X)$ represents the expected value of terminal wealth and $\sigma^2(X)$ represents the variance of terminal wealth. Replacing the expected utility with the CE gives a new expression of the indifference price:

$$sup_{\alpha_s} E\left[U(X_s^w) - \frac{\gamma_s}{2} \cdot \sigma^2(X_s^w)\right] = sup_{\alpha_s} E\left[U(X_s^{wo}) - \frac{\gamma_s}{2} \cdot \sigma^2(X_s^{wo})\right] \tag{12}$$

Inserting the equations for wealth of the seller without and with the weather derivative, produces explicit expressions for the CE of the wealth at time t = T for both cases:

$$CE^{wo} = \left(x_s \cdot q_f + \alpha_s \cdot \left(E(q_s) - q_f\right) - \frac{\gamma_s}{2} \cdot \alpha_s^2 \cdot \sigma_{q_s}^2\right) \tag{13}$$

$$\begin{aligned} CE^w = \Bigg(& x_s \cdot q_f + k_s \cdot F_s \cdot q_f + \alpha_s \cdot \left(E(q_s) - q_f\right) - k_s \cdot E(W) - \frac{\gamma_s}{2} \cdot \alpha_s^2 \cdot \sigma_{q_s}^2 \\ & - \frac{\gamma_s}{2} \cdot k_s^2 \cdot \sigma_W^2 + \gamma_s \cdot \alpha_s \cdot k_s \cdot COV(q_s, W)\Bigg) \end{aligned} \tag{14}$$

Here, $E(W)$ represents expected payoff of the weather derivative, while $E(q_s)$ represents expected q_s. The corresponding variances are given by $\sigma_{q_s}^2$ and σ_W^2 and $COV(q_s, W)$ denotes the covariance between q_s and W. The optimal amount of capital to invest in a risky portfolio is found via the first order conditions, and give the following solutions:

$$\alpha_s^{*wo} = \frac{E(q_s) - q_f}{\gamma_s \cdot \sigma_{q_s}^2} \tag{15}$$

$$\alpha_s^{*w} = \frac{E(q_s) - q_f + \gamma_s \cdot k_s \cdot COV(q_s, W)}{\gamma_s \cdot \sigma_{q_s}^2} \tag{16}$$

Furthermore, we insert these optimal amounts of capital shares into (13) and (14). By putting the equations equal and solving F_s, we obtain an expression for the price of the weather derivative of the seller:

$$F_s = \frac{1}{q_f} \cdot (E(W) + \pi_s) \tag{17}$$

where:

$$\pi_s = -\frac{\gamma_s}{2} \cdot k_s \cdot \sigma_W^2 \cdot \left(\rho_{q_s,W}^2 - 1\right) - \frac{\sigma_W}{\sigma_{q_s}} \cdot \left(E(q_s) - q_f\right) \cdot \rho_{q_s,W} \tag{18}$$

Here, $\rho_{q_s,W}$ represents the correlation between the return of the capital market investment and the payoff of the weather derivative. π_s represents a risk premium which can be either positive or negative. The price is a result of the expected payoff of the weather derivative, in addition to this risk premium, discounted by the risk-free rate.

By following a pattern similar to the one of the seller, we can calculate the optimal amount of capital to spend on risky production activity without using the option, α_b^{*wo}, and with using the option, α_b^{*w}, for the buyer. The optimal amounts of capital for the buyer are calculated as follows:

$$\alpha_b^{*wo} = \frac{E(q_b) - q_f}{\gamma_b \cdot \sigma_{q_b}^2} \tag{19}$$

$$\alpha_b^{*w} = \frac{E(q_b) - q_f - \gamma_b \cdot k_b \cdot COV(q_b, W)}{\gamma_b \cdot \sigma_{q_b}^2} \tag{20}$$

Here, $E(q_b)$ represents the expected value of q_b while $\sigma_{q_b}^2$ represents the variance of the return on production. $COV(q_b, W)$ represents the covariance between q_b and W. As for the seller, we use these optimal amounts of capital shares to find the price of the weather derivative for the buyer:

$$F_b = \frac{1}{q_f} \cdot (E(W) + \pi_b) \tag{21}$$

where:

$$\pi_b = -\frac{\gamma_b}{2} \cdot k_b \cdot \sigma_W^2 \cdot \left(\rho_{q_b,W}^2 - 1\right) - \frac{\sigma_W}{\sigma_{q_b}} \cdot \left(E(q_b) - q_f\right) \cdot \rho_{q_b,W} \tag{22}$$

The structure of the indifference price for the buyer is similar to the one for the seller. Here, $\rho_{q_b,W}$ represents the correlation between the return of the risky production and the payoff of the weather derivative. The risk premium for the buyer, π_b, can also be either positive or negative.

In this framework, a trade of a weather derivative between buyer and seller will only take place if the buyer is willing to pay a greater price than the seller is willing to sell for. This condition is expressed as follows:

$$-\frac{\left(E(q_b) - q_f\right) \cdot \rho_{q_b,W}}{\sigma_{q_b}} > -\frac{\left(E(q_s) - q_f\right) \cdot \rho_{q_s,W}}{\sigma_{q_s}} \tag{23}$$

Xu, Odening, & Mußhoff (2007) argues that indifference pricing unites the financial and the actuarial approaches used for pricing non-tradable assets, such as weather. This method can be categorized within the framework of financial pricing of derivatives. Thus, it has a significant theoretical foundation. However, because of the assumptions that have been made, the method is quite simple with an actuarial interpretation.

