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FACULTY OF TECHNOLOGY
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ELECTRICAL ENGINEERING

MASTER'S THESIS

OPTIMAL TRADING OF WIND POWER IN THE SHORT TERM MARKET

Examiners: Professor Jarmo Partanen
Professor Olli Pyrhönen

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Abstract

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The energy reform, which is happening all over the world, is caused by the common concern of the future of the humankind in our shared planet. In order to keep the effects of the global warming inside of a certain limit, the use of fossil fuels must be reduced. The marginal costs of the renewable sources, *RES* are quite high, since they are new technology. In order to induce the implementation of RES to the power grid and lower the marginal costs, subsidies were developed in order to make the use of RES more profitable.
From the RES perspective the current market is developed to favor conventional generation, which mainly uses fossil fuels. Intermittent generation, like wind power, is penalized in the electricity market since it is intermittent and thus difficult to control. Therefore, the need of regulation and thus the regulation costs to the producer differ, depending on what kind of generation market participant owns.
In this thesis it is studied if there is a way for market participant, who has wind power to use the special characteristics of electricity market Nord Pool and thus reach the gap between conventional generation and the intermittent generation only by placing bids to the market. Thus, an optimal bid is introduced, which purpose is to minimize the regulation costs and thus lower the marginal costs of wind power. In order to make real life simulations in Nord Pool, a wind power forecast model was created. The simulations were done in years 2009 and 2010 by using a real wind power data provided by Hyötytuuli, market data from Nord Pool and wind forecast data provided by Finnish Meteorological Institute.
The optimal bid needs probability intervals and therefore the methodology to create probability distributions is introduced in this thesis. In the end of the thesis it is shown that the optimal bidding improves the position of wind power producer in the electricity market.

Tiivistelmä

Lappeenrannan teknillinen yliopisto
Teknillinen tiedekunta
Sähkötekniikan koulutusohjelma

Jari Miettinen

Tuulivoiman optimaalinen tarjoaminen sähkömarkkinoilla

Diplomityö
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120 sivua, 44 kuvaa, 11 taulukkoa

Tarkastajat: Professori Jarmo Partanen
Professori Olli Pyrhönen

Hakusanat: Tuulivoima, Ennustaminen, Sähkömarkkinat, Sähkökauppa

Energiauudistus, joka on tapahtumassa ympäri maailmaa on saanut alkunsa yhteisestä huolesta, joka on ihmiskunnan kohtalo jaetussa maailmassa. Pitääkseen ilmastonmuutoksen vaikutukset tietyn rajan sisällä, fossiilisten polttoaineiden käyttöä on vähennettävä. Monet uusiutuvan energian tuotantokustannukset ovat tällä hetkellä korkeita. Madaltaakseen uusiutuvan energian tuotantokustannuksia on jouduttu ottamaan käyttöön useita erilaisia tuotantotukia. Tuotantotuet ovat kuitenkin tarkoitettu väliaikaiseksi ratkaisuksi ja lopulta erilaisten uusiutuvien energiamuotojen on seisottava omilla jaloillaan.
Uusiutuvan energiantuotannon kannalta katsottuna sähkömarkkinat on rakennettu suosimaan konventionaalista tuotantoa, joka pääasiassa käyttää fossiilisia polttoaineita. Jaksoittainen tuotanto, kuten tuulivoima, kärsii nykyjärjestelmästä luonteensa vuoksi, koska se on jaksoittaista ja siten vaikeasti hallittavaa. Tämän vuoksi säädön tarve ja säädöstä aiheutuvat kulut tuottajalle eroavat suuresti riippuen siitä minkälaista tuotantoa osapuolilla on kaupankäynnissä.
Tässä työssä tutkitaan, voiko sähkömarkkinoilla toimija, jolla on tuulivoimatuotantoa, käyttää Nord Pool:n erityisominaisuuksia hyväksi ja täten kuroa konventionaalisen tuotannon ja jaksoittaisen tuotannon eroa ainoastaan asettamalla tarjouksia sähkömarkkinoille. Tämän vuoksi tullaan esittelemään optimaalinen tarjous markkinoille, jonka tarkoitus on minimoida tasehallinnasta aiheutuvia kuluja ja siten alentaa tuulivoimalla tuotetun sähkön tuotantokustannuksia. Saadakseen simuloitua Nord Poolissa tuulivoimatuottajan käyttäytymistä jouduttiin luomaan tuulivoimatuotannon ennustemalli. Simuloinnit suoritettiin vuosina 2009 ja 2010 käyttäen oikeaa tuulivoimadataa, jonka tarjosi Hyötytuuli, markkinadataa Nord Poolista sekä tuuliennustedataa, jonka tarjosi ilmatieteenlaitos.
Optimitarjous tarvitsee todennäköisyysjakaumat ennusteen päälle, jonka vuoksi menetelmä niiden luomiseksi esitellään tässä työssä. Lopuksi työssä todetaan, että optimaalinen tarjous parantaa tuulivoimatuottajan asemaa sähkömarkkinoilla ja täten pienentää tuulivoiman tuotantokustannuksia.

Preface

I begun this work on February 2011 while studying in Technical University of Denmark. The environment in Copenhagen was really inspiring to start the work and would like to thank associate professor Pierre Pinson for the inspiring conversations regarding wind power forecasting and also providing material to continue my work in Finland.

I would like to give my best regards to my supervisor professor Jarmo Partanen for the guidance and giving me such an interesting topic for the thesis. I would like to thank the second thesis examiner professor Olli Pyrhönen, who is a good conversation partner in all fields of wind power. I would also like to thank Hyötytuuli and Jenni Latikka from Finland's Meteorological Institute for providing me data to do this thesis. Without their contribution, this study would have been impossible to carry out.

More importantly, I would like to thank my dear Lotte for supporting me in my studies and supporting me during our common history. This thesis was a long journey for both of us, but we made it! Big acknowledgement belongs to my family, and especially to my parents who have always supported me in my studies and in my life. Student life was an amazing time in my life and the biggest thanks belongs to my friends who have helped me in my studies, and friends who have only caused me trouble. You know in your heart, which category you belong. Now it is time for new challenges and I'll leave Lappeenranta with a big smile in my face.

Helsinki 24.1.2012
Jari Miettinen

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Abbreviations and symbols

A	area
A_w	weibull scale parameter
b	constant
c	constant
c_p	power coefficient
CDF	Cumulative Distribution Function
CFD	Computational Fluid Dynamics
DW	Deutscher Wetterdienst
d	deviation
E	energy production
e	error
EC	Evaluation Criterion
ECMWF	European Centre for Medium scale Weather Forecast
EST	Eastern European Time
F	probability distribution
FMI	Finnish Metrological Institute
G	cumulative distribution
H	Hessian matrix
HIRLAM	High Resolution Limited Area Model
IC	imbalance cost
Imp	improvement
k_w	weibull shape parameter
MAE	Mean Average Error
MOS	Model Output Statistics
MSE	Mean Squared Error
NCEP	National Centers for Environmental Prediction
NWP	Numerical Weather Prediction
OTC	Over-The-Counter
P	power production
PDF	probability distribution function

R	revenue
RMSE	Root Mean Square Error
SCADA	Supervisory Control And Data Acquisition
SDE	Standard Deviation of Errors
t	time
TSO	Transmission System Operator
u	wind speed
z	loss expextation function

Mathematical symbols

+	up regulation
-	down regulation
^	forecasted
—	mean

Greek symbols

α	Beta distribution scale parameter
β	Beta distribution scale parameter
ξ	capacity factor
η	efficiency
ρ	density
σ	standard deviation
μ	mean
θ	wind direction
π	price
λ	forgetting factor

Subindexes

abs	absolute

act	actual
ext	extra
m	month
MA	moving average
max	maximum
meas	measured
n	nominal
pen	penetration
pc	power curve
q	quarter
quad	quadratic
ref	reference
rot	rotor
tur	turbine
w	Weibull

1 Introduction

Numerous countries all over the world are struggling with increasing CO2 emissions, caused by their energy sectors. Scientists, all over the world, are unanimous that the human made CO2 emissions must be in order to limit the global warming. One way to deal with this global problem is to move towards cleaner energy sources, which are in many cases renewable energy sources. For instance, European Union is trying to implement its 20/20/20 targets, which purposes are to reduce greenhouse gas emissions by 20%, increase the amount of renewable source to 20% and reduce the overall energy consumption by 20%. However, the problem with implementing of renewable sources is that energy markets and the whole energy sector are constructed for the needs of conventional generation, which make the integration of renewable energy sources to the energy markets difficult.

Renewable energy sources are highly variable by their nature and thus their controllability is weak. In the Nordic energy market time span from market closure to delivery hour can be 36 hours, which equals eternity from renewable sources point of view, since the predictability and controllability of renewable sources is weak. This unfair design of the market will cause problems to the renewable energy sources by adding its marginal costs, since the energy market is designed so that the imbalances caused by differences in bid energy and actual energy delivery are always penalized. Thus, this is the environment where the renewable sources must be equally competitive as the conventional generation, in order to implement more renewable energy to the grid.

In this thesis it is discussed how the wind energy participant could reach the gap between marginal costs of conventional generation and renewable energy by using optimal bidding. This optimal bidding uses special characteristics of the Nordic electricity market, Nord Pool, by overestimating or underestimating produced energy at a delivery hour with a sensible manner. This method was introduced in the earlier research of (Linnet, 2005) and was further refined by

(Pinson, 2006). It assumes that the balancing energy costs are imbalanced, which can be used together with probabilistic forecasts as an input to gain an optimal probability, where the optimal bid can be found. In this study, the probabilistic forecast was created by assuming that the wind farm’s power can be divided into 25 equally sized bins, where forecast error can be assumed to follow a beta distribution (Bludszuweit, 2008).

As a result, this combination of probabilistic forecast and optimal bidding gave strong indications that the optimal bidding will increase wind power participants revenue by only taking the uncertainty of a forecast and imbalanced balancing energy costs into account. In chapter 0 short overview of the Nordic electricity market with it characteristics is represented. The weight is given to the aspects, which are important for participant who has wind energy. In chapter 3 overview of wind power forecasting is represented and also some of the special characteristics of wind power and wind itself are represented. In the fourth chapter the methodology to derive point forecasts, probabilistic forecasts and optimal bids are represented. Also the results induced by optimal bidding are represented.

2 Electricity market

The Nordic electricity market refers to the market area that is shared between Finland, Sweden, Norway, Denmark and Estonia. The idea is that there is one marketplace for selling/buying electricity as a commodity. The name of this common marketplace is Nord Pool and it was founded in 1995. The Nord Pool was a great step forward in the deregulation of energy market in Nordic countries. Before the deregulation of the energy market the companies, owned by the state, held a dominant position in transmitting and producing/selling electricity. In all of the Nordic countries the structure before deregulation was different. For example the Finnish power sector was dominated by the state owned company called Imatran Voima, IVO, which was responsible for the transmission of electricity. However, there was also a large share of generation owned by the Finnish industries, which established their own transmission company to interconnect their generation to the supply areas. Hence, there was two different transmission grids at that moment. (NordPool, 2011)

The actual deregulation started in the Nordic countries by following the example of England and Wales, which started the wave of deregulation in the energy markets. In the Nordic countries deregulation was led by Norway in 1990, followed by Sweden in 1991. In 1995 free competition in producing and selling electricity was partly introduced in Finland. Denmark and Estonia followed their example respectively a bit later. The idea of deregulation was to make it possible for the customers and the producers to follow the principles of free market whilst the energy transmission and distribution would be monopolized businesses. By doing so the quality and security of energy transmission and distribution would not be harmed by the free market (NordPool, 2011)

One of the important aspects in looking at the market mechanisms at the moment in the Nordic countries is that Sweden and Norway established in 1995 Nord Pool, which is the market place of electricity and emission trading at this day. At the moment the Nord Pool, is divided into physical marketplace and financial marketplace. The actual selling and purchasing of electricity takes place in the physical power market, whereas the financial market place is for buying financial products as in buying and selling options. Trading in physical power market always leads to physical trading of electricity, whereas financial contracts are settled with money (NordPool, 2011).

As a result, deregulation has also led to another common thing besides of the joint market: Nordic market area has gained a common transmission power grid. It means that the actual electricity transmission is possible over the nations' borders and while the AC -transmission is used, same voltage frequency can be seen at every point of the grid. The common grid allows to preserve the stability of electricity transmission and also naturally formulates the boundaries of the joint power market. The other nations that transmits electricity to the Nord Pool's area are connected with AC-DC-AC converters in order to maintain the quality of electricity in the Nordic countries. Even though, the Nordic countries share the market area, it still does not guarantee the wholesale electricity price that is formulated in the Nord Pool is same at every grid point, since the transmission capacity is finite and it is sized only with common agreements. Therefore, in some heavy transmission situations the common price area needs splitting because the limited transmission capacity prevents the power market from functioning properly. Hence, the price areas need to create depending where the transmission capacity is inadequate in relation to the requirements of the market. Usually the boundaries of the price areas are composed by the boundaries of the nations. However, for Denmark and Norway it was necessary to create internal price areas because of the inadequate transmission capacity inside the nation. Also Sweden will be split into four price areas in November 2011 (NordPool, 2010). All the presented issues lead to the conclusion that the location of consumption and production plays a highly important role in the Nordic market and especially in forming the market price. In the Nord Pool price areas and flows from price area to another can be seen. Besides the flows that can be seen from the figure, the Nord Pool market is also connected to markets in Germany, Russia, Netherlands and Poland (Partanen et al., 2010). In Figure 2.1 the current price areas in Nord Pool.

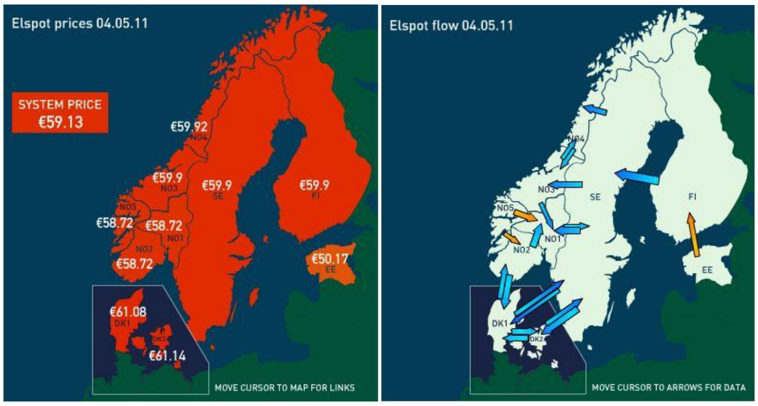

Figure 2.1 Nord pool system prices and flows (NordPool, 2011)

The future development of Nord Pool is that the market will integrate more with European energy markets since there is a need for a stronger inner market in the EU and also the it follows the principles of EU. It will also increase the competition in the markets and thus allow the customers to tender their electricity retailer. Since the European markets differs from another, market integration is achieved through market coupling, which means that efforts are made to combine the already working markets with various methods including so-called implicit auction (NordPool, 2011).

2.1 Electricity exchange

As a electricity trading place, Nord Pool is the market place where the electricity price is founded for every hour of the day, every day of the year. In Figure 2.2 the example of price formulation, where the system price is the intersection point of the demand and supply curve. System price is the price that is valid for all market participants, if there is not any restrictions in transmission capacity between any price areas. As it is possible to see from the Figure 2.2 the market reaches the lowest possible price naturally by arranging the different electricity producing methods by its marginal costs. Marginal costs are the costs of producing one unit of electricity. Therefore the two lowest methods to produce electricity are hydro power and nuclear power according to their marginal costs. The amount of wind power in the Nordic electricity market is still about 3 % of the total energy production in the Nordic countries, therefore its effect on the market price is low. However in some price areas for instance in DK1, where wind penetration may be over 50 %, there are clear signs that the amount of wind energy has an impact on the electricity price. The price reduction may be over 30 % when the wind penetration is over 50 % , compared to the situation when wind penetration is zero (Jónsson, 2008).

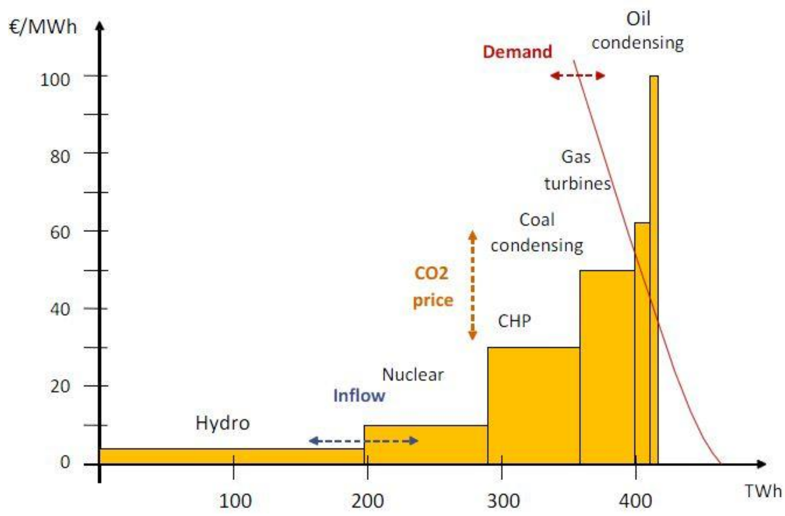

Figure 2.2 Foundation of the system price. System price is the intersection of the demand and supply curve. In this example system price is 55 €/MWh (Vehviläinen et al., 2010)

It can also be noticed from Figure 2.2 that electricity price is determined by the level of demand. The demand can also vary in function of electricity price but as the Figure 2.2 shows that the variation is rather small. In the Nordic power market the fluctuations in the level of hydro power determines the level of electricity price. During a less rainier year the electricity price increases and on the contrary, if the year is rainy, the price decreases in relation to a year with an average precipitation (Partanen et al., 2010). The carbon dioxide tax increases the marginal costs of the energy that is produced from the fossil fuels, uranium as an exception that has a low carbon dioxide emissions per produced unit of electricity.

As it was mentioned in the previous chapter the electricity exchange is divided in the physical and the financial marketplaces. The financial marketplace was previously owned by the Swedish and Norwegian transmission companies Svenska Kraftnät and Stattnett, respectively. In 2010 they sold their share of the company and thereafter the financial marketplace has been owned by the NASDAQ OMX. The clearing house that was previously owned by the separate company, Nord Pool clearing ASA and it also changed its ownership to NASDAQ. The physical market is still owned by the Nordic nations transmission companies (NASDAQ, 2011). In Figure 2.3 The structure of the Nordic electricity market, Nord Pool.

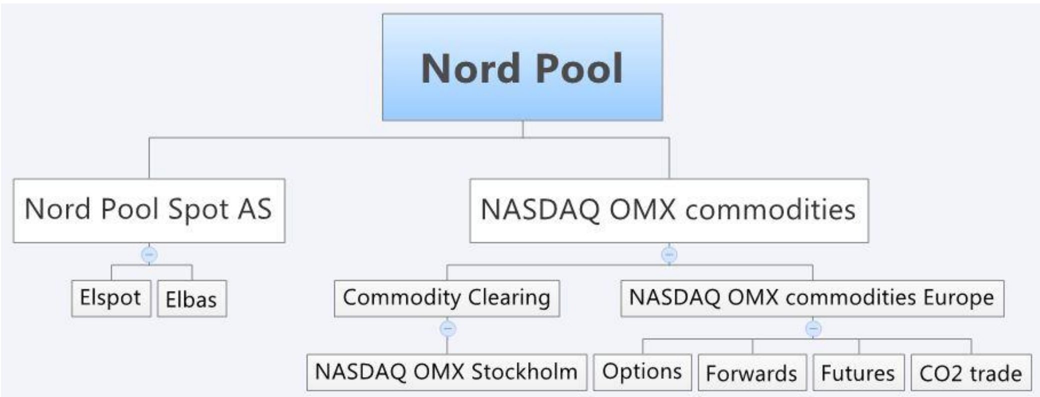

Figure 2.3 Structure of the Nord Pool. In the left branch the physical market and in the right branch the financial market.

2.1.1 *Physical markets*

The purpose of the physical marketplace is to allow to buy and sell electricity to meet the actual electricity demand. The physical market in the Nordic market is called as a Spot market. The turnover of the Spot market is 288 TWh, which responds to 72 % of the total electricity consumption in the Nordic market. The rest of the electricity is traded with Over-the-counter, *OTC* or in other words with off-exchange trades. Therefore, Spot -market can be seen as a liquid and efficient electricity marketplace (NordPoolSpot, 2009).

The Spot -market is divided into two parts: day-ahead market, Elspot and intra-day market, Elbas. Elspot- market is the more liquid one of the markets. The turnover of Elspot is more than one hundred time the turnover of Elbas. Hence, the 'main' market for having electricity exchange is Elspot. (NordPoolSpot, 2009)

2.1.1.1 Elspot

In the Elspot-market it is possible to trade physical power delivery of the delivery hours for the next day. In Finland the delivery hours are 01-24 whereas in most of the Nordic countries the delivery hours are one hour behind due to the time difference. Everyone who has a connection to the transmission grid and fulfills the requirements of Elspot have the possibility to access the Elspot-market. Also the participants need to have a balancing agreement with the respective transmission system operator, TSO (NordPool, 2011).

The Elspot-market closes at 1 p.m. Finnish time and before that all the purchase and sale bids to each delivery hour need to be submitted. A delivery hour can contain both purchase and delivery bids. There are three kinds of bids that the participant can use: hourly bid, block bid and flexible hourly bid. The hourly bid is the basic type of bids where the participant selects two or more price intervals, up to 62 and determines what is the volume that the participant wants to sell or purchase during that interval. Then the amount of power trade depends on which interval the system price lies in. In Table 2.1 is an example of placing hourly bids.

Table 2.1 Example of placing hourly bids. This example is covering just the first two hours of the 24 delivery hours. The system price for hour one is 20€/MWh and for the second hour 50 €/MWh, which means that in the first hour the participant needs to buy 30 MW and in the second hour the participant needs to sell 35MW of energy.

Price Hour / Price	-200	10	10.1	40	40.1	2000
1	50	50	30	30	-30	-30
2	50	50	20	20	-35	-35

The second type of the bids is block bid, which means that the participant has the opportunity to set bids for multiple hours and put a ‘all or nothing’ condition to all hours within the block. Block bids can be either sales or purchase blocks. The sales block is accepted when the bid price of the sales block is lower than the average Elspot area price. The purchase block functions in the opposite manner. The block can also be linked to each other in a manner that if one block is accepted, then the others are too. The block bids are used in cases where the cost of starting and stopping the power production is high. However, there has been discussions about whether the binary choices that the block bids introduce to the market, increases the market price and thus increases the income of the producers in a unfair manner (Vehviläinen et al., 2010) (NordPool, 2011).