There are several advantages concerning this valuation method. One of them is the fact that it evades the challenge of determining the market price of risk. This implies the cost of specifying a utility function. However, this is a necessary cost when no-arbitrage arguments are insufficient in the process of determining a price. Further, it considers individual risk and estimates its impact on the buyer´s willingness to pay for the weather derivative.

5 Empirical Analysis

In the following section, we will apply the indifference pricing method and the McIntyre method to find prices for our constructed wind speed put options. Weather derivatives with wind as the underlying are not very widespread (Brockett, Wang & Yang, 2005). To our knowledge, the application of wind derivatives has not been used in the energy sector earlier. Hence, we choose to apply pricing methods that mostly have been used when pricing temperature derivatives.

We construct both a yearly wind speed put option and a quarterly wind speed put option for each wind mill farm and weather station. All the constructed put options have strike levels of 3.5 m/s. We choose this strike level since power production starts when the wind speed exceeds 3 – 4 m/s. This strike level implies that the options give the buyer a payout each day the average wind speed is below 3.5 m/s. The payout is dependent on both the tick size and the difference between actual daily average wind speed and the strike level. The yearly options span over a year, while the quarterly options span over a quarter.

First, we use historical burn analysis to find prices for the different put options. Then, we find the related prices by using the McIntyre method. Furthermore, the indifference pricing approach is used to find both TrønderEnergi´s and the seller´s willingness to buy and sell the weather derivatives. Both the McIntyre method and the indifference pricing method have their basis in financial frameworks. The indifference pricing method is based on utility maximization (Alexandridis, 2013), whereas the McIntyre pricing method is based on the Black-Scholes model (McIntyre, 1999). Finally, we use the prices we have found to examine if TrønderEnergi can smooth operating income and gain extra profit by purchasing wind speed put options.

As mentioned, we have retrieved data from both TrønderEnergi´s own wind mill farms, in addition to independent weather stations located nearby. We use these related locations to examine if basis risk affects the profitability of the weather derivatives. This also provides insight concerning the decision making of actors considering buying weather derivatives. This can demonstrate in which degree the distance between the area the contract is written on and the location the buyer wishes to cover affects both price and profitability.

According to Alexandridis (2013), a common wind derivative has a constant tick size and strike level. This is a linear approach which implies that TrønderEnergi will receive a fixed amount of money per m/s the measured wind speed is below the predetermined strike level. In the same matter as Leggio (2007), we choose the tick sizes according to our linear AR(1) models. For the wind mill farm Valsneset, the AR(1) model shows that for each additional m/s the operating income increases by 2 269 NOK. Therefore, we choose this amount as the tick size. However, this tick size is only relevant for Valsneset. Each of the wind mill farms and weather stations have individual tick sizes that stem from their own linear AR(1) models.

A wind turbine usually starts operating at 2 - 3 m/s, while production of electrical power is not activated until the wind speed reaches 3 - 4 m/s (Norwea, 2012). When the wind speed exceeds 25 m/s, the turbine shuts down. Information from TrønderEnergi tells us that their turbines do not stop at 25 m/s, but gradually slows down until the wind speed reaches 34 m/s and the turbine and production is fully shut down. A wind speed of 25 m/s indicates full storm, and production is gradually or fully shut down to prevent damages. However, there are no cases of wind speed above 25 m/s for any of the wind mill farms or weather stations. Thus, we will not focus on hedging for extreme wind speeds, but rather on the downside risk.

The payoff received from the put option at the expiration day T is dependent on the strike level K, the tick size L and the daily average wind speed index I_T.

$$W_T = max(0, K - I_T) \cdot L$$

In the following sub sections, we find prices for our constructed wind speed put options by applying the historical burn analysis, the McIntyre method and the indifference pricing method.

5.1 Historical Burn Analysis

First, we use the Historical Burn Analysis to calculate yearly and quarterly prices for each wind mill farm and weather station. We choose to start with this method, as it provides a good indication for what the correct prices should be. These prices function as a benchmark which we can use for comparison when using other methods. Although this is a simple method with possible errors, we still choose to calculate prices for the weather derivatives with this method. Characteristics for both yearly and quarterly put options are presented in the tables below.

Table 8: Historical Burn Analysis: Yearly Put Option Characteristics for Valsneset

Parameters	
Tick size L	2 269.32 NOK
Strike level K	3.5 m/s
Time to maturity T	1
Expected payoff E(W)	59 838.55 NOK
Standard deviation σ_w	21 913.55 NOK
Contract size k	1

Table 9: Historical Burn Analysis: Quarterly Put Option Characteristics for Valsneset

Parameters	
Tick size L	2 269.32 NOK
Strike level K	3.5 m/s
Time to maturity T	1
Expected payoff E(W)	15 114.66 NOK
Standard deviation σ_w	14 368.03 NOK
Contract size k	1

The payout is based on a strike level of 3.5 m/s, which is the level used when calculating both yearly and quarterly payouts from historical data. These payouts are applied when finding the prices for the weather derivatives. Further, the averages of both yearly and quarterly payouts are calculated for each wind mill farm and weather station. These averages function as prices and are presented in the table below.

Table 10: Historical Burn Analysis: Yearly and Quarterly Option Prices

Location	Yearly Prices	Quarterly Prices
Valsneset	59 838.55 NOK	15 114.66 NOK
Ørland III	127 257.66 NOK	31 899.01 NOK
Bessakerfjellet	242 445.25 NOK	62 793.55 NOK
Buholmråsa fyr	226 310.82 NOK	59 758.05 NOK
Ytre Vikna	77 972.19 NOK	21 434.05 NOK
Nordøyan fyr	132 725.70 NOK	44 241.90 NOK

In table 10 the yearly and quarterly prices calculated with the historical burn analysis are presented. These prices represent the yearly and quarterly expected payouts for each location and suffice as bases for comparison with other methods.