The third kind of bids that can be demonstrated in the Elspot market is flexible hourly bid. It is a sales bid with a fixed price and volume, but without any specific deliver hour. The bid is accepted in the hour with the highest price, given that the price is higher than the limit set in the bid. If there is no such hour, the bid is rejected.

Immediately after the Elspot-market has closed the trading, all of the hourly selling and buying bids are combined thus creating one curve to illustrate the demand and one curve to illustrate the supply, see Figure 2.2. This procedure needs to be done for every delivery hour and the intersection of these curves is the system price of the delivery hour. System price does not take into account any restrictions in the transmission capacity. Therefore it is the lowest possible price that can be achieved in the joint market, if the market is assumed to work in a optimal manner.

2.1.1.2 Elbas

Elbas is an aftermarketplace for Elspot-market. In contrast to Elspot market that can defined as day-ahead closed auction market, Elbas is a continuous real time marketplace like the traditional stock market is usually presumed to be. The purpose of Elbas is to sharpen electricity trade offers when the actual electricity consumption of a delivery hour is more certain. Hence, it is possible to reduce the risk by leaving less electricity to the balance settlement, where it is impossible to affect the price of electricity that the participant must pay, or sell, in order to meet the demand.

The trading in Elspot is possible after the prices of Elspot are announced at 2 p.m. The trading is possible until one hour before the actual delivery hour. The actual trade in Elbas works so that the electricity buyers and sellers give offers to Elbas-market for each individual hour, and when the buyers and sellers price offers encounter, the trade is made.

Elbas is very convenient for the participants who trade wind power produced energy, since the interval from the Elspot gate closure to actual delivery is 12 – 36 hours. The wind power prediction can change a lot during that time interval, which means that the actual wind conditions on delivery hours can differ a great deal from the predicted wind conditions that the wind power prediction software provides before Elspot gate closure. Due to that, the financial losses might be great if the participant does not trade in Elbas.

2.1.2 Financial market

In the Nordic market the financial trade is made in NASDAQ OMX market with the NASDAQ OMX commodities, see Figure 2.3. Buying or selling financial commodities will never lead to actual power delivery, which means that the Spot-market remains the only place where it is possible to buy or sell power delivery. The financial commodities are always settled against a reference price when the financial contract is supposed to maturity. The reference price, which all the commodities are settled against, is the system price. In the financial trade, NASDAQ always shows as a counterparty for financial commodity, which assures that there is no risk for the counterparty and also the trade remains anonymous.

From the market participant perspective, who has obligation to deliver power to customers in predefined price, the financial market offers a way to distribute risk in the buying of electricity. Hence, many of the participants in the Nordic market uses financial products to ensure a level for market price in the delivery date and hence distributes the price risk.

The financial commodities in the Nordic market are: Forwards, Futures, Options and Contract for Difference, CfD. In the following parts these commodities are shortly represented.

2.1.2.1 Forwards and Futures

Forwards and Futures are contracts provided to sell or buy a certain commodity in the future. The specifics of the contracts (price, volume, time and place) are defined before making the contract. The main difference between Forwards and Futures is that Futures are weekly contracts and Forwards are for standard time periods above one week. There are also differences on how the settlement of a contract is made. The details of the differences can be found in the webpage of NASDAQ OMX. (NASDAQ, 2011).

All the Future and Forward contracts can be bought in order to cover either the base load or the peak load. The difference between the base load and peak load contract is that the base load contract is valid every day and covers all the delivery hours of the day. While the peak load contract is valid only from Monday to Friday covering hours from 9 a.m. to 9 p.m Eastern European time, *EST*

There are six different kinds of Forwards, which can be distinguished either by their time period from when they are valid or by their contract purpose, depending whether the contract is meant to cover base load or peak load. The three different time periods are: a month, a quarter of a year and a year.

2.1.2.2 Options

An Option is a right to buy or sell an underlying contract at a predefined price and date. The underlying contracts are specific a quarter of a year, or a year Forward contracts. Options are always binding only for the contract seller, not the buyer. There are two types of Options; Buying and selling options. A buying Option is called a call Option while the selling Option is a put Option. As an example, a call Option has the possibility to buy an underlying contract from the seller with a predefined price by paying the seller a premium for the risk the contract seller has to take. The size of the premium depends on the risk level, which the seller is willing to take. Put option works with the same manner than call option but the underlying contract, instead of buying, is selling of electricity at predefined volume.

2.1.2.3 Contract for Difference

The reference price for settling the financial products is always the system price. However, the actual physical delivery happens always with the area prices depending where the consumption takes place. Therefore, if the participant wants to gain the best possible income from Forwards and Futures, it is necessary to buy CfD contracts to cover the difference between the system and area price. CfD covers the expenses that comes from the splitting of the market to the price areas. Hence, CfD can be thought as an insurance for the case where the area price differs from the system price. The concern is quite valid since in 2009 only 25 % of the time all the price areas shared the same market price. However, Sweden and Finland shared the same market area 95 % of the time (Ruusunen, 2010).

2.2 Power balance management

In Finland the power balance management is divided into two parts: first, the regulating market, where the continuous balance between production and consumption is taken care by the frequency control. Secondly, the costs of regulation are pointed to participants who have had imbalances between actual consumption and traded electricity. In the balance settlement every electricity market participants actual consumption and production are examined for each delivery hour and the result of this examination is compared to the electricity trade that the market participants have done in the Spot-market. The surplus or the deficit electricity are handled with terms of balance settlement and thus the costs of regulation are pointed to the participants who have caused the need for up or down regulation.

2.2.1 Regulating market

The regulating marketplace is provided by the local TSOs, which uses the capacity that the regulating market participants offer to the regulation market freely, to keep up the system frequency in control. The frequency must stay within a certain limits from the base frequency since the secure system operation requires a constant frequency all the time. The base frequency is 50 Hz in the Nordic grid. The basic idea is that when the consumption and production meet each other perfectly the frequency in the grid stays at 50 Hz. However, if there is there is more production than consumption or less production than consumption, system frequency will rise or fall, respectively. Hence, there is a need for balance the change in frequency by adding or removing power from the grid. This power is called as a regulating power and it is traded in the regulating power market. When all of the participants have offered available regulating capacities to the regulating market with the price and volume information. Then it possible to form for every delivery hour a Nordic regulating power curve. Up regulations are arranged ordered by price from cheapest bid to the most expensive bid and the down regulation bids are formed in the opposite price order – the most expensive bid first. Now, depending on the regulation need, the Swedish and Norwegian TSOs, who have chosen to be frequency regulators, can choose who participates to the frequency regulation with a price effective manner. In Figure 2.4 in the left hand side, the regulating power curve is represented.

The hour when there is a need for increased power production is called as a up regulation hour and on contrary down regulating hour is when there is a need for decrease in production. The system frequency is controlled on a minute level, therefore there might be hours when there is both down an up regulating in an hour. Then the regulating hour is defined based on which of the regulation volumes is greater within the hour.

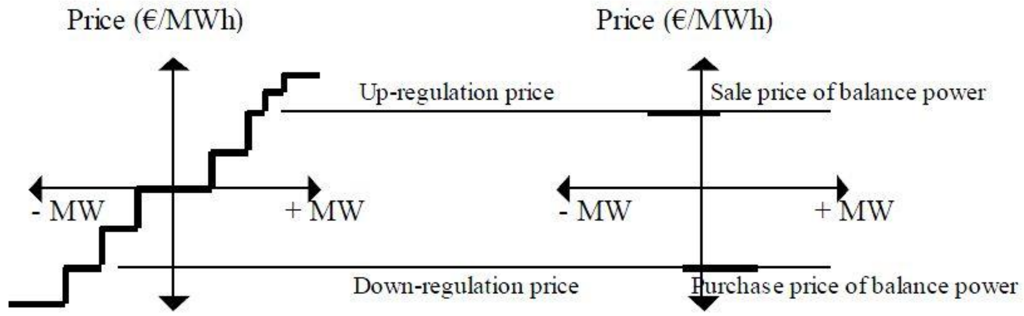

Figure 2.4 Regulation prices relation to the balancing power prices in balance settlement. (Partanen et al., 2010)

The up regulation price is formed by the most expensive up regulation price that is needed to keep the power system in balance, and if there is no up regulation need, the up regulation price is the same than the area price. For down regulation hour, the price is the most cheapest offer to keep the power system in balance and if the hour is not down regulation hour the price is the same than the area price. In Figure 2.4 the connection between regulation prices and balance power prices.

The reference level (origin) in regulation curve is Spot area price, hence the market ideally works with a manner that nothing can be gained from being out of balance. However, sometimes the regulating power price can differ from the ideal way. In 2010 up regulation and down regulation prices were negative 17% and 22% of the time, respectively. This phenomena can relate from very natural reasons although it is against the basic idea how the market should function. For instance, sometimes when there is a huge need for down regulation and there is a need for down regulate so called un-flexible generation as nuclear power or CHP plants. Shutting down or curtailing un-flexible generation may be very expensive since this kind of power plants are not created for this kind of operation. CHP plants are used in winter time mainly for producing heat and the electricity is merely a side product. Hence, there is a significant correlation between produced heat and electricity output and thus the electricity output is determined by the heat demand. Therefore, curtailment of the electricity output can be very expensive for the power plant owner, thus decreasing plant's electricity output can be only possible with a negative down regulation prices. In Table 2.2 and Table 2.3 balancing energy prices in relation to the Spot area prices and ratios between the balancing energy costs are illustrated in Finland 2009 and 2010. For now on term balancing energy cost is a difference between regulation price and area price.

Table 2.2 Regulating power costs in Finland, 2009. π_m^+ *and* π_m^- *is monthly averaged up and down regulation costs.* π_q^+*and* π_q^- *are quarter of a year averaged up and down regulation costs.*

	month	π_m^+ [€/MWh]	π_m^- [€/MWh]	π_m^-/π_m^+	π_q^+ [€/MWh]	π_q^- [€/MWh]	π_q^-/π_q^+
	1	4.52	3.71	0.82			
Q1	2	1.29	4.39	3.41	2.47	5.15	2.09
	3	1.61	7.36	4.58			
	4	0.75	5.39	7.20			
Q2	5	1.76	2.90	1.64	1.96	3.52	1.80
	6	3.39	2.27	0.67			
	7	1.42	3.30	2.32			
Q3	8	4.27	1.63	0.38	2.23	2.68	1.20
	9	0.99	3.11	3.15			
	10	2.85	1.71	0.60			
Q4	11	1.14	2.52	2.20	2.83	4.53	1.60
	12	4.49	9.38	2.09			
	mean	2.37	3.97	2.42	2.37	3.97	1.68

It is possible to see that in 2009 down regulation balancing costs, π_q^- exceeds up regulation balancing costs, π_q^+ on quarterly basis, which indicates that the excess energy is penalised more on average than the missing energy. Furthermore, there are only four months when the up regulating cost is higher than the down regulating cost, which indicates that clearly for some reason TSO has wanted to penalize excess energy. Therefore, for market participant perspective optimal revenue has been gained by under estimating the energy production and thus avoiding down regulation prices. It is rather complicate to analyze why down regulation prices are higher than the up regulation prices since it is difficult to say are the market participants deliberately overestimating their bids, or is the reason more technical.

From Table 2.3 one can notice that the balancing power costs in 2010 differs greatly from 2009. On average, the quarterly regulating cost ratio, π_q^- $/\pi_q^+$ is the same in both years, down regulation is penalised 1.7 times more than the up regulation. However, the distribution of regulation cost prices is different, the down regulation is more penalised in quarters 1 and 2 and up regulation is more penalised on the last two quarters. In March the regulation cost ratio reaches its maximum value while the minimum value is obtained in November.

Table 2.3 Regulating power costs in Finland, 2010

	month	π_m^+ [€/MWh]	π_m^- [€/MWh]	π_m^-/π_m^+	π_m^+ [€/MWh]	π_m^- [€/MWh]	π_q^-/π_q^+
	1	8.92	16.44	1.84			
Q1	2	2.54	24.19	9.52	4.27	18.05	4.23
	3	1.34	13.52	10.12			
	4	1.06	5.14	4,84			
Q2	5	2.64	3.64	1.38	2.13	3.86	1.81
	6	2.68	2.80	1.04			
	7	6.37	2.57	0.40			
Q3	8	2.83	2.63	0.93	4.04	2.42	0.6
	9	2.93	2.06	0.70			
	10	4.44	1.94	0.44			
Q4	11	9.73	2.38	0.25	7.09	5.27	0.74
	12	7.10	11.48	1.62			
	mean	4.38	7.40	2.76	4.38	7.4	1.69

If some trend from the regulation costs are tried to formulate based on these two years, in the first and second quarters of the years, the purchasing costs are much bigger than the sale costs, which indicates that there is a lot of down regulation in those quarters. However, based on these two years it is hard to say anything about third and fourth quarters since up regulation is more expensive in 2010 and down regulation in 2009 . High balancing energy prices indicates, high regulation volumes, In Table 2.4 and Table 2.5 this fact can be confirmed where the regulating volumes in 2009 and 2010 are represented, respectively. The need for down regulation is surprisingly large in the first quarters of the years since the consumption should be really high and therefore the production should be at its maximum. One reason behind this might be behaviour of the market participants, which induces imbalanced regulation prices.

Table 2.4 Regulating and balancing volumes in 2009.

	Regulating [MWh/h]		Balancing [MWh/h]	
	Up reg.	Down reg.	Purchase	Sale
Q1	12281	-65017	121835	-120606
Q2	18876	-35848	122435	-110949
Q3	18776	-34335	98757	-102925
Q4	44511	-48179	102337	-146232
sum	94444	-183379	445364	-480712

Table 2.5 Regulating and balancing volumes in 2010.

	Regulating [MWh/h]		Balancing [MWh/h]	
	Up reg.	Down reg.	Purchase	Sale
Q1	17381	-124822	99354	-131014
Q2	17577	-52983	124592	-126281
Q3	36519	-29441	103943	-95080
Q4	37120	-50880	111909	-111378
sum	108597	-258126	439798	-463753

If the regulating mechanism is considered in a wind power producer’s point of view, then the costs that comes from the balance settlement are emphasized since the predictability and thus the controllability of the wind power differs greatly from the conventional generation, which output can be controlled with a very accurate manner. Wind power investment can be for investors tough decisions to execute the investment, or not. Therefore the poor predictability of wind induces more balancing costs and complicates the integration of wind power to the grid and thus increases the marginal costs of wind power produced energy. Better prediction methods and advance bidding strategies could give a stronger position to wind power and reach the gap between conventional generation’s viability. These aspects are studied more carefully in the chapter 4.

2.2.2 Price spikes in the Nordic market

Price spikes in the Spot area prices, or in balancing energy can lead to serious losses to the market participants. Therefore, it is crucial to be aware of the risks, which lies in the market and take them into account with the best possible manner. For instance, if participant could forecast these price spikes in balancing energy market, one could offer bids to the Elspot-market, which guarantees that the losses, which are induced by the price spike are minimized and thus the profit is maximized. However, forecasting these spikes is not a trivial task and many state-of-the-art price prediction model tries to find a way to predict them. In Figure 2.5 Elspot area prices in Finland 2010. It can be noticed that most of the time area price seems to fluctuate around approximately its mean value, while sometimes, especially in the winter time, the area price seem to fluctuate more. The biggest price spikes occur in winter time, which usually originates from the combination of high consumption and outages from base load production capacity. In summertime the area price seems to be rather stable, which proves that there might be a correlation between less fluctuating prices together with available production capacity combined with low consumption. The mean Elspot price in 2010 was 56,64 €/MWh with a standard deviation, $\sigma_{spot,2010}$ of $144\,\frac{€}{MWh}$, which describes that the Elspot price fluctuates relatively a lot around its mean.

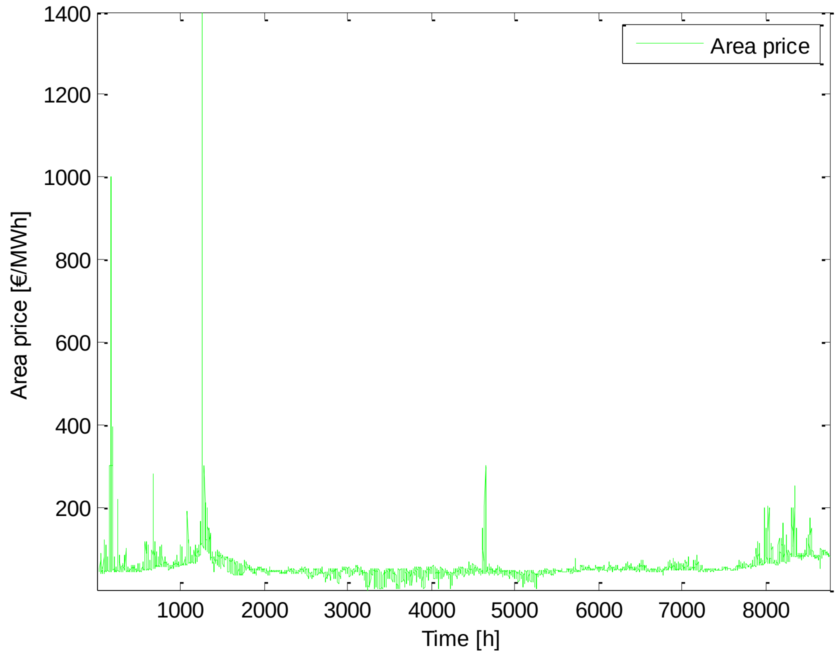

Figure 2.5 Spot area prices in 2010

However, all above mentioned explanations about price spikes still leaves a question, what is a price spike. There is no inclusive way to say, what is the limit price for the price spike since it depends on the characteristics of the market (mean and variance). In Table 2.6 Elspot area prices in Finland that exceed the limit area price, which is represented in the first column, in 2009 and 2010.

Table 2.6 Price spikes in Elspot price in 2009 and 2010.

Area price [€/MWh]	Amount of hours exceeding the limit area price [pcs]	
	2009	2010
> 100	22	359
> 200	8	47
> 300	6	29
> 400	2	13

One can notice right away that there was a lot more price fluctuations in 2010 than in 2009. It says a lot that in 2010 there was more hours that exceeded 300 €/MWh than in 2009 hours that exceeded 100 €/MWh. Also the mean area prices differs greatly between 2009 and 2010. In 2009 the mean area price was 36.98 €/MWh while 2010 it was 19.66 €/MWh bigger than in year 2009. Therefore, one must not make any conclusions about how the market functions since two years, which are in a raw, differs greatly from another. Also one can say that the price spikes are quite relative depending on the characteristics of the year and thus it is hard to define a price limit for spike hour. The spike hours are not independent events and usually the spike hours are highly correlated, since the reason behind them could be a weather phenomenon or a broken power plant. This might be the reason why in some years there are more hours with high prices than other years.

Price spikes in balancing energy prices are highly correlated to the price spikes in Elspot area prices, as it is possible to see by comparing the Figure 2.6, where the balancing energy prices are represented in relation to Elspot area prices, to Figure 2.5. There is a strong correlation between the time when the spikes occur and also with the amplitude of the peak prices. Figure 2.6 also illustrates the additional losses of a participant if it has a need to buy or sell its energy from balance mechanism, which is called in this thesis regulation costs.

Regulation costs are depending on the difference of Elspot area price and the balance energy price, and if they differ a lot then it possible to have huge losses since the income non imbalanced energy do not necessarily cover the costs of balancing energy.

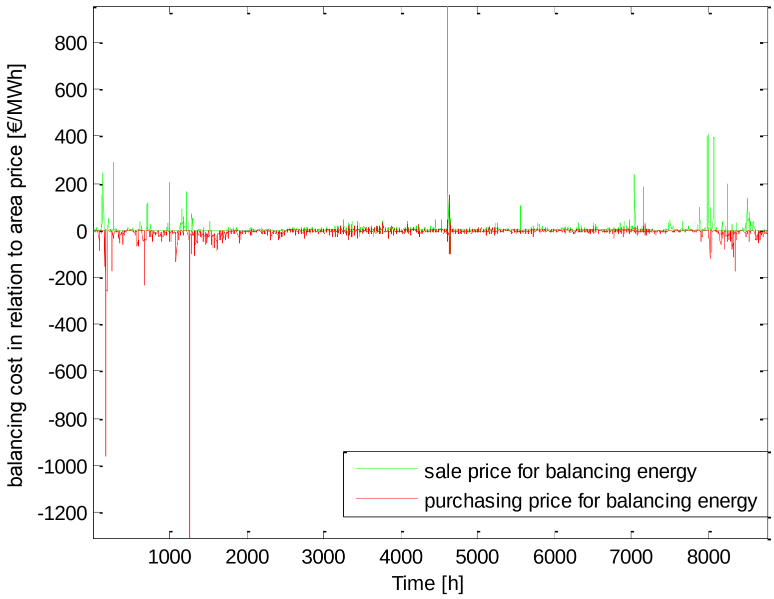

Figure 2.6 Balancing energy prices in relation to Elspot area prices in 2010

For wind power producer the characteristic of this balancing energy prices are crucial since they cannot impact on the amount of produced energy at delivery hour. Also the wind power participants have a relatively more balancing energy than conventional generation.

2.3 Formulating a participant's revenue function

Now that the whole chain from making the bids in the Spot-market and in the financial market to the explanation of regulating mechanism and balancing price formulation are explained. It is possible to create function to describe participant's revenue. Therefore in the following parts a revenue function is created, which describes the revenue of the whole bidding chain to the balance settlement.