5.2 McIntyre Pricing Method

As for indifference pricing, we set the strike level equal to 3.5 m/s. This is beneficial when comparing different prices. In accordance with Leggio (2007), we set implied volatility equal to historical standard deviation for daily average wind speed.

Table 11: McIntyre Pricing Method: Yearly Put Option Characteristics for Valsneset

Parameters	
Mean m	7.61
Strike level K	3.5
Time to maturity T	1
Probability density function P(k)	0.06
Standard deviation σ_w	3.68
Type of option parameter φ	– 1

With the parameters in table 12 the price of the weather derivative for Valsneset is calculated to 0.24 NOK. The results are similar for the rest of the wind mill farms and the weather stations, ranging from – 0.03 to 0.27 NOK. All results are included in appendix A.3. These prices seem unrealistic, as they are very low relative to expected payoff of the contracts. In addition, these prices are not in accordance with the benchmark calculated with the historical burn analysis.

The two articles on which we have based our McIntyre pricing method, McIntyre (1999) and Leggio (2007), both state that the McIntyre pricing method is a satisfying method when pricing weather derivatives. However, the underlying variables used in their research, are heating degree days and precipitation. Based on our results, this method seems inappropriate when pricing weather option with wind speed as the underlying. Thus, we do not analyze these prices any further.

5.3 Indifference pricing method

Throughout this section, we apply the indifference pricing method to find the prices for the different wind mill farms and weather stations. As in the rest of the thesis, we present the calculations and results for Valsneset, while results for the other wind mill farms and weather stations are presented in appendix A.2.

By using the following exponential function, the utility of operating income of Valsneset is maximized:

$$U(X) = 1 - e^{-\gamma \cdot X}$$

From historical data, the expected payoff $E(W)$ and its standard deviation σ_W are found. They are calculated to 202 354 and 56 682 NOK, respectively.

Further, the risk aversion parameter γ must be defined. The relative risk aversion (RRA) represents the amount of risk a decision maker is willing to take on relative to his wealth, whereas the absolute risk aversion (ARA) measures risk aversion for a given level of wealth (Copeland, Weston & Shastri, 2014). Gandelman & Murillio (2014) estimates that RRA on country level varies between zero and three. In this article, a figure displays Norway´s RRA to be between –0.1 and 2.5. When determining the buyer´s RRA we choose the average of 1.2.

Operating income X is calculated to 714 611.08 NOK, which is the historical average of the period 2013 to 2017. The buyer´s ARA can be found by:

$$ARA(X) = \frac{RRA(X)}{X} = \frac{1.2}{714\,611.08} = 1.679 \cdot 10^{-6}$$

According to Monoyios (2014), market participants typically have a risk aversion of 10^{-6}. Thus, we choose to set the seller´s ARA to this level. Jaggia & Thosar (2000) argues that when the risk horizon is longer, individuals tend to be more risk tolerant. However, the utility function used in this method does not take time into consideration. The objective of this thesis is not to focus on the time aspect of utility functions. Therefore, we choose a constant ARA measure when calculating both yearly and quarterly put option prices.

When estimating the return on the capital market investment, Oslo Stock Exchange Benchmark from Share Indices Oslo Stock Exchange approximates as market portfolio. Yearly data from 2013 to 2017 is obtained, and risky market return r_s is calculated to 13 %. The corresponding standard deviation σ_{r_s} is 0.08. The correlation between the market return and the payoff of the weather derivative is 0.31. This is, to some degree, in accordance with Brockett et al. (2009), who states that there is a low correlation between the payoff of weather derivatives and market return.

Furthermore, the risk-free rate is based on a five-year Norwegian government bond quoted at 1.44 % in 2018 (Norges Bank, 2019). We have adjusted this rate to 1.5 %, due to particularly low interest rates during the last couple of years. Additionally, Norges Bank increased the key rate from 0.75 % to 1.00 % on the 21st of March 2019, and further increases are expected (Winther & Christensen, 2019). Since our focus is on short term risk, the risk-free rate is set to 1.5 %. When calculating the quarterly option prices, the risk-free rate is divided by four.

When estimating the return on the production activity of the buyer, the return on net operating assets (RNOA) is used as measurement for TrønderEnergi´s production return. Power production is the main activity driving the wind mill farms´ revenues and RNOA reflects the return on TrønderEnergi´s assets that are generating revenue. RNOA is calculated as follows:

$$RNOA = \frac{OI \ \cdot 100}{Avg.\ NOA} = 1.51\ \%$$

Here, net operating income (NOA) is estimated by deducting operating liabilities from operating assets. The correlation between return on production r_b and the weather derivative´s payoff W is 0.63. Operating assets and liabilities are retrieved from the balance sheets in the annual reports from TrønderEnergi. Both the common and individual characteristics of the yearly put option written on Valsneset are presented in the tables below.