2.3.1 *Participating in Spot market*

Participant's revenue function is composed from the bids in the Spot market, and imbalance costs if the actual consumption/production differs from the contracted. In equation (2.1) the participant's revenue function $R_{t+k}$for time *t+k.*

$$R_{t+k} = Elspot + Elbas + IC = \pi_{t+k}^{spot} E_{t+k}^{spot} + \pi_{t+k}^{elbas} E_{t+k}^{elbas} + IC(d_{t+k}^{act}) \tag{2.1}$$

Where π_{t+k}^{spot} is the Elspot price for time *t+k*, E_{t+k}^{spot} is the contracted energy in the Elspot market, π_{t+k}^{elbas} is the Elbas price for electricity, E_{t+k}^{elbas} is the bid energy in the Elbas market with the new consumption prognosis for the time *t+k*, d_{t+k}^{act} is the deviation between actual and contracted energy and $IC()$ is the imbalance cost function. Thus the bid energy in Elbas in other way represented is $\left(E_{t+k|t'}^{pred} - E_{t+k}^{spot}\right)$, where $E_{t+k|t'}^{pred}$ is the new consumption prognosis for time *t+k* made at time t'. Notice that $t' > t$, since Elbas trade starts after the Elspot prices are announced. Imbalance cost for time *t+k* can be posed as:

$$IC_{t+k}(d_{t+k}^{act}) = \begin{cases} \pi_{t+k}^{+} d_{t+k}^{act}, & d_{t+k}^{act} > 0 \\ \pi_{t+k}^{-} d_{t+k}^{act}, & d_{t+k}^{act} < 0 \end{cases} \tag{2.2}$$

Where d_{t+k}^{act} is the deviation between actual, E_{t+k}^{act} and contracted energy. π_{t+k}^{+} and π_{t+k}^{-} are the balance energy prices for buying and selling, respectively. In equation (2.3) d_{t+k}^{act} is represented in function of contracted energy.

$$d_{t+k}^{act} = E_{t+k}^{act} - \left(E_{t+k}^{spot} + E_{t+k}^{elbas}\right) \tag{2.3}$$

Since the balance prices are actually function of area price it would be more convenient to make the revenue function in a form so that the imbalance cost prices are in function of π_{t+k}^{spot}. By doing so it is easier to see how the deviation between actual energy production and contracted energy effects the revenue. In equation (2.4) modified revenue function is represented with a modification of imbalance function, $IC^{*}(d_{t+k}^{act})$, which is now represented in function of π_{t+k}^{spot}.

$$R_{t+k} = \pi_{t+k}^{spot}\left(E_{t+k}^{act} - E_{t+k}^{elbas}\right) + \pi_{t+k}^{elbas} E_{t+k}^{elbas} + IC^{*}(d_{t+k}^{act}), \tag{2.4}$$

where $IC^{*}(d_{t+k}^{act})$ is a function of regulation costs, π_{t+k}^{ext+} and π_{t+k}^{ext-} , which are the differences between spot price and balancing energy prices. In equation (2.5) Imbalance cost function

$$IC^{*}(d_{t+k}^{act}) = \begin{cases} \pi_{t+k}^{ext+} d_{t+k}^{act} = \left(\pi_{t+k}^{+} - \pi_{t+k}^{spot}\right) d_{t+k}^{act}, & d_{t+k}^{act} > 0 \\ \pi_{t+k}^{ext-} d_{t+k}^{act} = \left(\pi_{t+k}^{-} - \pi_{t+k}^{spot}\right) d_{t+k}^{act}, & d_{t+k}^{act} < 0 \end{cases} \tag{2.5}$$

One could think that why the revenue function in equation (2.4) is preferred instead of revenue function represented in equation (2.1), since the revenue function in equation (2.4) seems to be more complicated than the original one. However, modified revenue function is a good way to represent the revenue since if the participant do not participate into Elbas market $\pi_{t+k}^{elbas} = 0$) then the revenue function includes two terms: first term tells what is the maximum possible income, which means that the contracted energy is the same than the generated, $d_{t+k}^{act} = 0$. The last term then represents the costs from imbalances when the contracted energy differs from the generated. In equation (2.6) revenue function for hour *t+k*, assumed that the participant do not participate into Elbas market.

$$R_{t+k} = \pi_{t+k}^{spot} E_{t+k}^{act} + IC^{*}(d_{t+k}^{act}) \tag{2.6}$$

It can be seen that clearly from the Equation (2.6) participant must minimize the imbalance cost term $IC^{*}(d_{t+k}^{act})$ in order to maximize the revenue at time *t+k*. In chapter 4.9 it is shown how a wind power participant can minimize this term by taking into account characteristics of wind power curve and uncertainty of forecasting.

3 Wind power forecasting

Predicting future has been an interest of the humankind since the dawn of time. Hence, people has found the very essential problem of the prediction centuries ago; there is an uncertainty in predictions. This underlying concept is the very gist of the wind power forecasting. How certain we can be about the tomorrows forecast or in statistical terms, what is the *confidence* of the forecast?

The purpose of the wind power forecast, not only provide best estimate of tomorrows power for market participant but to contribute to find a secure and economic power transmission operation. The time frame where wind power forecasting is mostly used is for the next 36 – 72 hours. This time frame is called in terms of wind power forecasting as short-term forecasting. In this time frame the impacts of the intermittent nature of the wind is intended to diminish by first-rate forecasting. Hence, that will give capacity value to the wind energy and the nature of the wind energy is something else than a negative load. Also an accurate forecasting will reduce the productivity gap between wind energy and the conventional generation in the electricity markets.

There are two main branches in the wind energy forecasting; a statistical and a physical. Both of these methods relies to their strengthens: pure physical method trust that by adding more computer power to the forecasting the quality of the forecast will increase, as it does. And the pure statistical method relies to the persistent nature of the wind and trusts that the history of wind power production contains all necessary information about making predictions on future power production. However, most of the commercial applications are hybrids that uses the both the physical and the persistence nature of the wind in making wind energy forecasts. Another way to separate wind energy forecasting is to separate it to 'meteorological' and 'energy conversion' stages. Meteorological stage usually consists forecasting of wind at the specific site, and it is based on Numerical Weather Predictions, NWPs that are provided on a grid in that specific site around the wind turbines with various heights. This operation is also referred as statistical downscaling. The latter stage relates to the energy conversion from wind to the power by modelling the wind park's power curve, which is not a trivial task as it is discussed later. However, each of these stages include a modelling error and hence the wind energy forecast error is a combination of these modelling errors and therefore it is possible to deduce that there must be more weight on the error that happens in the 'meteorological' stage than in the 'energy conversion' stage (Pinson, 2006). It happens to be that the NWP is the biggest single error contributor in the wind energy forecasting. (Monteiro et al., 2009)

Although, that the error source is well known and there have been major progress in NWP-models in last three decades, but as depressive it might sound but there are limits to the predictability of the flow in atmosphere, which can be proved with the chaos theory. Therefore the NWP cannot be 'perfect' in any way and the methods in handling the uncertainty must be given more weight in research. (Monteiro et al., 2009) (Lorenz, 1968)

3.1 Introduction to the wind forecasting

On the following parts basic principles and properties of wind power forecasting are shortly represented.

3.1.1 Nature of the wind generation

Atmosphere is constantly in changing state. The best way to see or feel it is by noticing the fluctuating nature of the wind or temperature by going outdoors. This constantly fluctuating nature of the wind is said to be in other words intermittent. Hence there is a need to use statistical methods to analyse the wind in order to understand its nature with a better understanding.

Wind is a non-stationary process although in many cases in meteorology, wind is assumed to be stationary in a short timescale like 10 min. (Dyrbye & Hanse, 1997). When wind is assumed to be stationary it leads to assumption that it has a mean value and the fluctuations around its mean are zero, in the corresponding time frame. This property of stationary can be very useful. For instance equation for logarithmic wind profile can be derived from the Reynolds-averaged Navier-Stokes equations, which is done by using this imaginary property of wind (Lange & Focken, 2005).

In a time frame of a year wind can be assumed to be Weibull-distributed. Weibull distribution can be explained with two parameters: a scale parameter A_w and a shape parameter k_w. The equation for probability density function of Weibull distribution can be formulated as:

$$f(u) = \frac{k_w}{A_w}\left(\frac{u}{A_w}\right)^{k_w-1} \mathrm{e}^{\left(-\left(\frac{u}{A_w}\right)^{k_w}\right)} \tag{3.1}$$

The two parameters are site depended and hence it is necessary to solve them for each wind turbine site separately from the measured wind data. The measurements must be carried out more than for a year in order to attain reliable parameters. In Figure 3.1 a probability distribution that Weibull distributed where the bins represents the measured wind and the solid red line represents a Weibull fitted data.

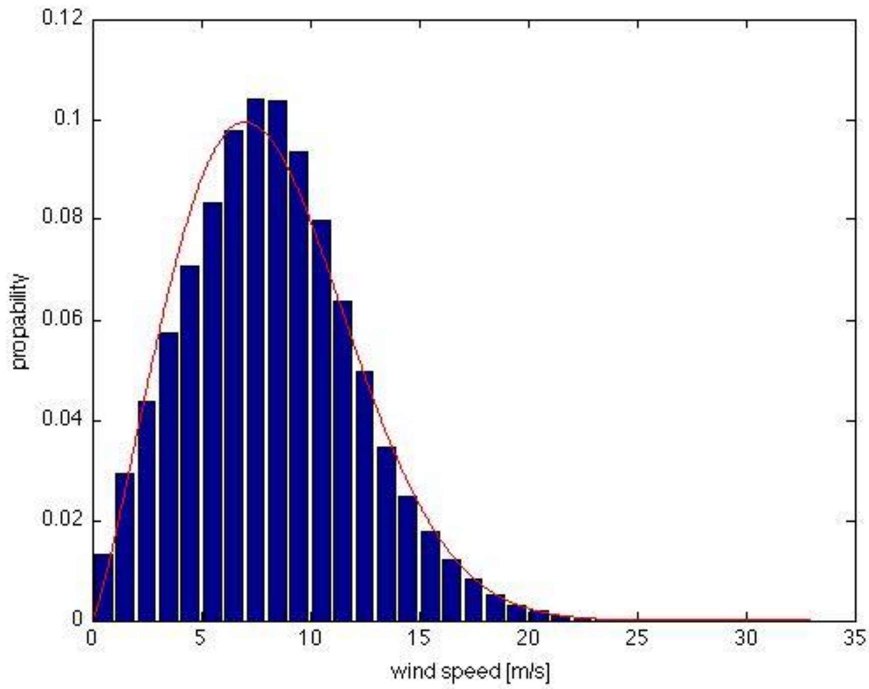

Figure 3.1Measured and Weibull fitted wind data in a Danish site. Scaling parameter A_w is 9,24 and a scaling factor k_w is 2,21

Weibull-distribution is a good tool to have a better understanding of prevailing wind conditions at different turbine sites, so that the turbines can be placed in the appropriate locations.

It can be said that the wind do not produce power, but the turbine does since the wind's kinetic energy transforms to mechanical and eventually for electrical energy in a turbine. Therefore there is always a transformation from wind to power. Wind speed is related to the turbine's output with the following manner:

$$P = \frac{1}{2} c_p \eta_{tur} \rho_{air} A_{rot} u^3, \tag{3.2}$$

Where c_p is the non-dimensional power coefficient, which takes into account the aerodynamic state of the turbine, η_{tur} is the turbine's efficiency to transform mechanic energy to electrical energy, ρ_{air} is the air density, A_{rot} is the area of the rotor and u is the velocity of the wind.

At the first sight the most interesting thing by looking equation (3.2) is that the turbines output is related to the wind velocity in third power. Hence, it gives a lot value for the high wind velocities. This gives a different perspective to examine the Weibull distribution in Figure 3.1. Now the distribution combined with the relation P ~ u^3, gives an actual value for wind energy resource at a site. Without going into too deep inside to the aerodynamics of a wind turbine it can be pointed out that the power coefficient c_p is a function of several variables and it is limited by the Betz limit (c_p equals 16/27). (Hansen, 2008)

Wind energy conversion to the power can be demonstrated with a power curve Figure 3.2. Power curve represents well the non-linear nature of transformation from wind to power. There are three areas in the energy transformation that limits the equation (3.2) to be valid at all the time. First of all, there is a cut-in wind speed where the turbine starts to rotate and produce energy. This wind speed is usually about 5 m/s. When the turbine starts to produce energy it reaches the area where the equation (3.2) is roughly valid until the rated wind speed is reached. In this area where the wind usually fluctuates (see Figure 3.1) the wind turbines power grows with a cubic relation to the power. The rated wind speed is determined by the size of the wind turbine, for instance typical nominal power of a turbine is nowadays 3 MW. The rated wind speed is usually between 12 – 14 m/s. After the rated wind speed the power output of the turbine will stay at a constant level until the cut-out wind speed is reached. The turbine must be shut down because the wind turbine structures will not endure the high forces that the high speeds induces. (Fox et al., 2007)

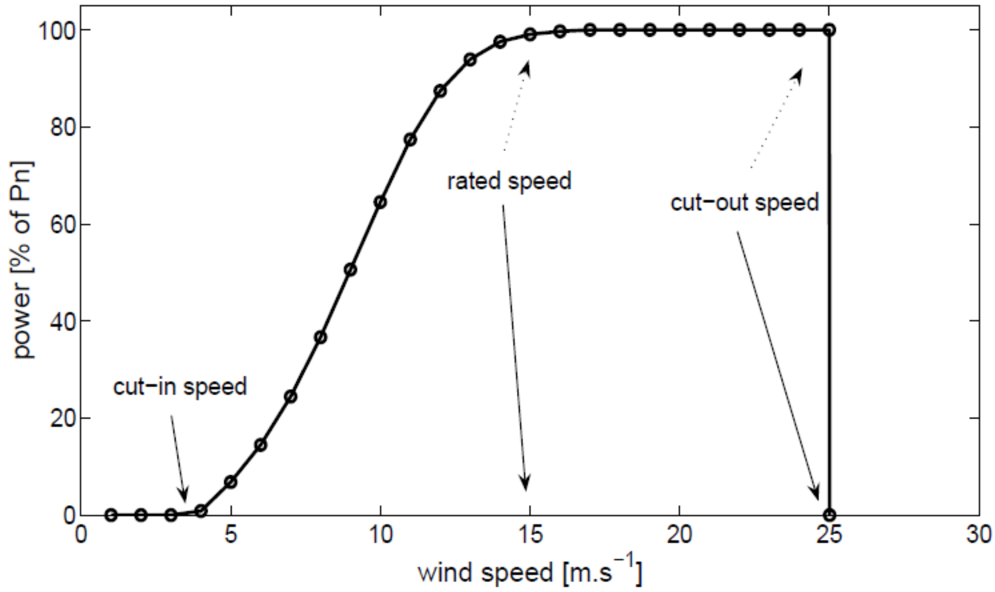

Figure 3.2Typical power curve of a wind turbine. Power is normalised with the turbine's nominal power. (Pinson, 2006)

It can be concluded that wind fluctuates usually in the non-linear part of the power curve meaning that small fluctuations in the wind speed leads to large variations in the power output.

By now it should be noticed that the wind power plant do not work with the nominal power and it is even quite rare that the turbines run with their nominal power. Then how the actual energy that can be harvested from the turbine can be illustrated? There are two commonly used methods: One is by using the capacity factor and the other is to measure wind power penetration. Capacity factor describes the wind turbine's actual output in relation to the situation where wind turbine is producing power with a nominal power. The capacity factor is measured in a time frame, which the user see to be appropriate, for instance the time frame can be quarter of a year, or a year. Capacity factor is a good tool in analysing feasibility of a turbine. The capacity factor, ξ_{tur} of a single turbine can be expressed with mathematical terms:

$$\xi_{tur} = \frac{E_{act}}{E_{max}} = \frac{\int_{t=0}^{t} P_t(t)dt}{\int_{t=0}^{t} P_n dt}, \tag{3.3}$$

where E_{act} is the actual output of a wind turbine in a time frame, E_{max} is the maximum energy of a wind turbine in time frame, $P_t(t)$ is the wind turbine's power at time *t* and P_n is the nominal power of a wind turbine.

The other commonly used factor is the wind power penetration, also called system capacity factor. Wind power penetration describes what is the share of the wind power production from the total electricity production. Wind power penetration is used in describe the power system in a wind power point of view. Wind power penetration can be calculated with the following equation:

$$\xi_{Pen} = \frac{E_{wind}}{E_{system}} = \frac{\int_{t=0}^{t} P_{wind}(t)dt}{\int_{t=0}^{t} P_{system}(t)dt}, \tag{3.4}$$

Where P_{wind} is the electrical system's total wind power production and the P_{system} is the system's total power production. E_{wind} and E_{system} are the corresponding energies in timeframe of t.

For the single wind turbine, capacity factor describes well the wind resources in the turbine site. In example the average capacity factor of a turbine in Ireland measured over one year is 0.36 as in Finland it is 0.2 (O'Malley, 2011) (Stenberg & Holttinen, 2010). Hence, establishing a wind turbine in Ireland yields 80% more energy than a turbine in Finland. The wind power penetration of a system is a key figure describing the effects of a massive wind production to the system. For instance there has been showed correlations between high wind penetration and higher regulation costs (Holttinen, 2004).

3.1.2 Nature of wind to power conversion

One of the most illustrative ways to represent the underlying problem of forecasting wind power is to show how the error distribution changes in the transformation process from wind to power. In Figure 3.3 is represented prediction error transformation from wind to power.

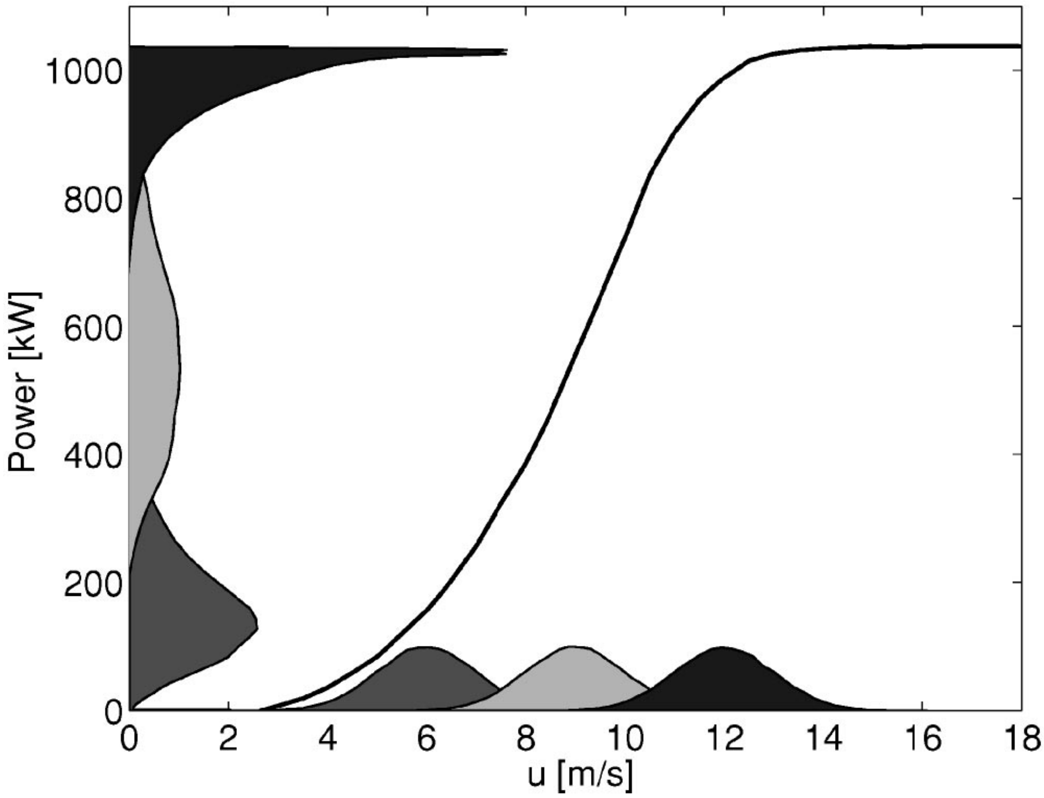

Figure 3.3 Representation of wind to energy conversion (Lange, 2005)

It can be noticed from the Figure 3.3 that the wind prediction error (x-axis) is Gaussian distributed while the output of the wind to power conversion (y-axis) is distributed with a some unknown distribution. This is usually the case as it was proved by (Lange & Focken, 2005) in their field work all over the Germany, where they tested hundreds of turbines sites in order to see whether the wind predictions and power predictions errors are Gaussian distributed or not. They showed with χ^2 -test that the wind prediction errors in one year were 92 % of the sites Gaussian distributed, and in a contrast, the power prediction errors at the same time were never Gaussian distributed. This shows how the non-linear transformation of power changes the nature of prediction error totally and thus difficult the prediction process.

3.1.3 The wind power production at the wind farm or area level

In many cases the analysis of wind energy is more reasonable to rise to the wind farm level, or the area level, instead of analysing single turbines in order to fully understand what is the nature of the wind power. This can done by *Upscaling* the wind power production of the corresponding wind farm or area of interest. It can be done with many ways, but the one of the most illustrative way is to formulate the wind farm power curve, see Figure 3.4.

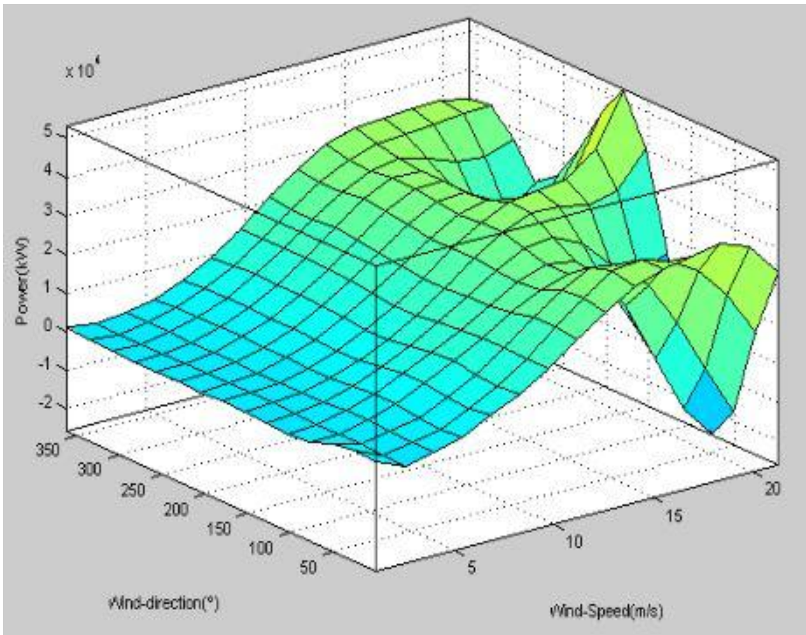

Figure 3.4 Wind farm power curve in function of wind speed and direction (The Anemos Project, n.d.)

The wind farm power curve represents, which is the power produced by the wind farm in a function of wind speed and direction. The wind farm power curve depends greatly on the direction where the wind blows, as it can be seen from the Figure 3.4. This comes from very natural reasons since the area around the wind farm is not symmetric to all directions and there might be obstacles on some wind directions. For instance it can be noticed from Figure 3.4 that there might be obstacles in wind directions 100° (East) and 250° (West) since the power drops dramatically at those points. The other interesting thing is that at the wind farm level the maximum nominal power is almost unreachable if the size of the wind farm is large. It can be notice from the Figure 3.4 that if the maximum power of the wind farm is 50 MW, then the wind farm could reach its maximum output at when the wind blows from south or south-west and the wind speed is more than 20 m/s. Single turbine reaches its maximum power when the wind speed is 12-14 m/s, see Figure 3.2. Therefore the wind direction and thus the surroundings and spatial smoothing have a significant influence on the power production. In the following part term spatial smoothing effect is discussed.

3.1.4 Spatial smoothing effect

One of the most important things when having discussion about the wind power production in system level is the discussion about the spatial smoothing of wind power. Although, that the nature of wind is intermittent and therefore the power production of a single turbine or a small wind farm varies relatively a lot, in large spatial area the harmful wind power fluctuation smoothens when the spatial area grows. The biggest reason behind this phenomenon is that the wind turbines in various spatial locations see different wind conditions at the same time and therefore their power production differs. Also by increasing the amount of wind turbines strengthens the smoothing effect. The smoothening effect causes that the power production in the area is levelled/smoothed and thus the power production is less time at the extremity ends. Therefore it is misleading to think that the wind power production, in a large geographic area goes in a short time frame from 0 – 100 % of the nominal power, but instead it the fluctuations might be in a system level only 20 % of the total capacity and on four hours ahead, 90 % of the time the fluctuations is less than 20 % capacity, as it was showed in (Fox et al., 2007). That study was done in Ireland, where they wanted to see how the wind power production changes over different time frames.

The smoothing effect is proved for instance in (Hasche, 2010) and (Focken et al., 2001) research works. They both prove the smoothing effect of wind power in

Germany with an empirical correlation curve, which was made by calculating the covariance of the wind farms’ wind production data series. In a result, it can be seen from Figure 3.5 that the correlation of wind production is depending exponentially to the distance of wind farms. Hence, in the market participant point of view, if the market participant has possibility to distribute its wind power generation in large spatial area instead of placing them close to each other, it will reduce the prediction error and thus improve its place in the markets.

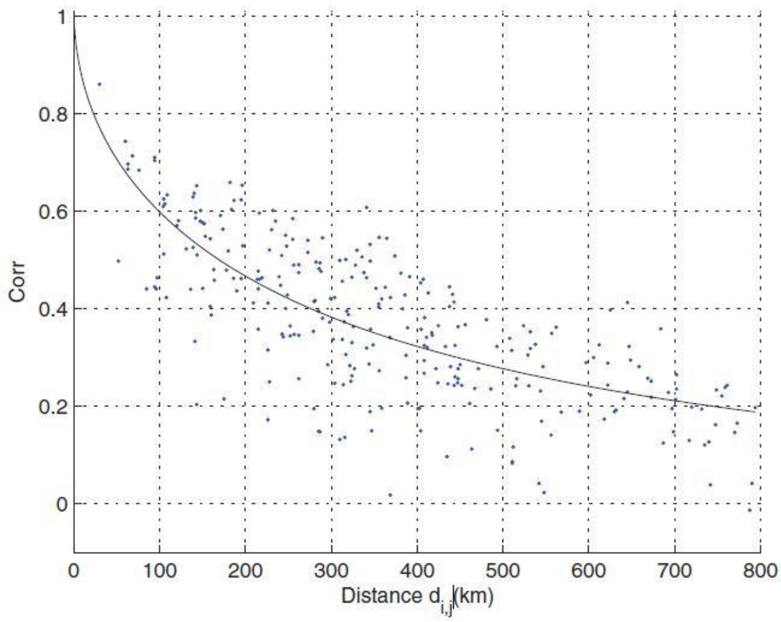

Figure 3.5 Correlation of wind production in function of distance. Dots represents the different correlation among the wind farms and the black solid line is the fitting curve (Hasche, 2010)

The very interesting fact is that the smoothing effect depends more on the size of the area rather than the amount of the wind turbines in the area. (Lange & Focken, 2005) proved in his thesis that if the amount of wind turbines in certain area is increased, and placed them in random places, then the improvement to the smoothing effect is neglected after the amount of turbines exceeds a certain number.

3.2 Formulating a forecast problem

The general problem of the prediction of a variable is to determine what is the future value of that variable when the current and past information of the variable is available. In wind power prediction the variable of interest is power, *p* and its development over time. The history of a variable is always represented with a finite time interval, depending on how dynamic and important are the changes on a variable. In wind power the wind velocities are usually measured as 10 minutes averages, which is sufficient enough to grasp the intermittent nature of the wind. This sampled wind data is characterized in statistical terms as discrete non-stationary and nonlinear time series. This means that the wind speed evolves over time without any particular mean value or variance. The nonlinear nature of power is that the development of the power cannot be described with linear models as it is described in (Lange & Focken, 2005). The nature of wind power data is bounded from zero power to the nominal power, so that the wind power fluctuates within this interval.

Forecasts has to be made with a conditional manner: 'With the given dataset and with the used prediction model, what would be the power, *p* at time *t'*. This kind of a forecast is called as a point forecast. This is the most typical way to produce forecasts, since many of the forecast users need the point forecast in their field, i.e. the electricity brokers need to make an offer to the markets. The other way to make forecasts is to generate probabilistic forecasts, which is a quite opposite way to make forecasts if they are compared against point forecasts. Probabilistic forecast can be formulated as: 'With the given dataset and with the used prediction model, the power at the time *t* is within the interval, *[a b]* with a confidence level α'. Hence, the probabilistic forecast does not give any single value but instead of that they give probability intervals with different probabilities. However, point forecast and probabilistic are linked to each other - probabilistic forecasts are usually centred around the point forecast. In other words the point forecast must be on the centre of a probabilistic distribution, which is the median of a distribution. In chapter 4.9 this phenomena is illustrated more carefully.

3.3 Numerical Weather Prediction

The purpose of numerical weather prediction is to model the non-linear state of the atmosphere. In general, there is an analytical solution to the state of atmosphere, however in order to solve the state with reasonable accuracy, numerical models must be used. Numerical models are based on the fundamental mathematical equations that describe the dynamics of the movements and processes that takes place in the atmosphere. The fundamental dynamical equations are: the horizontal momentum equations, the hydrostatic equation and the continuity equation. Solving of these equations is a dynamic problem, which requires taking into account the evolving of meteorological parameters, as the simulation runs forward. (Houghton, 2009) (Fox et al., 2007)

All the atmospheric phenomena that occur in the real world as we see it needs to be mapped on a discrete three-dimensional computation grid in order to model it. Due to limited computational capacity the resolution of this discrete grid must be finite. Hence, there is a finite horizontal resolution and also a finite number of vertical levels where the state of the atmosphere is modelled. Therefore, for particular grid size there will always be a sub-grid scale process that the model cannot solve, which means that the variables calculated at each grid point are average the values over the grid point representing the most likely state of the atmosphere in that grid point. These constraints give a demand for multiple models, which have various resolutions and cover different spatial areas, due to limit of computational power. Therefore, the commercial NWP models can be either global or limited area models. Global models try to capture the development of the synoptic weather phenomena with a quite coarse resolution ranging from 100 x 100 km^2 down to 50 x 50 km^2. (Lange & Focken, 2005) In Figure 3.6 The numerical grid of a global model is represented. Limited area models try to model local weather phenomena in higher accuracy by taking into account the local orography and higher grid resolution.

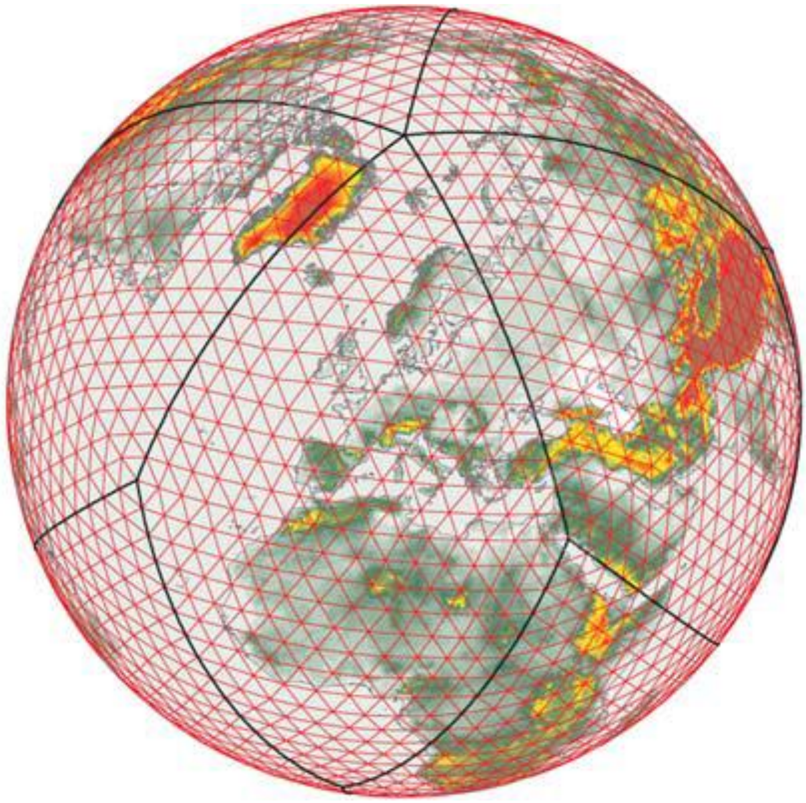

Figure 3.6 Numerical grid of the global model (GME) with spatial resolution of 60 x 60 km^2 (Giebel et al., 2005)

Setting up the boundary conditions where the simulation gets its initial point is a complicated problem. In a global model it requires gathering measurement data from radiosondes, buoys, surface stations, commercial aircrafts and multiple satellite platforms, see Figure 3.7 (WMO, 2010). The amount of measurement data is massive although the measurements network is more tighter in the western society countries leaving large areas virtually unobserved. This lack of knowledge of the present state of the atmosphere leaves a place for an uncertainty and a question: How to establish the initial state with the limited amount of data. The problem is solved by using data assimilation and data assimilation methods as 3D-VAR and 4D-VAR. These methods use a variation approach to optimize the initial state, often assimilating observations along a time window (Monteiro et al., 2009). More information about data assimilation for instance in (Järvinen, 2003).

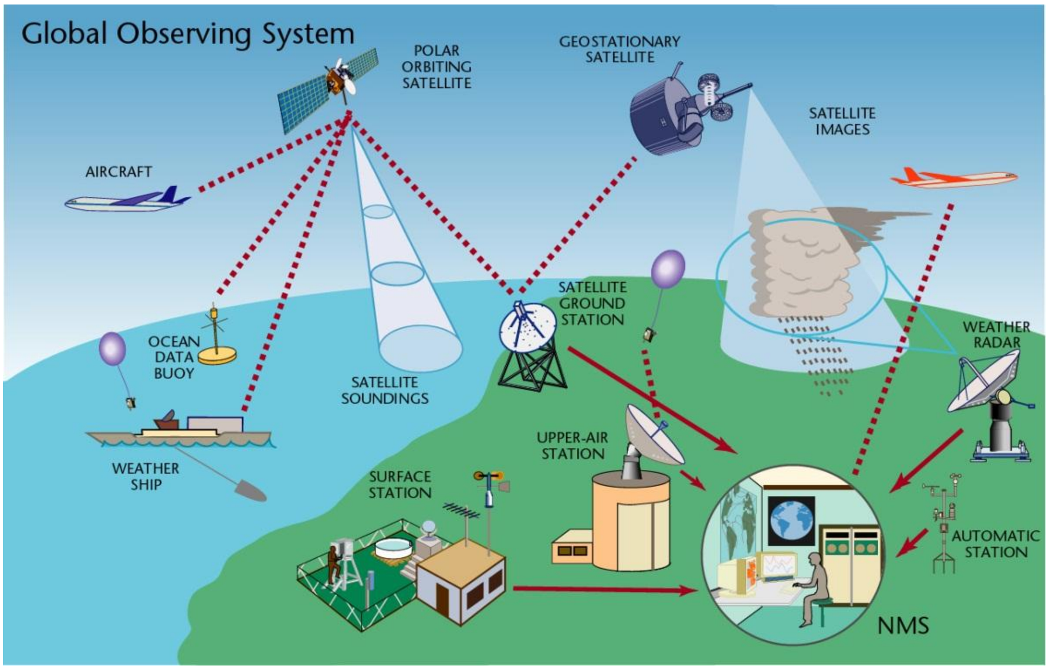

Figure 3.7 Global observation system (WMO, 2011)

The limited area model is usually nested inside of the low resolution model, so that the higher resolution model receives boundary conditions from the lower resolution model. In Figure 3.8 The Danish Meteorological Institute (DMI) HIRLAM (*High resolution limited area model)* domains. The domain that has a bigger coverage is HIRLAM-G, which covers the hole Europe and most of the northern America. It has a horizontal grid resolution 48 km and update interval of 90 s. The boundary conditions for this model comes from the ECMWF (*European Centre for Medium scale Weather Forecast*) global model for every six hour. Inside of the HIRLAM-G domain is nested HIRLAM-D, which covers Denmark and parts of Germany and also parts of the northern Europe countries. This model receives the boundary conditions from the HIRLAM-G model and it has a horizontal resolution of 5.5 km and time step of 30 s (Giebel et al., 2005). This how the higher resolution models with more frequent updating are nested inside of the lower resolution models with a less frequent updating time. By doing so, it is possible to decentralize computational power and also permit the models focus on the different scale of weather phenomena.

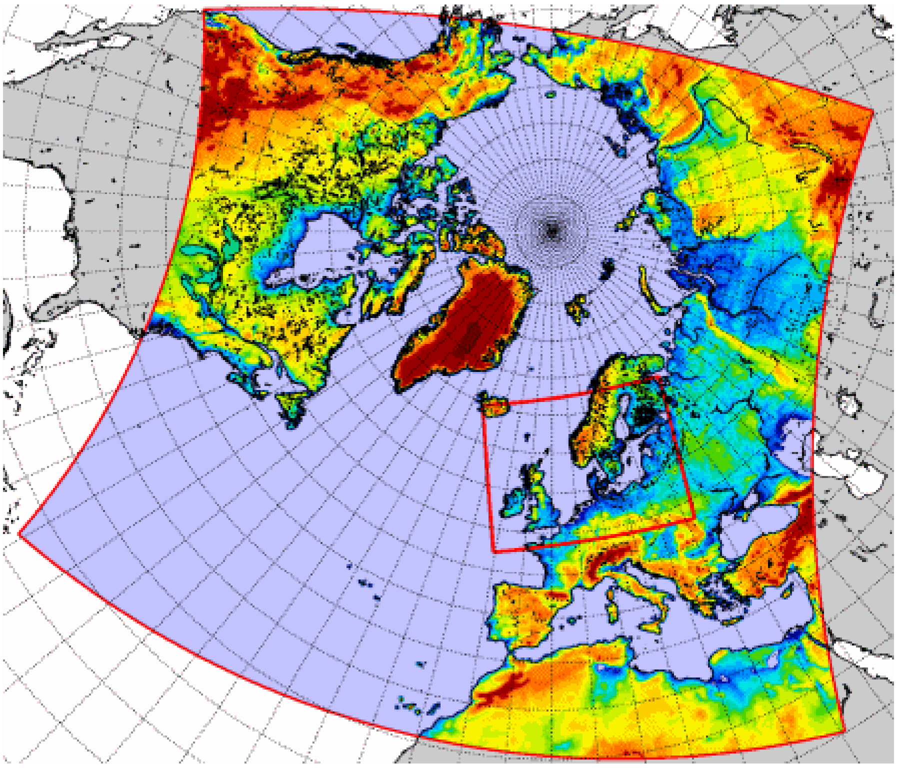

Figure 3.8DMI-HIRLAM domains (Giebel et al., 2005)

As a result it can be stated that although the huge progress that is happened in NWP in few decades it is still sadly true that the NWPs includes an error marginal that is sufficient to complicate integration of wind power to the power system and markets. The influence of this error is great since in many wind power forecasting systems NWP is one of the major inputs. Therefore, if there is a great uncertainty how the winds at a turbine site will development, it is quite certain that the wind power forecasting system will provide forecasting information based on false assumptions. This leads to the conclusion that in wind power forecasting the NWP is the biggest contributor to the forecasting error.

However the progress in achieving better NWP system is constantly in progress and the requirements for improved NWP are: Better atmospheric models, better observation network and better methods for data assimilation. (Fox et al., 2007)

3.4 Physical approaches of wind power forecasting

Since the NWP provides the wind forecast information in a grid size of approximately 5 - 10 km^2, it is clear that the NWP provides the most likely or average wind speed at that grid. Therefore, it is obvious that the wind conditions may change a lot inside of the grid since the local characteristics of a site. Also the placement of the wind turbines is usually optimized by taking into account the local orography, like hills or canyons so that the wind speed at the hub height is maximized and thus it differs from the average wind speed that the NWP provides. Hence, the main idea of the physical wind power prediction approach is to refine the wind field at the turbine site by using more detailed information of the area of interest. The detailed information may include information about the local orography, roughness or obstacles in a site. There are two alternative methods how to distinguish physical wind power forecasting: first, the models that are based on the logarithmic wind profile and geostrophic drag law, and secondly, the models that use computational fluid dynamics, CFD to refine the wind field at the area of interest. (Pinson, 2006) (Lange & Focken, 2005)

The other step in physical wind power forecasting is to transfer wind prediction to power prediction. This is usually done with a theoretical power curve that is provided by the wind turbine manufacture, see Figure 3.2. It might also be done with an empirical power curve especially in the case if the wind power prediction is upscaled to the wind farm level and the power production of a wind farm is modelled with power curve. (Pinson, 2006)

Physical prediction systems can be very sensitive to a systematic error. The power curve might overestimate or underestimate the real power production or the local roughness might be too large leading to underestimating the real power production. However, many commercial physical prediction system uses statistical methods to remove the systematic error. Therefore, Model Output Statistics, MOS is used for post processing the power forecast. The commonly used method to post process the data is to use linear regression, which can remove the systematic part of the error (Lange & Focken, 2005). In Figure 3.9 the main steps of a typical physical wind prediction approach.

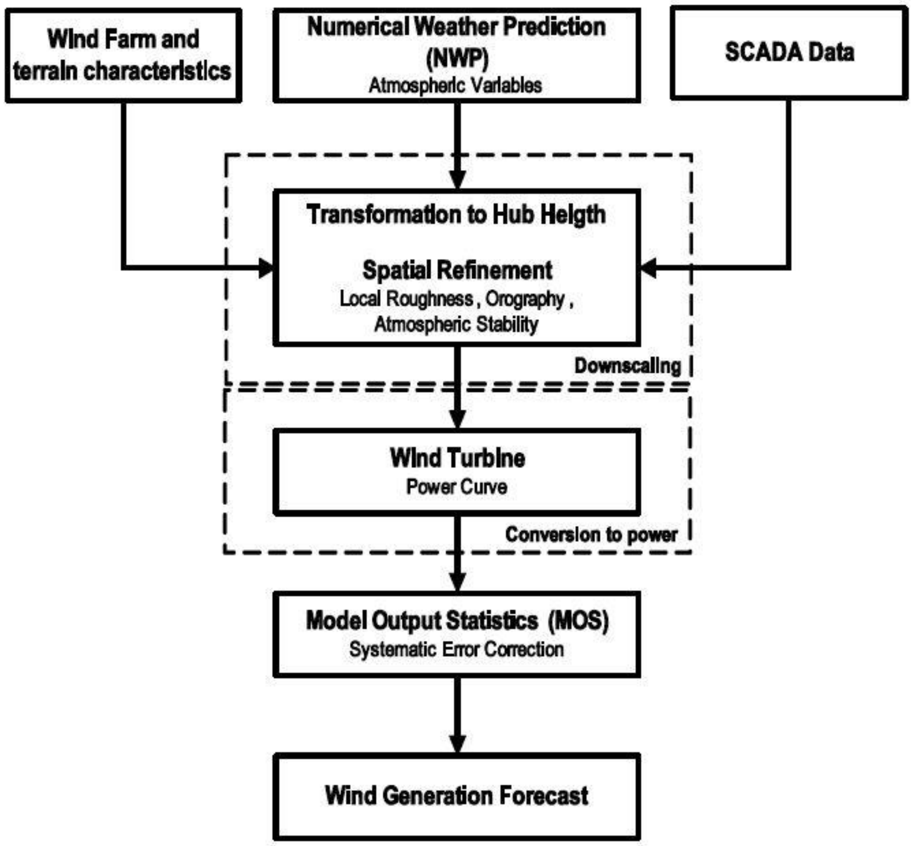

Figure 3.9 The main idea in physical forecasting (Monteiro et al., 2009)

3.5 Statistical approaches of wind power forecasting

The basic idea of the statistical approach is to use historical values of the power and power prediction, and also historical values of other explanatory variables can be used, and use those values as a reference to determine the development of wind power production. Some statistical models need to be 'taught' in order to attain models, which adapt in different meteorological situations. The training of a statistical model is carried out with a training set which includes the historical information of actual and predicted power and also historical information of other explanatory variables. By running this training set, the parameters of the model can be optimized so that the model's output corresponds the power production with the best possible manner. The optimization is done with minimizing a loss function that describes the models performance. The loss function is usually a function of prediction error, $e_{t+k/t}$ that can be calculated as following:

$$e_{t+k/t} = p_{t+k} - \hat{p}_{t+k/t} \tag{3.5}$$

The most typical loss functions that are used to minimize the prediction error are the absolute error and squared error loss function, which are represented in equations (3.6) and (3.7), respectively.

$$L_{abs}(e) = \sum_{t=0}^{N} c_1 |e|, \tag{3.6}$$

$$L_{quad}(e) = \sum_{t=0}^{N} c_1 e^2 \tag{3.7}$$

With c_1 and c_2 being constants. Typically minimizing the quadratic loss function gives better result in wind power prediction because it gives more weight on the larger errors. One of the main problems is to choose appropriate explanatory variables, which explain the development of the power production. There are also auto-adaptive models, which tunes the model parameters during the operation in order to reach optimal performance. (Pinson, 2006)

The statistical prediction models can be separated into structural and black-box models. The structural models are based on the model's creator expertise on the field that creator is modelling. In example, in wind power prediction models creator tries to model nature's phenomena by adding structures to the model, which consider these phenomena. For instance model's creator can add some structures, which consider the diurnal variations of wind, or makes a model that includes changes in the terrain roughness, or takes the dust on the rotor blades into account and its effects on the power production (Pinson, 2006) (Madsen, 2011). Black-box models instead of structural models are artificial-intelligence based models like Support Vector Machines, SMV or Neutral-Networks, NN, which both are self-learning models that use the model's artificial-intelligence on predictions and make the decision based only on that. Therefore these methods do not know anything about the physical phenomena that are underlying behind the wind power production.