Table 12: Indifference Pricing Method: Common Yearly Put Option Characteristics for Seller and Buyer

Parameters	
Tick size L	2 269.32 NOK
Strike level K	3.5 m/s
Time to maturity T	1
Expected payout E(W)	59 838.55 NOK
Standard deviation σ_w	21 913.55 NOK
Risk-free rate r_f	1.5 %
Contract size k	1

Table 13: Indifference Pricing Method: Individual Yearly Put Option Characteristics

Parameters	Buyer	Seller
Expected return on risky activity, E(r_b) & E(r_s)	1.51 %	13.00 %
Standard deviation, σ_{q_b}& σ_{q_s}	2.02 %	8.14 %
Correlation, $\rho(q_b$,W) & $\rho(q_s$,W)	0.47	– 0.17
Absolute risk aversion, γ_b & γ_s	$1.68 \cdot 10^{-6}$	10^{-6}

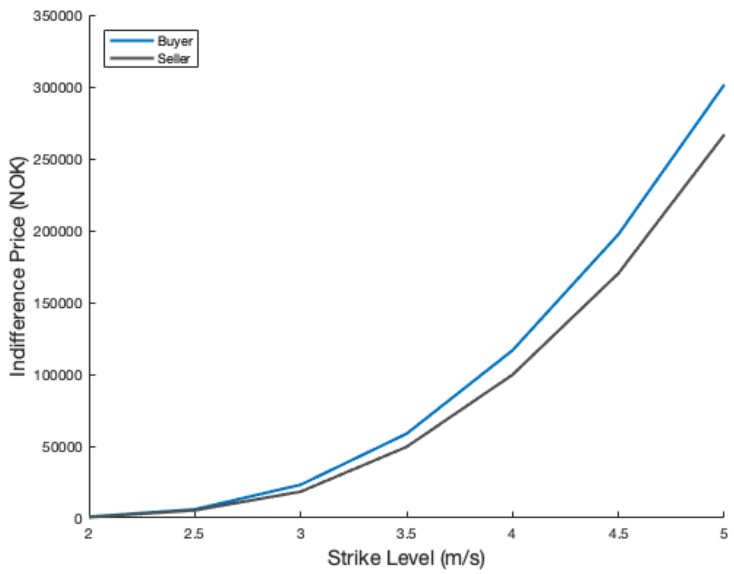
5.3.1 Results from Indifference Pricing

On the basis of the characteristics in table 12 and 13, the indifference price of the seller and buyer is calculated from equation (15) and (19). With the predetermined strike level of 3.5 m/s, the indifference price of the seller and the buyer are 49 517 and 58 667 NOK respectively for Valsneset. In table 14, yearly indifference prices of both the seller and the buyer with different strike levels are presented. As we can see, the price of the buyer exceeds the price of the seller in all cases. This is observed in figure 7 below. Thus, trading between TrønderEnergi and the seller is possible, as long as equation (23) holds.

Table 14: Indifference Pricing Method: Yearly Put Prices with Different Strike Levels

Strike level (m/s)	Seller (NOK)	Buyer (NOK)
2.0	481.46	899.63
2.5	5 369.34	6 034.95
3.0	18 365.45	23 168.89
3.5	49 517.11	58 667.32
4.0	99 693.42	116 658.06
4.5	170 263.09	197 395.40
5.0	266 816.94	301 566.57

Figure 7: Yearly Indifference Prices of Buyer and Seller



As observed from table 14, a small change in the strike level leads to a large change in prices. Due to the large amount of data points, an increase of 0.5 m/s gives many additional non-zero payout data. This leads to a considerable increase in expected payout, and thus, in the price as well. Figure 7 illustrates the indifference prices with different strike levels. A range of possible prices is reflected by the area between the two lines. The yearly indifference price of both the buyer and the seller increases as the strike level increases. Further, we will show quarterly prices with different strike levels

Table 15: Indifference Pricing Method: Quarterly Put Prices with Different Strike Levels

Strike level (m/s)	Seller (NOK)	Buyer (NOK)
2.0	121.71	232.19
2.5	1 356.84	1 521.22
3.0	4 688.00	5 824.42
3.5	12 756.32	14 439.24
4.0	25 965.81	27 774.22
4.5	44 873.98	45 072.26
5.0	71 140.63	65 383.14

Figure 8: Quarterly Indifference Prices of Buyer and Seller

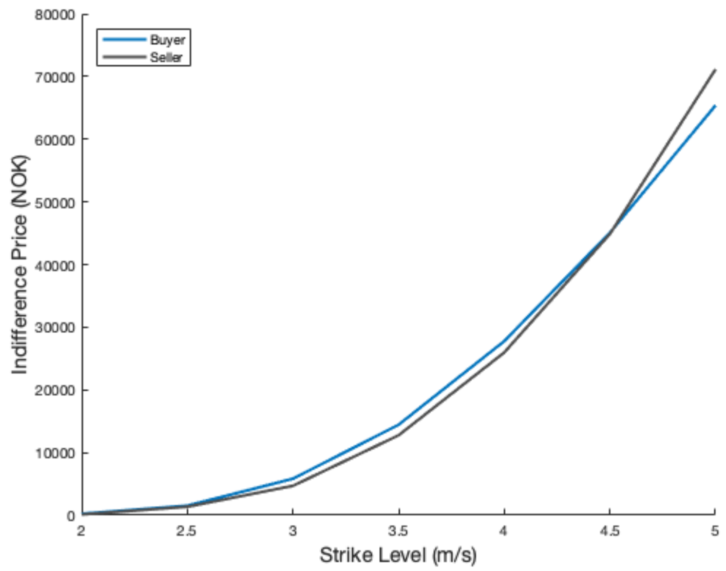


Table 15 shows indifference prices with different strike levels. We observe that the price changes are smaller for quarterly put options than for yearly. This indicates that the prices are less sensitive to changes in the strike level. The reason for this is that an increased strike level gives fewer additional non-zero payout data points, as the period is shorter. As one can observe from both figure 8 and table 15, when the strike level exceeds 4.5 m/s, equation (23) is violated, as the seller´s indifference price will be higher than the buyer´s. Transactions will not take place in such cases.