Typical statistical approaches relies a lot on the persistence nature of the wind, therefore the statistical approaches performance really well in the time horizon of less than 5 hour.

3.6 Defining the quality of forecasting

As mentioned before, forecasts always contain an prediction error because of the chaos in atmosphere, therefore it is impossible to achieve a perfect wind power forecast. However, the forecast does not need to be perfect since the purpose of a forecast is to provide information to users that have a different sensitivities to the different magnitudes of the prediction error. Some forecast users need forecasts just to have an idea what is the magnitude of the of the variable of interest, and some users are very sensitive to the prediction error, like small electricity markets participants with a lot of wind power. Although, the forecast users sensitivity to the forecast error differs a lot, it still leaves a question, what is a good and bad forecast. Different forecast users have a different sensitivity to the forecast error and it is clear that the quality of a forecast is not easy to define, thus it is hard to define whether the forecast is good or not.

There are methods to discuss how good the forecast really is. In (Murphy, 1993) was showed that there are three kinds of goodness of forecast. Firstly, there is correspondence between forecasters' judgements and their forecasts, which is called *consistency*. Consistency of a forecasts is that the forecast always represents the forecasters' true intentions. Meaning that the forecasters' have the best knowledge of the meteorological event, and the consistency measures how unanimous the forecasters' judgements are with the predictions. For instance, in weather situations that are easier to predict, like big high pressure fronts, the consistency in those events is bigger than for weather phenomena that are more dynamic like low pressure systems (Lange & Focken, 2005). The second kind of goodness is *quality*, which measures the correspondence between forecasts and observations. It is measured with several statistical methods that serve both the evaluation assessment of the prediction and with more extent, the decision making process. Some of these statistical quality assessment methods are represented in the following chapter 3.6.1.1. Finally, the last type of goodness is the forecast's *value* to the people that uses the forecast. The value of the forecast is depending a lot on the application where the forecast is used. Hence, the users may give many different kind of requirement to the accuracy of the forecast depending on the value that they give to the accurate forecast. All these three types of goodness has also a dependency of each other, like it was shown in (Murphy, 1993) that the level consistency depends linearly to the quality and value, but the consistency relation to the quality has a non-linear dependency (Murphy, 1993).

Evaluating the accuracy of the forecast requires that the power production observations at the site of interest are available. Nowadays, SCADA (Supervisory Control And Data Acquisition) is quite popular among in collecting data from wind turbines. Usually the data is available on wind farm level, but also it is common to have information in wind turbine level also. Although, that the data is available, it is important to give attention to the data itself: how reliable the data seems to be. This phase's importance cannot be overestimated in analysing the quality of a prediction for obvious reasons, since if the data which is used in evaluating model's accuracy is incorrect, the conclusions are also incorrect. Hence, every analysis of the prediction model accuracy must begin from the analysis of the observation data.

3.6.1 Evaluation of different forecast methods

The evaluation of the forecast depends greatly on the type of the forecast. Evaluating a point forecast is really straight-forward thing, since the forecast can be evaluated to the measurement at the time. The evaluation can also be done against a reference model, which is discussed in the chapter 3.7. As a result of evaluating a point forecast it is possible to represent curves, where the different error types can be illustrated in function of look-ahead time. Evaluating period is typically long, more than a year in order to have preferable results. Then the error in different look-ahead times is represented as the average errors.

The other way to evaluate forecast is to use probability distributions of predictions and turn them into prediction error distributions. This is the most effective way to understand the effect of the power curve to the prediction error, as well as influence of the other explanatory variables to the prediction error. This method is widely used in state-of-the art prediction methods in decision making process as well, since it gives an opportunity to handle the uncertainty of the prediction.

3.6.1.1 Evaluating point forecasts

It is important to distinguish different prediction models by their accuracy. There are number of different statistical methods to analyse how well the model performs. Hence, it is easier to compare different models by using these measurements of accuracy. Also by measuring accuracy of a model it can be noticed how accurate the model actually is. For instance it could be very convenient to say, which is the average prediction error at different look-ahead times. The evaluation of the point-forecast starts by defining the error at different look-ahead times, which can be formulated as in Equation (3.5). It can be noticed from the Equation (3.5) that if the prediction error is positive then the model underestimate the power production and on the other hand if the error is negative the model overestimates the power production. In many cases this prediction error is normalised with the nominal power of the turbine, or turbines, depending on the interest.

The most obvious way to measure error is to calculate the mean error over the whole evaluation period with different look-ahead times. This error measurement is called *bias* and it also represents the systematic part of the error, which is discussed later.

$$bias_{t+k|t} = \bar{e}_k = \frac{1}{N}\sum_{t=1}^{N} e_{t+k/t} \tag{3.8}$$

The other version the bias is to take absolute value of it. It is called mean average error, MAE, which represents the average error but do not tell is the model over- or underestimating the actual power. In equation (3.9) MAE of the prediction.

$$MAE_{t+k} = \frac{1}{N}\sum_{t=1}^{N} \left|e_{t+k/t}\right| \tag{3.9}$$

It would also be a good idea to give more weight to the bigger error, therefore the widely used error measurement is mean square error, MSE, which gives more weight to the larger errors.

$$MSE_{t+k} = \frac{1}{N}\sum_{t=1}^{N} \left(e_{t+k/t}\right)^2 \tag{3.10}$$

However, MSE is not so used since it is more difficult to represent because the units of the actual error differs from the actual error. Hence, the more used error measurement is the root mean square error, RMSE, which gives more weight to the larger errors and also represents the error in same units as the actual error. In equation (3.11) RMSE of the prediction (Fox et al., 2007)

$$RMSE_{t+k} = \sqrt{MSE_{t+k}} = \sqrt{\frac{1}{N}\sum_{t=1}^{N} \left(e_{t+k/t}\right)^2} \tag{3.11}$$

There is also an alternative method for illustrate squared error type. It is called standard deviation of errors, SDE and it is given by

$$SDE_{t+k} = \sqrt{\frac{1}{N-1}\sum_{t=1}^{N}\left(e_{t+k/t} - \overline{e}_k\right)^2} \tag{3.12}$$

Now that the all typical error types are represented, the prediction error can be separated into systematic and random components. Systematic component measures if the model under- or overestimates the wind power production in different look-ahead times. Bias measures only the systematic part of the error, which illustrates whether the model systematically predicts the future falsely or not. So in the ideal model the systematic part of the error should be zero and there should not be any correlation between the errors on different look-ahead times. However this is not the case for most of the models. Random part of the error should be ideally *white noise*, which is Gaussian distributed with zero mean. The random part of the error is measured by SDE. In contrast, both systematic and random parts of the error contribute to the values of MAE and RMSE. (Pinson, 2006)

The RMSE can also be decomposed for different parts like (Hou et al., 2001) showed in their research. This error decomposition could give the real contributor of the RMSE. Also the decomposition of RMSE showed that there are limits in reducing the RMSE by post processing the prediction with MOS, which was proved by (Lange & Focken, 2005). They manage to show that the decomposition of RMSE could give valuable information of the performance of the model and see where the actual source of error is.

3.6.2 Model Output Statistic

The purpose of MOS is improve prediction accuracy by removing the systematic part of the prediction error. The MOS correction is made by post-processing the data. Very straightforward way to implement this post-processing is to use linear transformation of the predicted values such that offset of the mean systematic error is reduced and thus the accuracy of the prediction is improved.

The bias and standard deviation of the bias are very sensitive to a linear manipulations of the time series. In the following equations a linear MOS is presented. The linear transformation is based on the following equation where the predicted value, x_{pred} is transformed with the help of two constants α and β.

$$\dot{x}_{pred} = \alpha x_{pred} + \beta \tag{3.13}$$

The parameters α and β can be chosen by minimizing the RMSE of the linear transformation. In Equation (3.14)

$$\arg min_{\alpha,\beta} \sqrt{\sum \left(\alpha x_{pred} + \beta - x_{meas}\right)^2} \tag{3.14}$$

The above condition lead to non-ambiguous solutions for α and β, Equations (3.15) and (3.16). (Lange & Focken, 2005)

$$\alpha = \frac{\sigma(x_{meas})}{\sigma\left(x_{pred}\right)} r\left(x_{pred}, x_{meas}\right), \tag{3.15}$$

where $r\left(x_{pred}, x_{meas}\right)$ is cross correlation coefficient between predicted and measured time series.

$$\beta = \bar{x}_{meas} - \alpha \bar{x}_{pred} \tag{3.16}$$

The implications of this transformation is that the bias becomes zero and since the RMSE in minimized the RMSE of the prediction should be lowered.

3.7 Reference prediction models

The reference prediction models are used to evaluate advanced prediction models and see whether they could manage to improve prediction accuracy. The reference models need to grasp the nature of the wind power and also be simple enough to implement. There are two major reference models that are used to evaluate other models: first one is the persistence model and the other one is mean climatology. Persistence model is based on the assumption that predicted power is the same as the last measured value of the power, which can be stated as:

$$\hat{p}_{t+k/t} = p_t, \qquad (3.17)$$

Where $\hat{p}_{t+k/t}$ is power prediction for time *t*+*k* made at time *t* and p_t is measured power at time *t*. Hence, the persistence model is a model that is based on the idea that the error for wind speed at infinite short time interval ahead is zero and therefore the power output do not change. Also the nature of the wind favours this persistence model since the changes in a mesoscale weather phenomena, which drives the surface layer winds, are quite slow. For example fronts that passes over Europe takes more than one day to pass by. Therefore the persistence model is really hard to beat in short look-ahead times up to five hours. The general formulation of a persistence model is to take into account not just the last measured value of power but the mean value of *N* last value, equation (3.18) (Pinson, 2006)

$$\hat{p}_{t+k/t}^{MA} = \frac{1}{N}\sum_{i=0}^{N-1} p_{t-i}, \qquad (3.18)$$

where $\hat{p}_{t+k/t}^{MA}$ is the forecast for the time *t*+*k* made at time *t*. (Pinson, 2006)

The other commonly used reference method is to use mean climatology value, which is the average wind speed at the site. It can be calculated by using equation (3.18) and allow the sample size *N* to go infinity or at least use all available history values of power production. It is not a dynamic model by any reason, so it can be rather inaccurate with short look-ahead times. On the other hand it performs much better with longer look-ahead times than the persistence model. (Pinson, 2006)

There are also other reference models, which are more advanced and combines the good qualities of the persistence and mean climatology models, so that the reference model could perform rather well in all look-ahead times. This is a good idea, since it would be more illustrative to compare different advanced models to the reference model that performs well. However, many of these advanced reference models requires a training set to function properly and therefore the they are more complicate to implement. Hence, the most used reference model is the persistence model since it is so easy to implement. (Fox et al., 2007)

The most illustrative way to analyse improvement of an advanced prediction against reference model is to plot different evaluation criterion on different look-ahead times. These evaluation criterion, *EC* could be either MAE, RMSE or SDE. The improvement by implementing an advanced prediction model can be also calculated by using the equation (Fox et al., 2007)

$$Imp_{t+k,ref}^{EC} = \frac{EC_{ref,t+k} - EC_{t+k}}{EC_{reft+,k}} \tag{3.19}$$

3.8 Uncertainty in wind power forecasting

The wind power forecasts are traditionally provided in a form of point forecasts. Mostly because that they were easy to understand and also they seem to be trustworthy enough. The uncertainty estimation in wind power is a rather new phenomenon and it is just begun to got stand in forecasting just couple decades ago. This come from the forecast users who have noticed the usefulness of the uncertainty information.

There are tens of ways to implement the uncertainty information to the forecasts. One is to use definitions, which were used in (Pinson & Kariniotakis, 2009) so that the uncertainty can be added to the forecast by either using a skill forecast based on risk indices or either using a probabilistic forecast. In the following chapters these two complementary methods are shortly illustrated with their shortcomings and advantages.

3.8.1 Foundations of the wind power uncertainty

In complement to the point forecasts of wind generation in short time frame, say for the next 24 hour, uncertainty intervals can provide valuable information about the online performance of the given prediction method. Prediction model analysis methods that were represented in the previous chapter give information about the performance of the model in a long time period, since they average the performance of the model. However, if there is a need to know what is the forecast uncertainty of a given forecast in a given time, then the traditional statistical evaluation methods are not good enough. The underlying idea in deriving probabilistic predictions is that the uncertainty should be greater on medium power range in comparison to the low and high power ranges.

The problem is solved in the state-of-the-art forecast methods by representing the *interval forecasts*. These forecasts can tell in relation to the point forecast, which interval the forecasted values lies in pre-defined probability level. Such an interval can give valuable information about the accuracy of the point prediction. In order to understand the prediction accuracy, two different intervals can be distinguish by (Pinson, 2006): confidence intervals and prediction intervals. Confidence interval measures the confidence of the estimated point forecast from the target distribution whereas the prediction interval measures the accuracy of a point forecast. In Figure 3.10 these different intervals are illustrated in a probability density curve, pdf of a prediction. Dark shaded area represents the confidence interval, where the *mean* is the mean value of the probabilistic distribution and *prediction* is the prediction of that mean. The measured power at that prediction time is *measure*, which is shown in the figure in black thick vertical line.

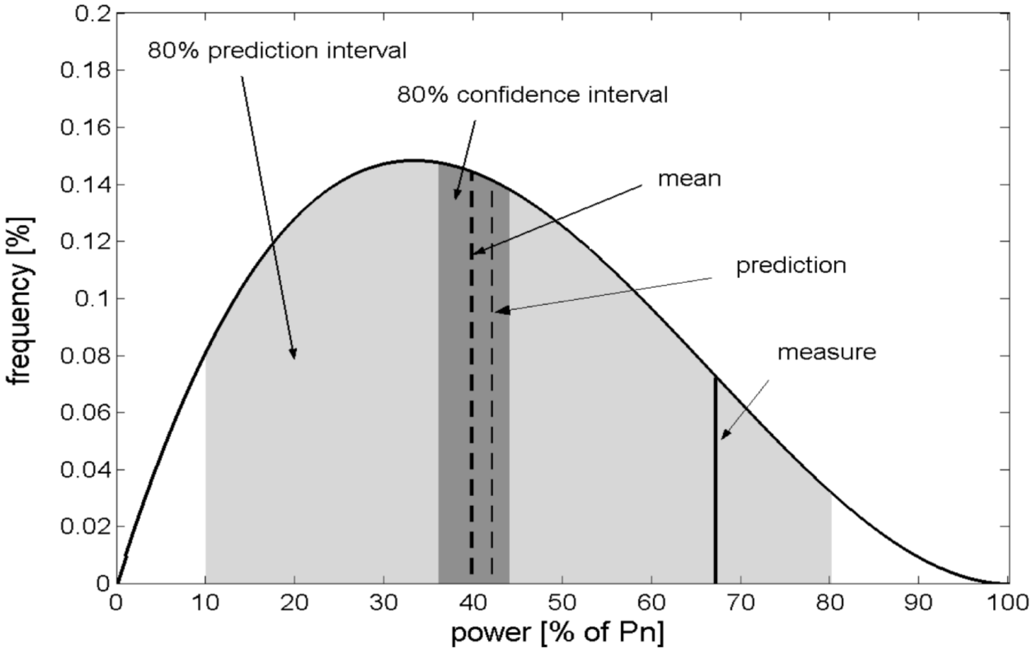

Figure 3.10 Difference between confidence interval and prediction interval in probabilistic prediction.

3.8.2 Methods deriving the Interval forecast

As a phenomena, interval forecast are a brand new thing in wind power generation. Most of the methods that provide probabilistic interval predictions have developed in the 21st century. A difficult subject in deriving wind power forecast is that the nature of the wind power is non-stationary, nonlinear and also bounded. Therefore one cannot make any assumptions how the prediction error is distributed as it was mentioned in previous chapters. One of the first state-of-the-art method in interval prediction designed prediction is based on the fuzzy inference model. This model can produce conditional error distributions by using help of forecast conditions that are in form of probability distribution. The basis of this model is that it evaluates the past performance of the model by analysing the error distribution with adapted resampling method, which uses an idea that more information can be derived from the data if the sample of data if is cleverly ran certain number of times. This method is excellent in a sense of that it could be integrated in top of every point forecast method, since it evaluates the past performance of the model in creating probabilistic forecasts. Also this method is non-parametric, which means that it does not make assumptions how the prediction error is distributed. Therefore, this method can lead to really good results, since it is really hard to say how the wind power prediction error is distributed as (Lange & Focken, 2005) showed. The result of the previously mentioned method to do interval forecasts is shown in Figure 3.11

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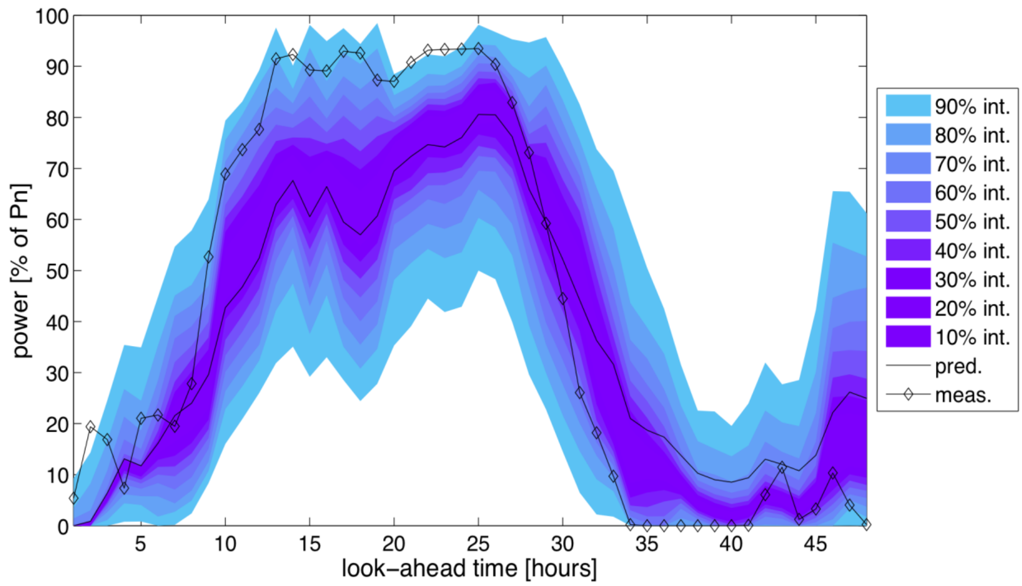


Figure 3.11 Typical interval forecast representation

The Interval forecast in Figure 3.11 is created from intervals, which represents different nominal coverage rates. It means that in a long run inside 90 % nominal coverage rate interval, there should be only 10 % of the time forecasted values that lies outside of that interval. Another name for this interval forecast is quantile forecast since the forecast is formulated from probability quantiles, which create probability intervals. Therefore, probability interval formulates from the upper and lower boundaries and the area between these boundaries. It can be seen from the Figure 3.11 that the uncertainty is greater when the forecasted power is in its medium range in comparison to the uncertainty when the forecasted power is at low level. This comes from the nature of the power curve as it was discussed in chapter 3.1.2. Another thing is to notice that the method produces forecasts that are centred around the median of the predictive distribution and not on the median of the probability distribution.

3.8.3 Ensemble forecasting

It is important to remember that not all of the wind prediction error comes from the prediction model, but one of the major error sources in wind prediction still comes from the NWP system. The error in NWP originates from outcome that behaviour of some weather phenomenon are really hard to predict. For instance, there is a clear difference in predictability between low pressure system and high pressure system. Therefore, the accuracy of NWP is greatly influenced by that and by using ensemble forecasting it is possible to know beforehand how predictable a weather phenomenon really is. Hence, the result of an ensemble forecast analysis is to see how predictable the weather is. In practice there are couple commonly used ways to create ensemble forecasts. Of course many of the methods can only be implemented where the NWP is created, but there are methods to do ensemble forecasting without NWP providers help, as it is discussed later in this chapter. The most popular methods to provide ensemble forecasts are represented in the following paragraphs.

Maybe the most popular way to create weather ensembles is to do it where the predictions are made – the place where the NWP is created. Such ensemble forecast is made by running NWP models multiple times with different initial conditions and researching how the outcome varies with a different initial conditions. Also the NWP provider could change between different NWP runs the numerical atmosphere model in order to achieve prediction ensembles. In parallel to the ensemble forecast or perturbed forecast, the unperturbed forecast is created with the best estimate of the initial conditions and created with the numerical model that is usually used in operational use. From the largest NWP providers both ECMWF and NCEP provides ensemble forecasts with a different properties. ECMWF runs ensemble forecast twice a day with a 50 perturbed members where NCEP runs the ensemble forecast with 11 perturbed members (Giebel et al., 2005).

A multi-scheme ensemble forecast is that the model is run with the identical data inputs but the data assimilation techniques or numerical integration schemes or physical parameterisations are varied. Depending on the choices the ensemble members are created (Giebel et al., 2005).

The multi-model ensemble forecast is to use different NWP providers (NCEP,EMWF,DW) operational forecasts as an ensemble members to create ensemble forecast (Giebel et al., 2005).

The last, but certainly the most simplest way to implement ensemble forecast is to use poor man’s ensemble. It is done by using NWP forecasts with a same lead time but issued at different times. Therefore, these forecasts are obtained with different initial conditions by using the model. For instance poor man’s ensemble forecast can be implemented to ECMWF, which is run every 24 hours for the next 7 days. Therefore there is a 72 hour period where all these 5 different time origins forecast overlap each other as it is represented in Figure 3.12 (Giebel et al., 2005) (Pinson, 2006).

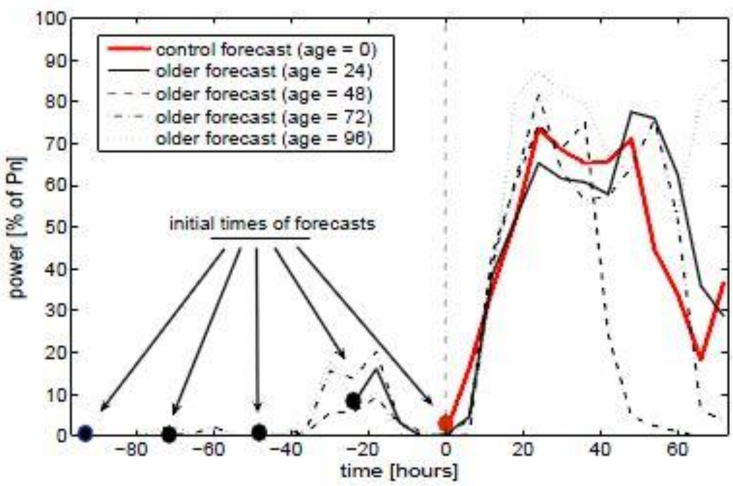


Figure 3.12 Poor man’s ensemble forecast with 5 ensemble (Pinson, 2006)

The evaluation of an ensemble forecast can be done by evaluating the variance of the ensemble members and creating a skill index depending on it, as it is done in (Pinson, 2006). When the variance is small and the distribution of the ensembles members is tight, it means that the weather phenomena at that time is quite predictable, see look-ahead times 0-20 h in Figure 3.12. On contrary, if the ensemble members are spread in a wide area it means that there is a great uncertainty in the weather phenomena, as it is possible to notice from Figure 3.12 look-ahead times 40-72 h.

4 Optimal trading of wind power in electricity market

Trading wind power in the electricity market requires prediction model that predicts the level of wind power in the delivery hours. The purpose of a prediction model is to minimize the prediction error, $e_{t+k/t}$ by giving the best estimate of the variable of interest. In the simplest case the predicted power is assumed to stay at the last measured value, this prediction model is also known as the persistence, which properties are more discussed in the chapter 3.7. However, the prediction accuracy of the persistence model is quite poor in prediction horizons larger than seven hours ahead, therefore in this thesis some measurements are taken to create a model which could provide point forecasts that exceed the accuracy of persistence on every look-ahead hours. The proposed prediction model is a statistical model, which is divided into two parts: first the power curve part that models the wind farm power in function of wind direction and wind speed, as it is shown in Figure 3.4, and secondly the regressive part, which takes into account the persistence nature of wind.

After formulation of the prediction model one could use it for placing the bids to the electricity market by using appropriate inputs to the model. This would lead to a revenue, which would be gained with the minimum prediction error, since the model tries to minimize prediction error. The maximum revenue would be then obtained if the balancing energy costs for up and down regulation would be the same. However, the balancing energy costs are always imbalanced as it was shown in Table 2.2 and Table 2.3 in Finland, which means that the maximum revenue will not be gained by minimizing the prediction error but instead placing bids with a more carefully and thus minimizing the regulation costs. Therefore, a generic way to find the optimum bid is created by taking account the imbalance in balancing energy costs and it will be shown that the revenue will be bigger by using the optimal bids instead of using point forecast as bids. In Figure 4.1 flow diagram of deriving optimal bids is represented. The steps that the flow diagram shows are used in the thesis and they will be presented in the following chapters finally ending with the complete forecast model, which can derive forecast error minimizing bids and optimal bids.

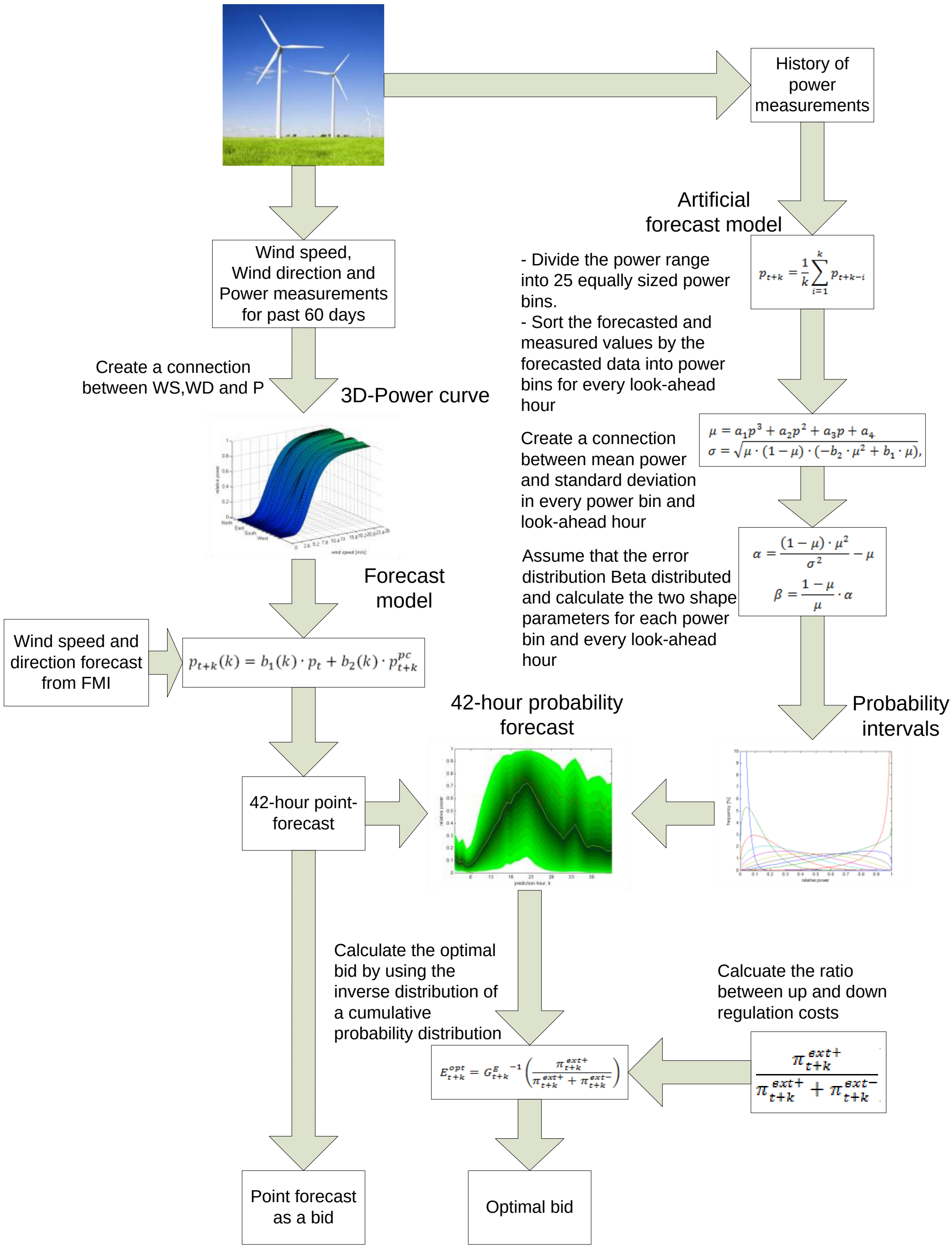


Figure 4.1 Flow diagram of making forecast error minimized bids and optimal bids.

4.1 Mathematical methods

In this chapter the main mathematical methods and tools are briefly represented. For more description of the methods one must look for the references.

4.1.1 Non linear least-squares

Least squares, *LS* problems, which tries to model exponential behavior are a bit more difficult to model than the linear behavior LS -problems. In this thesis, the model is an exponential model, which is required to solve by using nonlinear optimization methods. In the thesis, LS- problems are solved by using trust-region reflective algorithm, which is a powerful yet quite simple optimization method. A trust region method formulates a region around the current search point, where the quadratic model for the local minimization is trusted to be correct, and steps are chosen to stay within this region. The size of the region is modified during the search. Trust region problem can be formulated with following way around the current search point, x_k (MathWorks, n.d.).

$$q_k(s) = f(x_k) + \nabla f(x_k)^T s + \frac{1}{2} s^T H_k s, \tag{4.1}$$

where s is a trial step computed by minimizing the objective function q, which reflects the behavior of function f in a neighborhood *N* around the point x_k. H_k is a Hessian matrix in the current search point (MathWorks, n.d.). Typically, the trust region is assumed to be an ellipse such that $\|Ds\| < \Delta$, where D is a diagonal scaling matrix and Δ is the trust region radius.

4.1.2 Beta distribution

Beta distribution is in probability theory and statistics a continuous probability distribution, which is defined on the interval from zero to one. Beta distribution can be formulated by using two shape parameters α and β, and its probability density function is:

$$pdf(x) = \frac{1}{B(\alpha, \beta)} x^{\alpha-1}(1-x)^{\beta-1}, \tag{4.2}$$

where $B(\alpha, \beta)$ is a beta function, which can be formulated as a following manner

$$B(\alpha, \beta) = \int_0^1 x^{\alpha-1}(1-x)^{\beta-1}dx, \tag{4.3}$$

It is possible to notice that the beta function is the integral of the numerator part of density function, which normalizes the pdf on the interval [0,1].

Cumulative distribution function, CDF of a beta distribution can be formulated by using the ratio of an incomplete beta function and a beta function, see equation (4.4). Incomplete beta function, $B_x(\alpha, \beta)$ differs from the equation (4.3) beta function only with its integral limits: it is integrated from 0 to *x*.

$$CDF(\mathrm{x}; \alpha, \beta) = \frac{B_x(\alpha, \beta)}{\mathrm{B}(\alpha, \beta)} \tag{4.4}$$

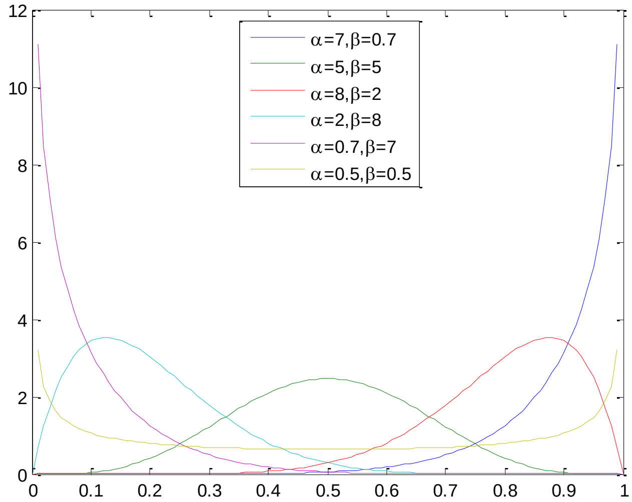
Other distribution's properties such as beta distributions mean, μ and variance, σ^2 can be calculated with equations (4.5) and (4.6), respectively.

$$\mu = \frac{\alpha}{\alpha + \beta} \tag{4.5}$$

$$\sigma^2 = \frac{\alpha \cdot \beta}{(\alpha + \beta + a) \cdot (\alpha + \beta)^2} \tag{4.6}$$

As it is possible to notice from the equations above, both beta distributions mean and variance can be explained with the shape parameters, which is a quite convenient property of beta distribution.

From Figure 4.2 it is possible to see how the change of shape factors affect the shape of the beta distribution pdf. Also it is possible to see how the change of shape factors reflects to the mean and variance of a distribution. One could notice by looking at the distributions in Figure 4.2 that the shape of beta distribution can vary a lot, thus it can describe many different distributions as uniform distribution, Gaussian distribution and exponential distribution.



	μ	σ²
α=7,β=0.7	0,909	0,01
α=5,β=5	0,500	0,023
α=8,β=2	0,800	0,015
α=2,β=8	0,200	0,015
α=0.7,β=7	0,091	0,01
α=0.5,β=0.5	0,500	0,13

Figure 4.2 Properties of beta distribution with different values of α and β.

4.2 Analysis of the wind farm data

The wind farm of interest in this thesis is Raahe's wind farm in south-west Finland, which consists five 3.2 MW wind turbines. All of the turbines are located at the coast, which usually provides the best possible power at a site. The data was provided by wind energy organization Hyötytuuli and it consists wind farm data from January 2008 to September 2011. The sample frequency of the data is 10 minutes, which means that the amount of data points is more than 150000. The variables that are used in this thesis are wind speed, wind direction and wind farm's output power. The wind is distributed with the following Weibull distribution at the site, Figure 4.3. The mean wind speed at the site was 6.39 m/s, which is a really good mean wind speed for a Finnish site. The maximum wind speed is 24.5 m/s, which is really close to the cut-off wind speed of a wind turbine.

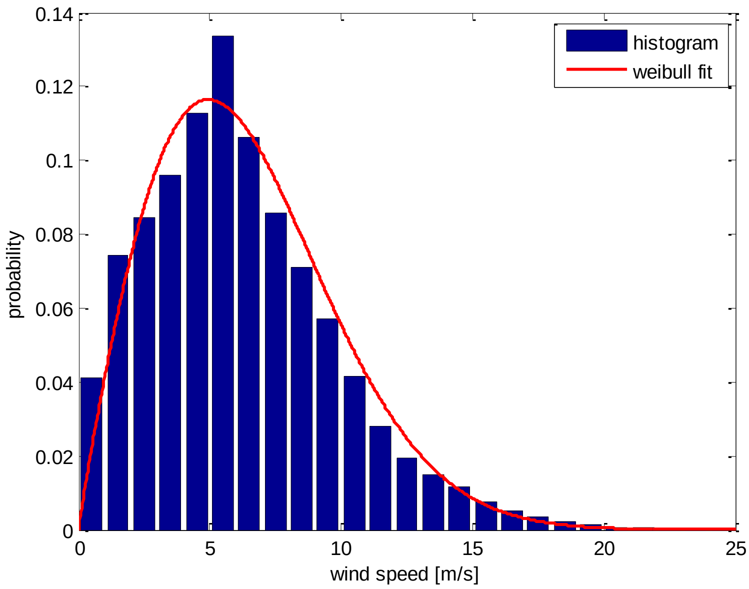


Figure 4.3 Weibull distribution of wind and the Weibull fit.

Wind rose, which illustrates the distribution of wind direction at the site is represented in Figure 4.4.

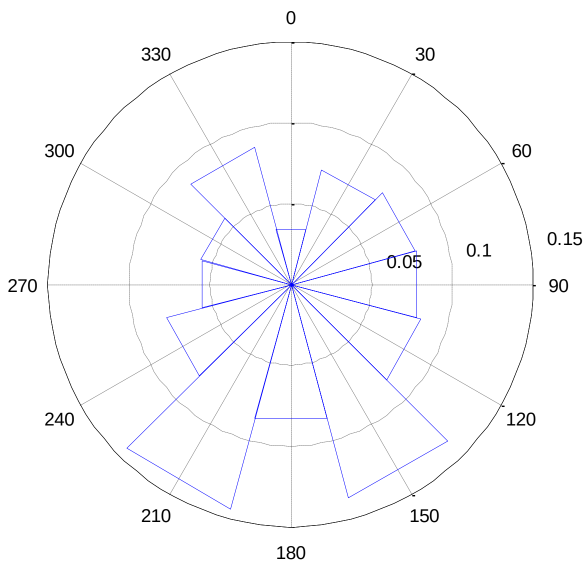


Figure 4.4 Distribution of wind direction

The figures above are merely distributions with mean values. However the winds at the site are changing all the time. There are daily variation in wind, especially in the wind speed and also the wind is varying through the seasons. Therefore, the wind rose, as well as the histogram of wind speed changes its shape all the time. The wind rose also explains that the dominant wind directions are from south-east or south-west, which means that the wind turbines are usually turned into that direction. The dominant wind direction is important to know since from that direction it is possible to harvest more energy than the other directions. Also, if possible wind turbines should place in a manner that the dominant wind directions are obstacle free and thus the flow of wind is undisturbed. In Figure 4.5 the energy distribution of the wind farm from different wind directions.

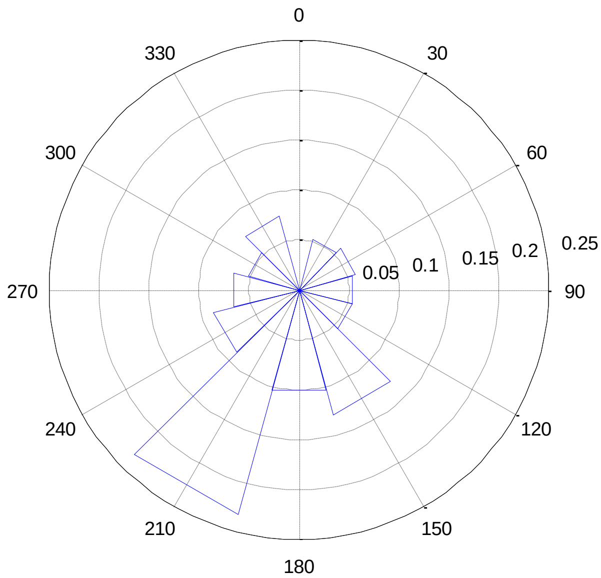


Figure 4.5 Energy rose of the site

It can be noticed from the figure above that almost 25 % energy comes from south-west, which was the other dominant wind direction and also is the dominant wind direction in Finland (WindAtlas, 2011). The other dominant wind direction on the site was from south-east, see Figure 4.4. However, the turbines are sited at the west cost of Finland, which means that the continent is located on the south-east. Roughness of the continent is much higher than the ocean's and therefore the wind that are coming from the continent are much lower than the winds, which are blowing from the ocean, which can develop freely. For this reason winds from south contains almost as much as energy than winds from south-east. Although, it is more than twice as likely to have wind blowing from south-east than from south.

4.3 Hourly and daily correlation of power

There are many natural phenomena behind the wind, which usually are periodically since the earth is turning around its axel in constant time and the earth is also revolving the sun in a specific time. This causes some dependence to the wind on different time windows. For instance, there might be some dependence on a daily level or an annual basis. In Figure 4.6 the mean wind speeds in different quarters of a years 2009 and 2010 are represented. It can be noticed that on average the nights are much windier than the days. It can be seen clearly that when the sun rises in the morning, mean power decreases and stays at the lower level. There are also some quarterly variations in the wind speed. In 3rd and 4th quarters wind speeds seem to be much stronger than the other two quarters. This means that autumn and early winter seems to be good time for wind power.

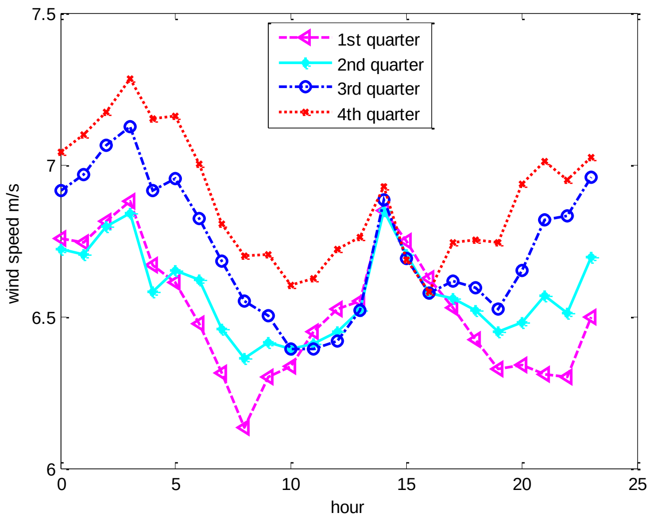


Figure 4.6 Correlation of hourly power in different quarters of in years 2009 and 2010 The time scale is UTC time

Although, that the nature of wind is intermittent and the atmospheric boundary layer is very turbulent at a time, wind has also a persistent nature. In Figure 4.7 sample autocorrelation of the wind energy data with different lags. It can be seen that there is a strong correlation of wind power lags up to 10 hours. Especially lags up to 5 hours the autocorrelation coefficient is more than 0.7, which shows how strong the correlation really is. When the lag time is increased the correlation coefficient seem to diminish exponentially approaching zero.

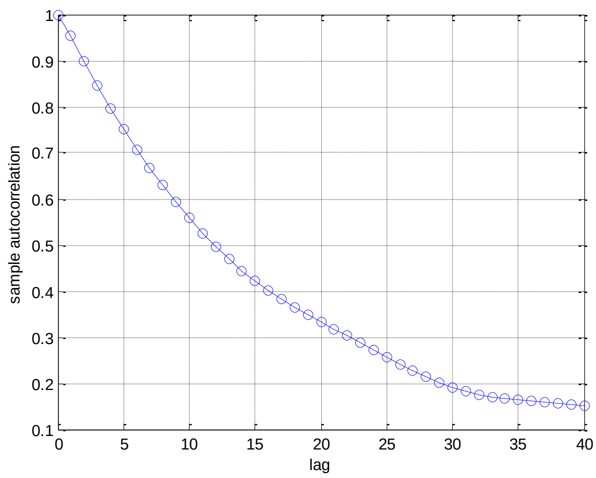


Figure 4.7 Autocorrelation of wind power with different lags. The unit of lag is one hour.

By understanding the natural phenomena behind the wind power and wind itself, it is possible to draw conclusions of nature of wind power. By understanding these phenomena it is possible to use them to model wind power's behaviour and thus create prediction models, which could predict more accurately to the future.

4.4 Data from FMI

FMI runs their NWP model several times in a day: 6 a.m., 12 p.m, 18 p.m. and 12 a.m. UTC time. Nordic electricity market closes at 11 a.m. UTC time, which means that the forecast that is made at 6 a.m. must be used in order to use forecast data in the prediction model.

The prediction horizon that the FMI provides is 42 hours with a resolution that is varying from one hour to three hours. However, in this study hour resolution is needed, therefore linear interpolation is used to values, which resolution is three hours in order to have prediction data, which resolution is one hour. However, the FMI can offer prediction data starting at 6 a.m UTC time and the prediction horizon covers every hour of the next day, which is the main purpose. In the Figure 4.8 wind speed and direction forecast provided by the FMI.