In the tables below, the effect of both yearly and quarterly put options on operating is presented.

Table 16: Indifference Pricing Method: Yearly Operating Income with and without Yearly Put Option

Year	Payout (NOK)	OI without option (NOK)	OI with option (NOK)	Change
2013	85 502.15	1 497 707.55	1 529 117.49	2.10 %
2014	80 699.89	880 840.79	907 448.47	3.02 %
2015	36 121.92	– 623 696.36	– 641 666.68	– 2.88 %
2016	46 949.41	149 631.33	142 488.53	– 4.77 %
2017	49 919.39	1 668 572.11	1 664 399.29	– 0.25 %
Average	59 838.55	714 611.08	720 357.41	0.80 %

Table 17: Indifference Pricing Method: Quarterly Operating Income with and without Quarterly Put Option

Quarter	Payout (NOK)	OI without option (NOK)	OI with option (NOK)	Change
Q1 2013	10 602.00	511 908.24	508 618.98	– 0,64 %
Q2 2013	28 295.85	53 491.27	67 895.86	26.93 %
Q3 2013	35 139.49	– 127 334.53	– 106 086.30	16.69 %
Q4 2013	11 464.80	1 059 642.58	1 057 216.11	– 0.23 %
Q1 2014	9 875.33	840 853.92	836 837.99	– 0.48 %
Q2 2014	19 622.06	– 332 351.58	– 326 620.78	1.72 %
Q3 2014	51 202.50	– 349 391.84	– 312 080.60	10.68 %
Q4 2014	0.00	721 730.30	707 839.03	– 1.92 %
Q1 2015	3 625.24	662 522.65	652 256.63	– 1.55 %
Q2 2015	10 657.30	– 399 995.38	– 403 229.35	– 0.81 %
Q3 2015	14 962.39	– 808 659.36	– 807 588.23	0.13 %
Q4 2015	6 876.99	– 77 564.30	– 84 578.57	– 9.04 %
Q1 2016	2 094.39	– 48 982.48	– 60 779.34	– 24.08 %
Q2 2016	41 754.56	– 402 630.22	– 374 766.92	6.92 %
Q3 2016	3 100.46	– 433 840.99	– 444 631.79	– 2.49 %
Q4 2016	3 100.46	1 035 085.02	1 024 294.21	– 1.04 %
Q1 2017	2 055.63	– 48 982.48	– 60 818.11	– 24.16 %
Q2 2017	14 661.70	– 43 040.06	– 42 269.62	1.79 %
Q3 2017	25 890.12	– 7 763.76	4 235.09	154.55 %
Q4 2017	7 311.94	955 437.57	948 858.25	– 0.69 %
Average	15 114.66	138 006.73	139 230.13	0.89 %

Table 16 and 17 shows what historical operating income would be with and without hedging with yearly and quarterly put options, respectively. Hedged operating income is calculated as follows:

$$Hedged\ OI\ =\ OI\ before\ the\ hedge - Put\ option\ price\ +\ Payout$$

From table 16 we observe that using a yearly put option has a positive effect on operating income in 2013 and 2014. For the years 2015 to 2017, the effect is negative. During the five-year period, the operating income of Valsneset would increase by 28 732 NOK in total, if a yearly put option had been purchased. Table 17 shows tendencies to positive effects of the hedge in quarters two and three, and negative effects in quarters one and four. This is in accordance with the observed seasonality.

For a counterparty to be willing to sell these options, there must be a possibility to gain profit. We observe that the payout varies from year to year and quarter to quarter. As the buyer gains a profit in some periods and loses in others, there is an incentive for both the buyer and the seller to enter into these contracts.

In the table below, an overview of the buyer´s total profitability of both yearly and quarterly put options for all wind mill farms and weather stations is presented. There are some cases where the price of the buyer does not exceed the price of the seller. This implies that equation (23) does not hold, and finding prices are not possible by using this method. In tables 18 and 19, such cases are described as not feasible.

Table 18: Total Payoff from Yearly and Quarterly Options 2013 – 2017

Location	Yearly options (NOK)	Quarterly options (NOK)
Valsneset	28 731	24 468
Ørland III	18 342	Not feasible
Bessakerfjellet	Not feasible	– 162 482
Buholmråsa fyr	Not feasible	55 184
Ytre Vikna	Not feasible	32 159
Nordøyan fyr	29 159	Not feasible

Table 18 presents the total payoff from purchasing yearly and quarterly put options throughout the five-year period. The total payoff (TP) is calculated as the sum of the difference between operating income with and without hedging, as shown below:

$$TP = \sum_i (Hedged\ OI_i - OI\ before\ the\ hedge_i)$$

Valsneset is the only wind mill farm where prices were found for both yearly and quarterly options. From table 18, it can be observed that purchasing yearly options are more profitable than quarterly options in the period 2013 to 2017. When the payout from the options exceeds the price, the buyer gains a profit. This is the case for all locations during this period, except for Bessakerfjellet. For Bessakerfjellet it is not profitable to purchase options, as the price exceeds the payout in this period.

An objective when purchasing a wind speed derivative, can also be to smooth operating income. We examine the effects the hedge has on the volatility in operating income. The standard deviation functions as a measure for volatility, and we calculate the percentage change in the standard deviation in operating income with and without hedging. The desired effect is a decrease in standard deviation.