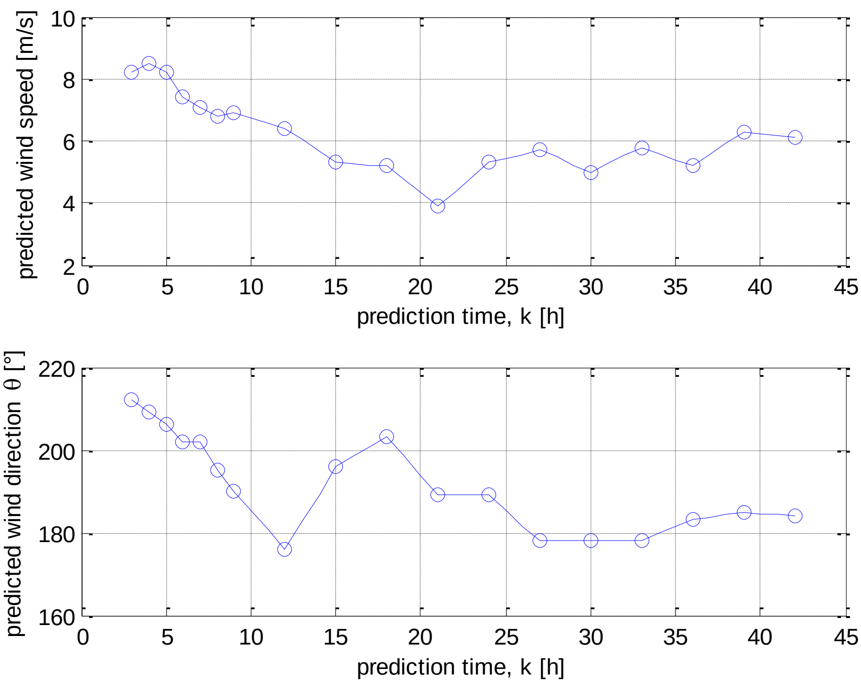


Figure 4.8 Prediction of wind speed and wind direction by FMI. Circles represents measurement points and the line between them is the linear interpolation curve.

4.5 Prediction model

The basic idea in statistical prediction is to fit a model function to actual data and thus it can provide wind power predictions on different time horizons. In this thesis the modeling is carried out in two steps: firstly so called *power curve* model is created, which can describe the connection between wind speed, wind direction and power production. The latter step is to create time varying model where wind farm power value at time *t* is considered with the prediction of power curve model.

4.5.1 Modeling power curve

Power curve model is created by fitting the power curve model function, $p^{pc}()$ to the history data of wind speed, wind direction and power production in a horizon of N_{hor}. Fitting the data to the model creates a relationship between power, wind direction and wind speed. The power curve model that is used in this thesis is double exponential model, which is shown in equation (4.7)

$$p_{t+k}^{pc}(\theta) = a_1(\theta)e^{-a_2(\theta)e^{-a_3(\theta)\cdot u_{t+k|t}}}, \tag{4.7}$$

where constants $a_1(\theta), a_2(\theta)$ and $a_3(\theta)$ are model's constants in function of wind direction θ and $u_{t+k|t}$ is a *k*-step wind forecast made at time *t*. The power curve model is also known as Gompertz function, which conveniently reminds wind turbines power curve. The basic idea is to fit the model to the history data of wind speed, direction and power by using nonlinear LS- algorithm in function of wind direction. As a result, the LS-fitting will provide best estimates of the model parameters, which describe the connection between wind speed, wind direction and power. In Matlab it is possible to fit a data, which behaves with a nonlinear way by using *lsqnonlin*- function, which makes a LS- fit by using the trust region method that was represented in chapter 4.1.1.

Wind is usually blowing from a dominant wind direction, while other wind directions are much rarer, which means that the amount of fitting point is scare on some directions and thus the model cannot create reliable fit. For that reason the model is fitted in 30° sectors in order to have more data points to fit the model, which leads to a more reliable prediction model. However, if the number of data points is scare and the fitted data points are close each other, it is then really difficult to model the power curve. The difficulty is caused by the fact that reliably fitting needs values all over the power curve in order to have a accurate fit.

Therefore, fitting horizon, N_{hor} must be long enough to have sufficient number of fitting points, which are hopefully scattered on a wide range of power values. One could now ask why not to use all of the history data to model a power curve. There is a down side in the long fitting horizon, it does not take into account small changes that happens in the wind farm site as: the blades are getting dirty, which diminish the power production, wind turbines need to be maintained and wind conditions varies through the year. Therefore, the length of fitting horizon must be a compromise of a well adaptive model and a accurately fitted model. In this thesis a value for N_{hor} 60 days, which equals 7200 ten minutes samples, which takes into account the seasonal effects of the wind and some of the changes that happens in the wind farm and affects the output power. From the Figure 4.6 it can be seen how the wind changes during different seasons. This two months history information also provides sufficient number of data points to each sector to fit the prediction model. In Figure 4.9 example of fitted power curves with measured values in two different 30 degree sector.

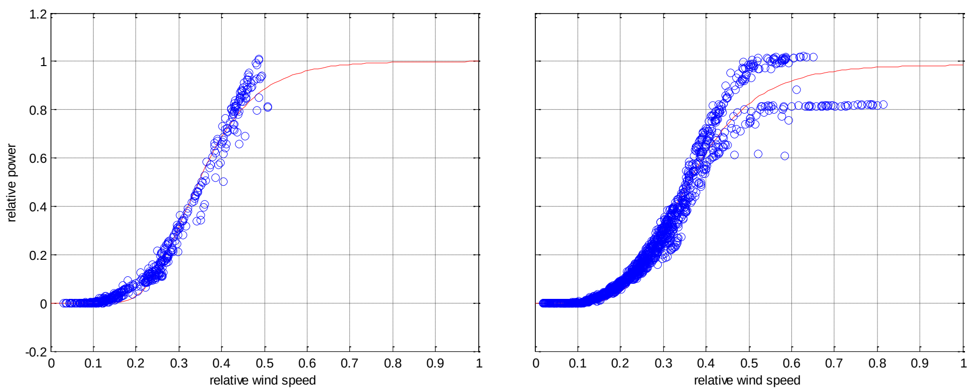


Figure 4.9 Fitted power cueve model with a red line and measurements with the blue dots in two different 30° sectors

It is possible to notice from the figure above that the quality of the fitted power curve can vary in comparison to the measured values. On the left hand side of the Figure 4.9 the measured power values fits quite well to the model, but on the right hand side it is possible to notice that for some reason one of the turbines stop producing power when the wind speed grows. Therefore the measured power divides into two different branches and the fitted power is a compromise between these two different branches of power. One could weight last measured power values and thus have a better estimate of future power values, but in this thesis this was not considered. However, in the both cases the measured power values are distributed in a wide power range, which makes it possible to have a reliably fit. After the measured power and wind values are fitted to the model function to the rest of the 30° sectors, then it is possible to see how the wind power varies in function of wind speed and wind direction. In Figure 4.10 3-dimentional power curve.

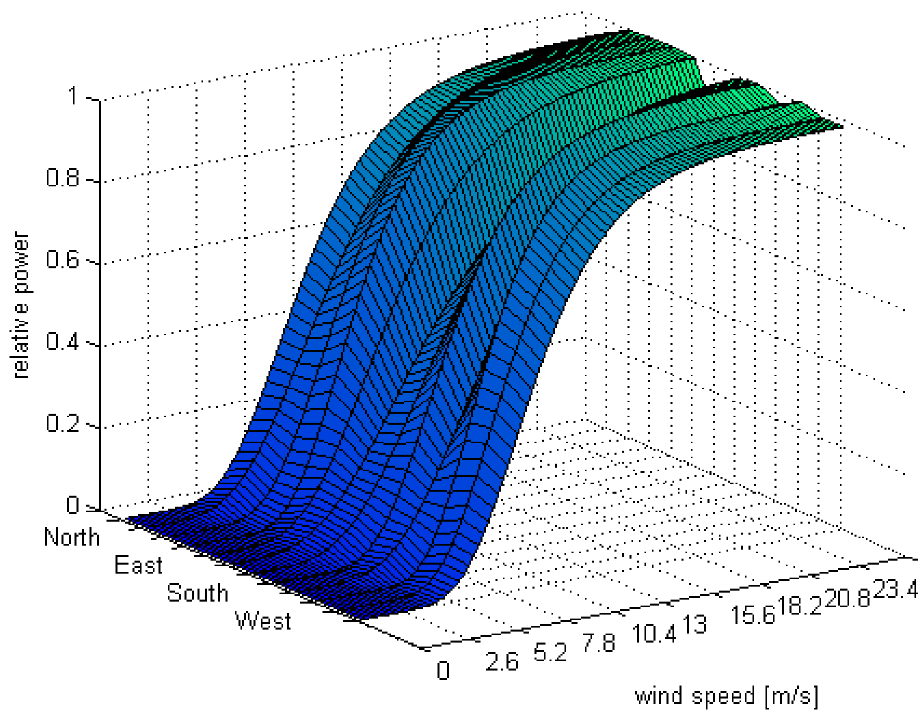


Figure 4.10 3-dimentional power curve.

It is possible to see from the Figure 4.10 that the power curve varies depending where the wind blows. It seems that on some direction there might be some obstacles so that the wind farms power output is decreased in comparison to the sectors, which are next to them.

The power curve estimation is carried out ones in a day, when the Finnish meteorological institute, FMI provides wind forecast at 6 a.m. UTC time and this forecast data is used as an input in equation (4.7) to have a power curve estimate of the wind farm power for each delivery hour.

As a down side, the power curve do not take into account situation when the wind speed reaches the cut-off wind speed, which is illustrated in Figure 3.2. However, it will not lead to a significant source of error since only 0.05 % of the time wind speed exceeds 22 m/s, which is a value when a turbine might shut down.

4.5.2 *Estimation of the prediction model's parameters*

The nature of wind is intermittent but still it has a persistence character. Even though there is always a wind to power transformation in wind power forecasting, which amplifies the small changes in wind to the larger deviations in the power, but still the persistence forecast model performs well in the short prediction hours. This means that there is a strong correlation between measured power at time *t* and measured power values up to 7 hours ahead as it is possible to see from the Figure 4.7. Therefore, it is reasonable to include power values p_t to the prediction model when forecasting k-step ahead. In equation (4.8) the prediction model, which includes power values p_t besides the power curve estimate, p_{t+k}^{pc}.

$$p_{t+k}(k) = b_1(k) \cdot p_t + b_2(k) \cdot p_{t+k}^{pc} \tag{4.8}$$

The weight of each term is assumed to have a non-linear relationship and the constants $b_1(k)$ and $b_2(k)$ are solved with adaptive LS- fitting for each prediction horizon separately. The adaptive LS- fitting process with an exponential weighting can be expressed as in Equation (4.9).

$$\begin{bmatrix} b_1(k) \\ b_2(k) \end{bmatrix} = \arg min \sum_{s=t+k}^{1+k} \left[\lambda^{s-t} \cdot \left(p_s^{meas} - b_1(k) \cdot p_{s-k} + b_2(k) \cdot p_s^{pc}(u_{pred}, \theta_{pred})\right)\right]^2, \tag{4.9}$$

where λ is a forgetting factor $(0 < \lambda \leq 1)$. The exponential weighting allows to give less weight to older observation and eventually fade them off. Notice that the sum is calculated from *t + k* to *1 + k*, where t > 1.

A proper value for a forgetting factor can be found by varying the λ from 0.99 to 1 and calculating forecasted values for each values of λ. Then the squared error can be calculated for each values of λ and the value, which gives the minimum sum of squared error is chosen. The squared error is calculated by calculating the mean of RMS prediction errors on each prediction horizon and then calculating the sum of those means, see equation (4.10)

$$RMSE(\lambda) = \sum_{k=1}^{42} \sqrt{\frac{1}{N} \sum_{t=1}^{N} \left(e_{t+k/t,\lambda}\right)^2} \qquad (4.10)$$

In Figure 4.11, where the sum RMSE in function of λ is shown, it can be seen that the minimum RMSE is obtained when λ equals 0.98. This value is therefore used in the further study. Forgetting factor could also be solved with a more robust manner, but again, the point of making this forecast model is not to make a state-of-the-art model but rather have a good estimate of the future wind power production.

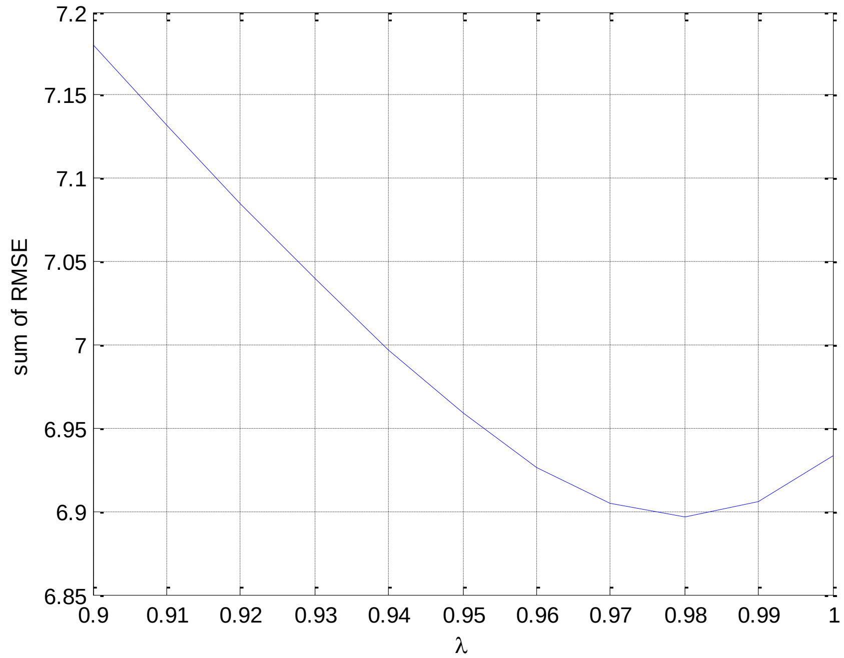


Figure 4.11 Sum of RMSE in function of forgetting factor

When the λ is chosen then the effective number of past values, T_0 can be calculated with the following formula:

$$T_0 = \frac{1}{1-\lambda} \tag{4.11}$$

As a result the effective number of past days is 50, which makes sense since the changes in the seasons takes time and the weather can be seen quite similar in that time period.

4.6 Analysis of the prediction model

Prediction model, which is presented in chapter 4.5 must be analyzed in order to understand how well it performs in comparison to the persistent model and thus the different mean errors (MAE, RMSE, BIAS) on different prediction horizon hours must be calculated. Also the MOS corrected model is compared to the model without the correction is this study. The MOS correction can be made by using the methodology presented in chapter 3.6.2. It is also studied how the development of the constants in equation (4.9) varies in function of the prediction horizon.

One of the first main evaluation method is to measure prediction model's performance by looking at the normalized MAE and RMSE. MAE is very informative since it is tells what is the average prediction error in a look-ahead hour. For instance, it can be seen from the Figure 4.12, where MAE of the forecast is represented alongside with the MAE of persistence forecast and MOS corrected, that the MAE in 24 hour ahead forecast is about 11 % of the nominal power for the created model. It can be noticed that the model, which is not MOS corrected outperforms the model where statistical correction is used on every look-ahead hour.

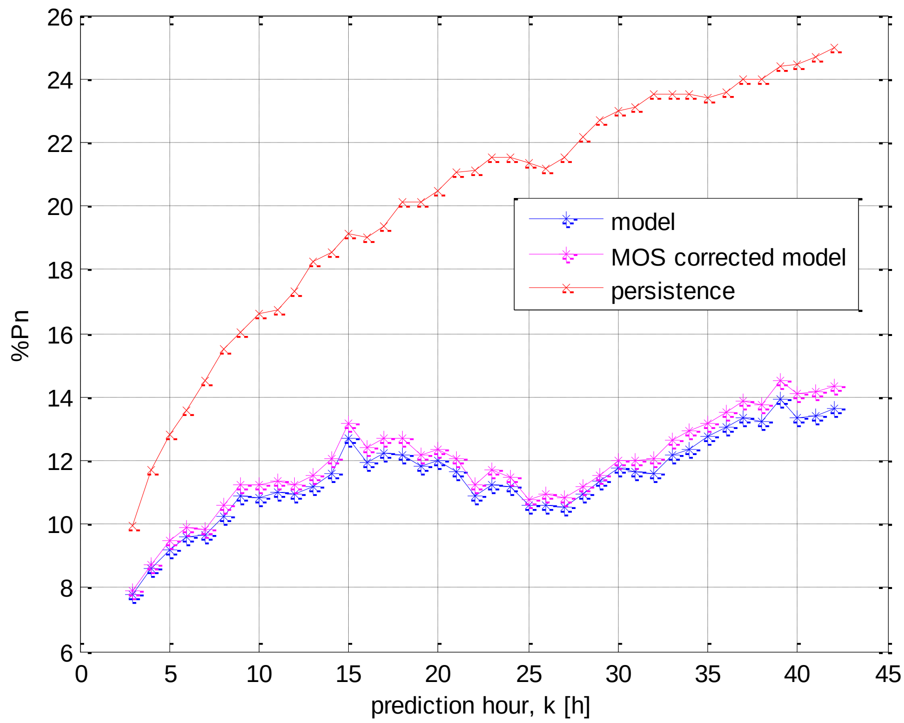


Figure 4.12 Mean absolute error for the prediction and the reference model

RMSE weights more of the larger prediction errors and therefore it can give valuable information how frequently model predicts badly wrong. In electricity market large prediction errors are what matters and they must be avoided, since the regulation losses are depending linearly to the prediction error. From the Figure 2.6 one can calculate what would happen if wind power participant have large prediction error on one of those price spikes. In Figure 4.13 RMS prediction errors for the studied model, MOS corrected, and the persistence model. It can be seen that the squared errors are larger than the MAE on different look-ahead hours. MOS corrected model is now on some look-ahead hours slightly better than the model without correction, which is quite natural since the used loss function that MOS minimizes is squared.

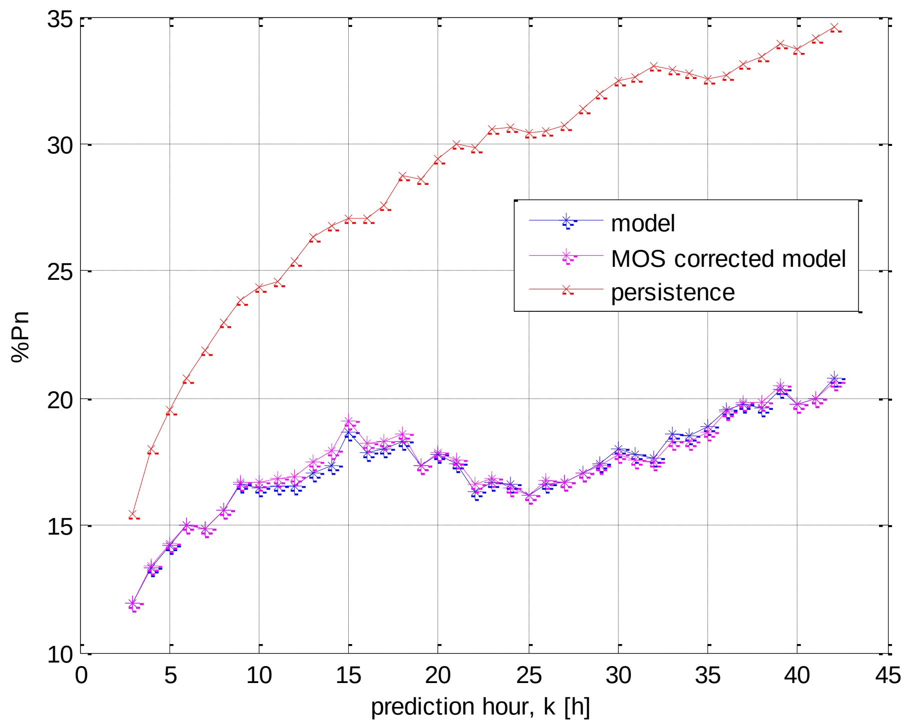


Figure 4.13 Root Mean Squared Error for the prediction and persistence model

It is possible to see from the Figure 4.12 and Figure 4.13 that the trend of the prediction error is quasi-linearly growing. For some reason there is an improvement in accuracy on prediction hours 20 – 30 h. The persistent nature of wind power can be seen from the figures, since model is performing really well on the prediction hours up to 7 h. The good performance on the later prediction hours can be explained with the quality of meteorological forecast. These prediction errors depend greatly what kind of terrain the wind farm is located. When the terrain is really rough and hilly then the prediction errors are more larger and especially the RMSE will grow. Therefore, different MAE and RMSE are not directly interpret to each other, and if one must compare different models and their prediction errors, then the complexity of the surroundings must be considered (Pinson, 2006). However, some comparison is made to the site in Ireland for 5 different forecast models, which MAE and RMSE are represented in the Figure 4.14. One could see that the prediction errors in Figure 4.14 are on same magnitude that the prediction errors on Figure 4.12 and Figure 4.13, which means that it is possible to assume that the model works with a sufficient manner.

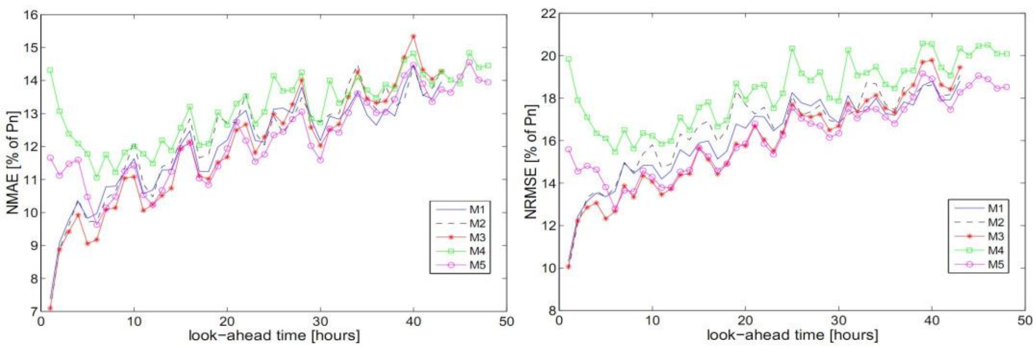


Figure 4.14 five different prediction models MAE and RMSE in a site in Ireland

One could also notice directly how this current market system does not favor wind power from the figures above, since the delivery hours are look-ahead hours from 13 – 36 h (Finnish time) where the MAE error varies between 10 – 14 %. Thus, if the market structure would allow the wind power participant make its bids to the market 3 hours before actual delivery hour and the meteorological forecast would be available on that hour, then the MAE would only vary between 8 – 13 %.

As it was discussed in 3.6.1.1 prediction error can be separated into systematic and random components. In Figure 4.15 bias of the different prediction horizon hours is represented. Bias represents the systematic over- or underestimation of the model. As it can be seen from the Figure 4.15 that the model systematically underestimates power on every look-ahead hours. The underestimation is quasi-linearly growing on the function of prediction hour. The MOS corrected bias is also represented on the figure below. It is possible to see how the MOS correction reduces the systematic part of the error and thus the bias is lowered. Ideally the bias should be only white noise.