Table 19: Change in Standard deviation in Operating Income with Yearly and Quarterly Options

Location	Yearly options	Quarterly options
Valsneset	+ 1.47 %	– 1.07 %
Ørland III	+ 0.30 %	Not feasible
Bessakerfjellet	Not feasible	– 0.89 %
Buholmråsa fyr	Not feasible	– 0.89 %
Ytre Vikna	Not feasible	– 0.34 %
Nordøyan fyr	– 0.80 %	Not feasible

In table 19 we see the percentage changes in standard deviation in operating income for all locations by purchasing yearly and quarterly options. As we observe, purchasing yearly put options for Valsneset and Ørland III leads to an increase in standard deviation. Furthermore, purchasing quarterly options would lead to a decrease in standard deviation in all cases that are feasible. In addition, the effect on standard deviation would also be positive if TrønderEnergi purchased yearly put options for Nordøyan fyr during the five-year period.

In the tables below, the yearly and quarterly indifference prices of the seller and the buyer are presented for all locations with both yearly and quarterly options. In addition, the price of the put option is set to the average of the seller and the buyer´s prices. In the cases where equation (23) does not hold, a transaction will not take place and there is no feasible price.

Table 20: Indifference Pricing Method: Yearly Option Prices

Location	Seller	Buyer	Price
Valsneset	49 517.11	58 667.32	54 092.21
Ørland III	122 638.41	124 539.97	123 589.19
Bessakerfjellet	263 012.45	201 674.37	Not feasible
Buholmråsa fyr	201 408.10	192 137.09	Not feasible
Ytre Vikna	– 14 359.31	56371.40	Not feasible
Nordøyan fyr	112 344.45	133 667.49	123 005.97

Table 21: Indifference Pricing Method: Quarterly Option Prices

Location	Seller	Buyer	Price
Valsneset	12 756.32	15 026,21	13 891.26
Ørland III	31 641.94	29 620,90	Not feasible
Bessakerfjellet	70 303.70	71 531.61	70 917.66
Buholmråsa fyr	55 446,98	64 621.76	60 034.37
Ytre Vikna	12 874.31	22 847.44	17 860.87
Nordøyan fyr	90 503.38	46 048.29	Not feasible

From tables 20 and 21, it is observed that the prices calculated with the indifference pricing method are in compliance with the prices calculated by using the historical burn analysis. The latter is consistently a bit higher than the former, but in general the indifference prices are close to benchmark. Thus, we consider these prices to be quite reliable.

Table 20 presents indifference prices for both the seller and the buyer, as well as the prices of the yearly put options. In accordance with equation (23), we observe that it is possible to write yearly contracts for Valsneset, Ørland III and Nordøyan fyr. All these contracts would be profitable for TrønderEnergi to enter into. Further, table 21 presents indifference prices for quarterly put options, in addition to actual prices of the put options. For the quarterly put options, transactions are possible for Valsneset, Bessakerfjellet, Buholmråsa fyr and Ytre Vikna. However, it would only be profitable to enter into contracts written on Valsneset, Buholmråsa fyr and Ytre Vikna. Purchasing quarterly put options to hedge operating income for Bessakerfjellet would be unprofitable for TrønderEnergi.

5.4 Basis Risk

One aspect of weather derivatives we wish to examine in our thesis is basis risk. By finding prices as well as testing the effects of the wind derivatives on operating income for both the wind mill farms and their closest weather station, we gain insight into the basis risk. The indifference pricing method does not provide prices for both quarterly and yearly options for all locations. Therefore, our base for studying the basis risk is limited.

Valsneset is the only wind mill farm for which we find a price for yearly put options for itself and its related weather station, Ørland III. Even though the distance between them is only 12.6 km, the difference between the prices is quite large. The price of a yearly put option written on Ørland III is more than twice the price of the same option written on Valsneset. This demonstrates how basis risk can affect the price level of a weather derivative.

For quarterly options, we find a price for Bessakerfjellet, as well as its related weather station, Buhomlråsa fyr. Buholmråsa fyr is located 20.5 km from Bessakerfjellet, but the difference between these two prices is not very large. Here, we observe that a put option written on TrønderEnergi´s own wind mill farm has the higher price, and also a negative payout in total during the period.

Based on theory, we assume that TrønderEnergi cannot purchase a put option written on their own wind mill farms. This means that if TrønderEnergi wishes to hedge operating income for Valsneset and Bessakerfjellet, they have to purchase options written on Ørland III and

Buhomlråsa fyr, respectively. We observe that this results in a much higher price, and a lower total payoff during the five-year period for Ørland III compared to Valsneset. Thus, according to our calculations, TrønderEnergi would have been better off writing a put option on Valsneset, if this was a possibility.

However, purchasing put options written on Buholmråsa fyr in order to hedge operating income for Bessakerfjellet, results in a lower price and a much higher total payoff for the five-year period. In this case, TrønderEnergi would have been better off purchasing put options written on the independent weather station Buholmråsa fyr.

These two cases demonstrate that basis risk affects the price and payoff of weather derivatives. However, the basis risk has an ambiguous effect for the two wind mill farms. Therefore, we can only say that basis risk affects the price of weather derivatives, but not in which direction or degree.

6 Conclusion

The objective of this thesis was to find prices for constructed wind speed put options and examine if TrønderEnergi could smooth and increase operating income by purchasing these options as a risk management strategy.

Even though we found prices for all locations, it is not realistic to assume that a counterparty is willing to sell a weather derivative written on the buyer´s locations. The buyer´s own measurements are not independent and thus, not reliable to a counterparty. Therefore, only the put options written on the weather stations are realistic to evaluate.

Yearly prices were found for Ørland III and Nordøyan fyr. The price of a yearly wind speed put option for Ørland III was found to be 123 589 NOK. The total payoff during the period 2013 to 2017 was 18 342 NOK, and the standard deviation of operating income was increased by 0.30 %. For Nordøyan fyr, the price of a yearly put option was found to be 123 006 NOK. During the five-year period, the total payoff was 29 259 NOK and the standard deviation was increased by 0,80 %. According to our calculations, TrønderEnergi would have increased operating income by purchasing one or both of these contracts. However, only the contract written on Nordøyan fyr would have decreased the standard deviation of operating income.

A quarterly price was only found for Buholmråsa fyr among the independent weather stations. The price of the quarterly put option was found to be 55 184 NOK. According to our calculations, the total payoff during the period was 60 034 NOK, while the standard deviation was decreased by 0.89 %. Hence, purchasing this contract would have increased operating income while reducing the volatility in operating income.

The objective of hedging with weather derivatives is to minimize downside risk, not to maximize profits. The results demonstrate that the downside risk is reduced by purchasing yearly put options each year written on Nordøyan fyr and purchasing quarterly put options each quarter written on Buholmråsa fyr from 2013 to 2017. This is not the case for Ørland III, as the standard deviation of operating income would increase.

By purchasing one or several contracts, TrønderEnergi would have gained a profit during the five-year period. Although, the payoffs are positive, they are relatively small for a five-year period. The same can be stated for the changes in the volatility. Therefore, TrønderEnergi would have to consider if getting acquainted with and purchasing the weather derivatives would be beneficial.

For further studies, a larger dataset with a longer period could be applied. An alternative approach to retrieving information from historical data could be to model the dynamics of the wind speed process to simulate and forecast wind speed (Alexandridis, 2013). As a non-linear model fitted our data best, a non-linear approach when choosing the tick size should be considered. In addition, using the wind mill farm´s actual financial data, rather than estimates, would provide a more accurate analysis.

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Appendix

A.1 AR(1) Models

Table 22: Model Summary Ørland III

Models	R^2	RMSE	BIC
OI = – 14 733.42 + 2 743.82*DAWS	0.756	5540.433	17.252
OI = – 17 147.63 – 54.59*DAWS^2 + 3 544.79*DAWS	0.759	5515.217	17.247
OI = – 6 457.18 – 30.57*DAWS^3 + 687.59*DAWS^2 – 1 738.61*DAWS	0.775	5323.979	17.181

Table 23: Model Summary Bessakerfjellet

Models	R^2	RMSE	BIC
OI = – 64 583.48 + 9 862.28*DAWS	0.803	25384.013	20.296
OI = – 85 359.60 – 273.95*DAWS^2 + 15 213.14*DAWS	0.812	24773.719	20.252
OI = – 44 344.39 – 54.83*DAWS^3 + 1 473.87*DAWS^2 – 891.34*DAWS	0.828	23725.366	20.169

Table 24: Model Summary Buholmråsa Fyr

Models	R^2	RMSE	BIC
OI = – 54 254.58 + 9 382.70*DAWS	0.705	31031.332	20.698
OI = – 67 103.26 – 201.85*DAWS^2 + 12 947.96*DAWS	0.708	30871.647	20.692
OI = – 31 864.61 – 61.69*DAWS^3 + 1 580.54*DAWS^2 – 2 021.71*DAWS	0.718	30353.993	20.662

Table 25: Model Summary Ytre Vikna

Models	R^2	RMSE	BIC
OI = – 52 050.69 + 7 514.01*DAWS	0.665	22144.373	20.037
OI = – 52 439.89 – 5.54*DAWS^2 + 7 614.94*DAWS	0.665	22157.789	20.047
OI = – 6 014.69 – 77.67*DAWS^3 +2 220.31*DAWS^2 – 11 276.62*DAWS	0.684	21504.773	19.996

Table 26: Model Summary Nordøyan Fyr

Models	R^2	RMSE	BIC
OI = – 52 428.64 + 6 823.46*DAWS	0.712	20573.723	19.890
OI = – 53 304.75 – 10.43*$DAWS^2$ + 7 033.11*DAWS	0.712	20582.976	19.900
OI = – 16 164.40 – 50.76*$DAWS^3$ + 1 559.08*$DAWS^2$ – 7 269.66*DAWS	0.731	19904.163	19.841

A.2 Indifference Pricing Method

Ørland III:

Table 27: Ørland III: Yearly Operating Income with and without Yearly Put Option

Year	Payout (NOK)	OI without option (NOK)	OI with option (NOK)	Change
2013	159 976.023	1 497 707.55	1 534 094.39	2.43 %
2014	145 936.82	880 840.79	903 188.43	2.54 %
2015	104 916.741	– 623 696.36	-642 368.83	– 2.99 %
2016	141 786.795	149 631.33	167 828.94	12.16 %
2017	83 671.8983	1 668 572.11	1 628 654.82	– 2.39 %
Average	127 257.66	714 611.08	718 279.55	0.51 %

Bessakerfjellet:

Table 28: Bessakerfjellet: Quarterly Operating Income with and without Quarterly Put Option

Quarter	Payout (NOK)	OI without option (NOK)	OI with option (NOK)	Change
Q1 2013	61 996.76	3 568 736.30	3 559 815.41	– 0.25 %
Q2 2013	50 137.36	1 303 353.85	1 282 573.56	– 1.59 %
Q3 2013	101 589.70	627 883.82	658 555.86	4.88 %
Q4 2013	20 805.30	5 770 405.56	5 720 293.21	– 0.87 %
Q1 2014	28 604.72	4 904 908.87	4 862 595.93	– 0.86 %
Q2 2014	94 431.33	– 1 069 581.72	– 1 046 068.04	2.20 %
Q3 2014	239 135.64	– 729 661.89	– 561 443.91	23.05 %
Q4 2014	6 570.74	4 137 187.48	4 072 840.57	– 1.56 %
Q1 2015	2 724.45	3 849 502.09	3 781 308.89	– 1.77 %
Q2 2015	57 571.06	– 1 640 992.95	– 1 654 339.55	– 0.81 %
Q3 2015	43 435.13	– 3 568 577.74	– 3 596 060.27	– 0.77 %
Q4 2015	29 973.11	– 503 936.52	– 544 881.06	– 8.12 %
Q1 2016	0	222 754.56	151 836.90	– 31.84 %
Q2 2016	211 328.12	– 1 771 623.99	– 1 631 213.53	7.93 %
Q3 2016	43 644.70	– 1 722 992.45	– 1 750 265.41	– 1.58 %
Q4 2016	43 644.70	5 703 236.73	5 675 963.77	– 0.48 %
Q1 2017	8 822.63	222 754.56	160 659.53	– 27.88 %
Q2 2017	71 694.67	– 88 987.40	– 88 210.39	0.87 %
Q3 2017	96 362.69	459 588.83	485 033.87	5.54 %
Q4 2017	43 398.14	4 509 853.33	4 482 333.82	– 0.61 %
Average	62 793.55	1 209 190.57	1 201 066.46	– 0.67 %

Buholmråsa Fyr:

Table 29: Buholmråsa Fyr: Quarterly Operating Income with and without Quarterly Put Option

Quarter	Payout (NOK)	OI without option (NOK)	OI with option (NOK)	Change
Q1 2013	61 996.76	3 568 736.30	3 570 698.70	0.05 %
Q2 2013	50 137.36	1 303 353.85	1 293 456.85	– 0.76 %
Q3 2013	101 589.70	627 883.82	669 439.15	6.62 %
Q4 2013	20 805.30	5 770 405.56	5 731 176.50	– 0.68 %
Q1 2014	28 604.72	4 904 908.87	4 873 479.22	– 0.64 %
Q2 2014	94 431.33	– 1 069 581.72	– 1 035 184.75	3.22 %
Q3 2014	239 135.64	– 729 661.89	– 550 560.62	24.55 %
Q4 2014	6 570.74	4 137 187.48	4 083 723.86	-1.29 %
Q1 2015	2 724.45	3 849 502.09	3 792 192.18	-1.49 %
Q2 2015	57 571.06	– 1 640 992.95	– 1 643 456.26	– 0.15 %
Q3 2015	43 435.13	– 3 568 577.74	– 3 585 176.98	– 0.47 %
Q4 2015	29 973.11	– 503 936.52	– 533 997.77	– 5.97 %
Q1 2016	0.00	222 754.56	162 720.19	– 26.95 %
Q2 2016	211 328.12	– 1 771 623.99	– 1 620 330.24	8.54 %
Q3 2016	43 644.70	– 1 722 992.45	– 1 739 382.12	– 0.95 %
Q4 2016	43 644.70	5 703 236.73	5 686 847.06	– 0.29 %
Q1 2017	8 822.63	222 754.56	171 542.82	– 22.99 %
Q2 2017	71 694.67	– 88 987.40	– 77 327.09	13.10 %
Q3 2017	96 362.69	459 588.83	495 917.16	7.90 %
Q4 2017	43 398.14	4 509 853.33	4 493 217.11	– 0.37 %
Average	62 793.55	1 209 190.57	1 211 949.75	0.23 %

Ytre Vikna:

Table 30: Ytre Vikna: Quarterly Operating Income with and without Quarterly Put Option

Quarter	Payout (NOK)	OI without option (NOK)	OI with option (NOK)	Change
Q4 2015	92.53	– 318 156.41	– 335 924.75	– 5.58 %
Q1 2016	0	76 634.141	58 773.27	– 23.31 %
Q2 2016	362.11	– 906 740.63	– 924 239.40	– 1.93 %
Q3 2016	55 256.11	– 1 189 467.00	– 1 152 071.79	3.14 %
Q4 2016	14 423.08	2 926 089.37	2 922 651.57	– 0.12 %
Q1 2017	7 764.47	1 879 932.63	1 869 836.23	– 0.54 %
Q2 2017	17 360.48	– 13 186.14	– 13 686.53	– 3.79 %
Q3 2017	91 110.44	501 185.34	574 434.91	14.62 %
Q4 2017	6 537.18	3 057 492.09	3 046 168.40	– 0.37 %
Average	21 434.05	668 198.15	671 771.32	0.53 %

Nordøyan Fyr:

Table 31: Nordøyan Fyr: Yearly Operating Income with and without Yearly Put Option

Year	Payout (NOK)	OI without option (NOK)	OI with option (NOK)	Change
2015	0	– 318 156.41	– 441 162.38	– 38.66 %
2016	341 115.94	906 515.85	1 124 625.81	24.06 %
2017	57 061.15	5 425 423.92	5 359 479.10	– 1.22 %
Average	132 25.70	2 004 594.45	2 014 314.18	0.48 %

A.3 McIntyre Method

Common put option characteristics for all locations are the strike level of 3.5 m/s, time to maturity of one year and the option parameter of –1.

Table 32: McIntyre: Individual Put Option Characteristics and Prices

Location	Mean	P(k)	Standard deviation	Price
Ørland III	6.08	0.09	2.83	-0.03
Bessakerfjellet	8.12	0.05	4.11	0.27
Buholmråsa fyr	7.44	0.06	3.53	0.23
Ytre Vikna	7.96	0.05	3.35	0.14
Nordøyan fyr	8.98	0.04	3.95	0.06