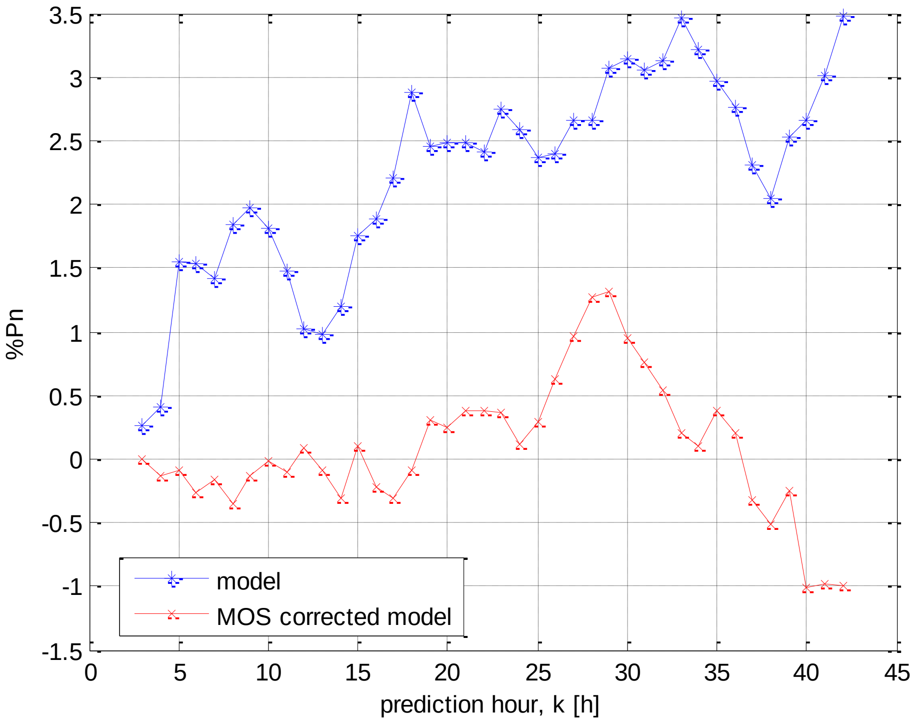


Figure 4.15 Mean Error on different look-ahead hours

However, the MOS correction do not give any significant benefits since the RMSE is only reduced a little and the MSE is increased on every look-ahead hour. The possible gain is probably lost in the method how the corrections are created. The prediction model was created by using statistical methods, which itself minimizes the RMSE of the prediction. MOS are more suitable for forecasting methods, which uses physical prediction, where the remove of the systematic part of the error might give more accurate predictions. The MOS corrected predictions are therefore not used on later analysis.

The last type of measurement that is studied is cross correlation coefficient of the measured and predicted values on different look-ahead hours. The cross correlation coefficient provides information how correlated are the measured and predicted time series on different prediction hours. Coefficient varies from 1, which means perfect correlation to the perfect uncorrelation, -1. One could see that from the Figure 4.16 that the coefficient is decreasing while the predictions are made to the further to the future. The reason behind this is the increasing uncertainty of predicted wind speed and wind direction. However, on the prediction hours lower than 4 h the correlation can be seen as really good since the coefficient is above 0.88.

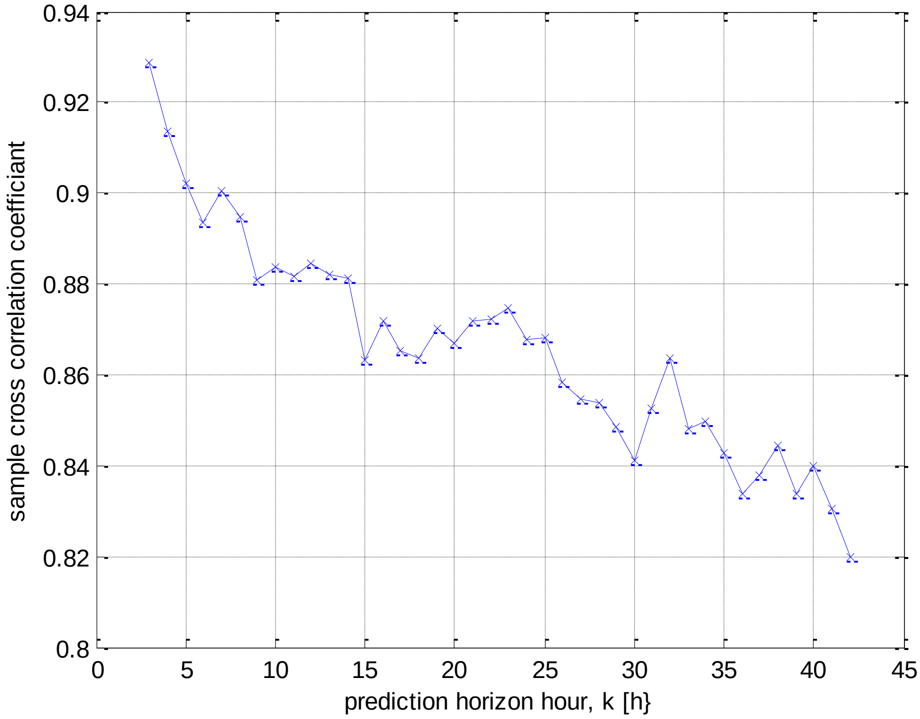


Figure 4.16 Cross correlation coefficient on different prediction hours.

The development of the constants in equation (4.8) can be seen in Figure 4.17. This figure can also be think as a weight of the different terms in equation (4.8).

The most obvious phenomenon, which this figure shows is that the b_1, which is the weight for the last measured power decreases as the prediction horizon grows and thus the weight of power curve term, b_2 increases. Of course, this phenomenon makes sense since the Figure 4.7 shows that the correlation of power decreases exponentially when one is measuring values further to the future. The weight of the last measured power reaches its minimum at predictions 18 time steps ahead and thus the weight of power curve term obtains the maximum value.

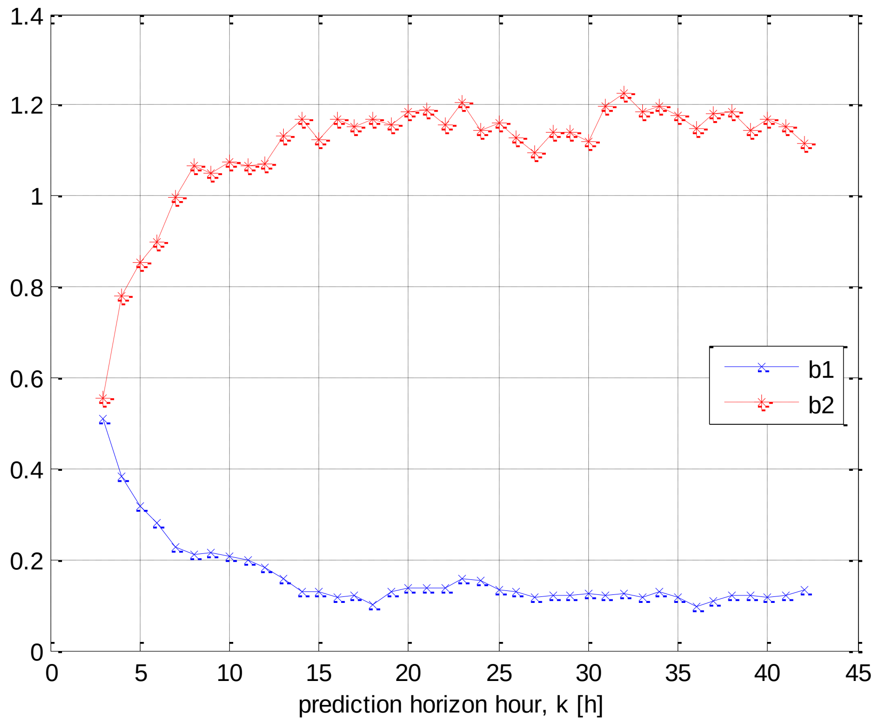


Figure 4.17 Development of the prediction constants in equation (4.8)

4.7 Creating probabilistic distributions

There are many methods to create probabilistic intervals to the forecast. For instance fuzzy inference model with adapted re-sampling was represented thoroughly in (Pinson, 2006). However, making of probabilistic intervals usually requires its own thesis, since it demands advanced mathematics. However, there is an indirect approach to obtain the prediction intervals without using state-of-the-art mathematics. It is based on using beta distribution to obtain probabilistic distributions and it is represented thoroughly in (Bludszuweit, 2008). In the next paragraphs the methodic for formulating probabilistic distributions is explained

First of all, forecast data is created by using the methodology represented in chapter 4.5. After that the forecast results and corresponding power measurements are sorted into equally sized power bins, by the forecasted data. This step must be done for each forecast horizon hour separately. The amount of power bins, N_{bin} must be chosen depending on how much forecast data is available, in (Bludszuweit, 2008) there was around one million data points available, and N_{bin} was chosen to be 50. In this thesis N_{bin} was chosen to be 25, when the amount of forecast data points is 151072.

Methodology assumes that the distribution of the measured power in each forecast bin follows a beta distribution and the shape factors of beta distribution α and β can be linked to the variance, σ^2 and mean, μ of a forecast bin with the relationships which are represented in equations (4.12) and (4.13). It is possible to solve those equations in function of μ and σ^2 and have:

$$\alpha = \frac{(1-\mu)\cdot\mu^2}{\sigma^2} - \mu \tag{4.12}$$

$$\beta = \frac{1-\mu}{\mu}\cdot\alpha \tag{4.13}$$

Thus, it is possible to solve for each forecast bin, $N_{bin,i}$ parameter pair $\{\alpha_i, \beta_i\}$ by using the pair $\{\mu_i, \sigma_i^2\}$ and hence create a beta pdf for each forecast bin by using the equation (4.2). This process is repeated for each look-ahead hour in order to consider the increasing uncertainty when forecasting further to the future, which shows in the increase of a bin variance.

Mean and variance of a forecast bin $N_{bin,i}$ can be calculated in that forecast bin by using the measured power data. Notice that the mean and the variance must be calculated from the measured power data and not from the forecasted data. Equations for calculating mean and variance are represented in equations (4.14) and (4.15)

$$\mu_i = \frac{1}{N_i}\sum_{t=1}^{N_i} p_{t,i}^{meas} \tag{4.14}$$

$$\sigma_i^2 = \frac{1}{N_i}\sum_{t=1}^{N_i}\left(p_{t,i}^{meas} - \mu_i\right)^2 \tag{4.15}$$

where N_i is the size of the forecasted values in bin *i* and $p_{t,i}^{meas}$ measured power value in bin *i*.

4.7.1 Results of creating probability distributions

The main problem of the previously explained method is that it requires massive amount of forecast data. FMI provided forecast data, which was provided once in a day. The wind farm data was available 3 whole years, which means that the amount of forecast data points in the specific look-ahead hour is only 1095. The method also divides every prediction hour into N_{bin} amount of bins, which size is $1/N_{bin}$. In this study, N_{bin} was decided to be 25, which in terms of power is 4 % of the nominal power of the wind farm (460 kW). One could now notice that even if the power data would be distributed evenly to the power curve, which means that all the wind speeds are equally likely, then in one bin would only be 44 values. The reality is that there would not be any values in some bins and on some bins there would be more values. Of course, on statistically point of view the number of data points is still insufficient.

Therefore, it is necessary to create forecast data with a some other manner. The chosen method is a modified persistence forecast. This forecasts method creates one step-ahead forecasts, which are then shifted in time, depending on the how far to the future the prediction is made. The forecast is made by calculating the mean value of the past measured values and then shifting the mean value to the corresponding look-ahead hour. In equation (4.16) the model for previously mentioned artificial forecast method.

$$p_{t+k} = \frac{1}{k}\sum_{i=1}^{k} p_{t+k-i} \tag{4.16}$$

Since the data is measured with a 10 minutes frequency, and the one hour resolution is needed since the market functions with a one hour resolution. Thus, the “prediction horizon”, k in equation (4.16) contains 6 times k values, where the mean value can be calculated. As a result, instead of 1095 prediction values it is possible to have more than 150000 prediction values, for each look-ahead hour.

Now that the predicted values are obtained, it is possible to use methodology represented in the chapter 4.7 in order to create probability distributions for each and every look-ahead hours. Thus, the beta distribution shape factors α and β are obtained for each forecast bin, $N_{bin,i}$ for every forecast hour. By doing so, it is possible consider the increasing uncertainty of prediction, when looking further to the future. However, a power curve that is divided into 25 equally sized bins is quite coarse on accuracy point-of view. In order to increase accuracy of these probability intervals, mean values and variances of the power bins are analyzed in order to create models for mean value and variance, which depend on different look-ahead time and predicted power.

The model for mean value is assumed to be a cubic model although that in (Bludszuweit, 2008) linear model was used to illustrate the connection between the mean forecast and mean measured power. The connection between mean forecasted and mean measured power should be quasi-linear but as the shape of probability distribution changes depending on what point of power curve it is looked, it is natural to assume that the relation is not linear but a bit more complex.

$$\mu = a_1 p^3 + a_2 p^2 + a_3 p + a_4, \tag{4.17}$$

where p is the forecasted power and a_1, a_2, a_3 and a_4 are the parameters, which are approximated. The standard deviation was fitted by using the same approximation function as in (Bludszuweit, 2008). The function is presented in equation (4.16).

$$\sigma = \sqrt{\mu \cdot (1 - \mu) \cdot (-b_2 \cdot \mu^2 + b_1 \cdot \mu)}, \tag{4.18}$$

Where b_1 and b_2 are the approximation parameters. The results of fitted and real mean measured power and standard deviation are represented in Figure 4.18 and Figure 4.19 for couple of look ahead times, respectively. It can be seen from the Figure 4.18 that the fitted values, which are represented as solid lines, matches the real values (dots) quite well. The quasi-linear nature of the mean measured values can be seen also. For larger forecasted power values it seems that the measured power values start to scatter to a wider area than for small forecasted values. Ideally the shape of measured power values should be quasi-symmetric since the wind farm power curve is quite symmetric above and below power values 0.5 p.u..

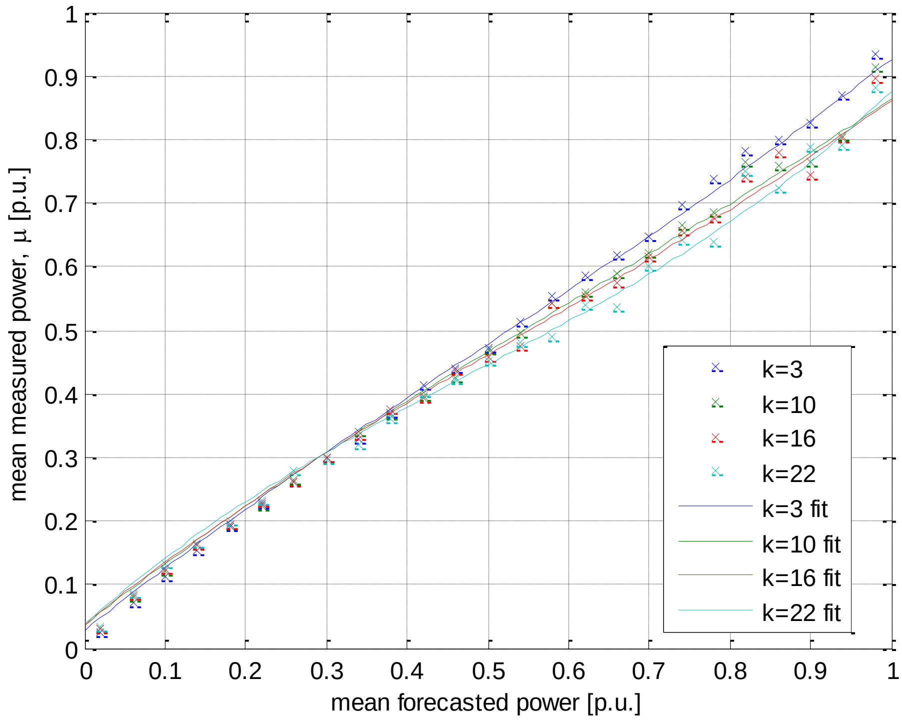


Figure 4.18 polynomial approximation of measured power in relation to the mean forecasted power on different look-ahead times. Fitted values marked with solid lines and real values marked with dots.

From the Figure 4.19 can be seen how the standard deviation varies on different forecasted power values. It can be noticed that the actual values fit quite well to the fitted curve, especially forecasted values below 0.5 p.u.. Standard deviation reaches its maximum at 0.6 p.u. on different look-ahead times. This is quite natural since, the variation should be at maximum when the forecasted power is on midrange. Also, the standard deviation increases as the forecasts are made further to the future, which shows that the uncertainty of forecast increases as the look-ahead time grows. Ideally the curvature of the standard deviation should be quasi-symmetric since the wind farm power curve is quasi-symmetric. In this case the curvature is not symmetric since on different look-ahead times standard deviation starts from values below 0.05 p.u and the end values are in range of 0.01 – 0.2 p.u..

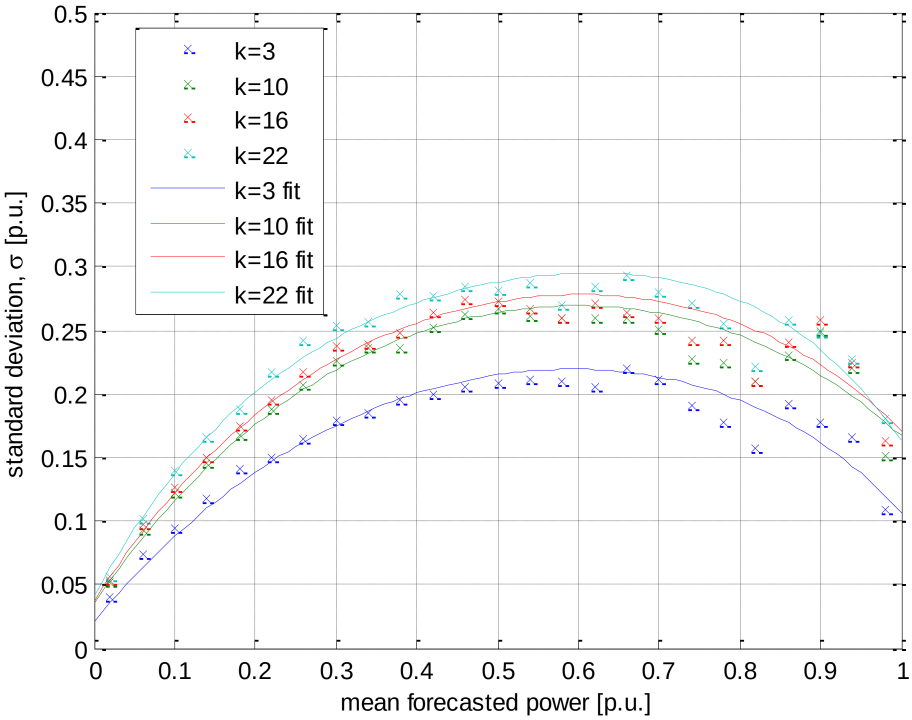


Figure 4.19 Standard deviation in relation to the mean forecasted power on different look-ahead times. Solid line represents fitted model and the dots are the real values.

Now that the models for mean values and standard deviation are obtained it is possible to calculate α and β for each forecasted power values on different look-ahead times. Thus, it is possible to calculate probability densities by using the equation (4.2). In Figure 4.20 probability distributions on prediction horizon six hours ahead on ten different forecasted power values.

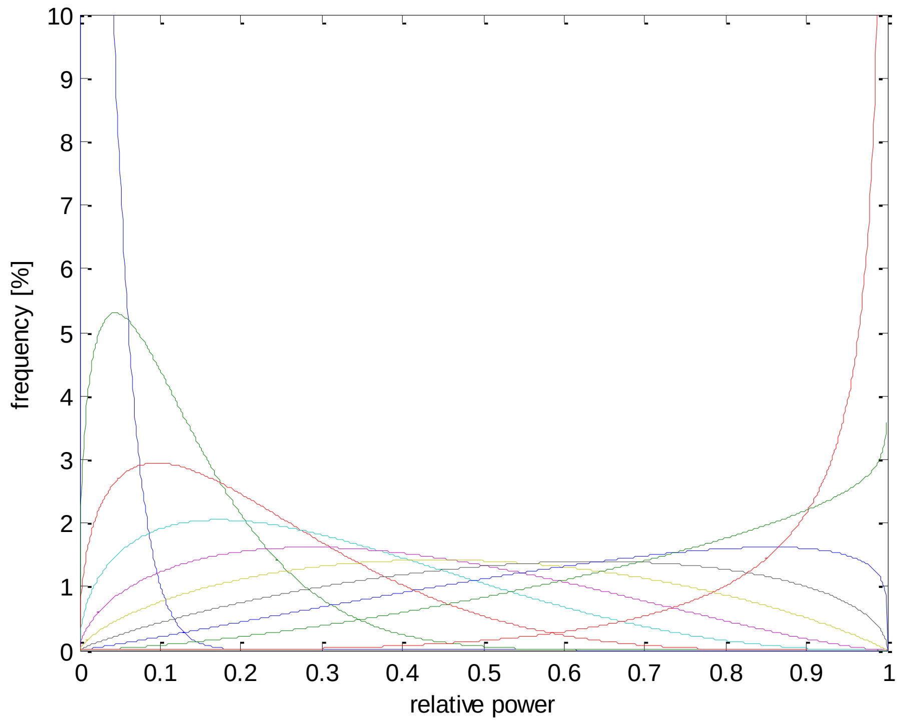


Figure 4.20 Probability distributions on prediction horizon 6 hours ahead

It is possible to see from the figure above that, because of the bounded nature of wind power the distributions on the near minimum and maximum power are distributed differently than the distributions on the mean, where the probability distribution is distributed on a wider power range.

Now that the probability distributions are founded, a question remains that how accurate are these probability distributions. One way to look at this problem is to create probability quantiles, which describes certain probability areas where the power should be in a certain probability. An example of these power quantiles can be found from the Figure 3.11. One property of this quantile representation is that if one is looking in a long time scale the actual power and the forecasted power values. The actual power values should appear inside of these probability quantiles with a frequency, which corresponds the probability of a certain quantile. In example, inside of the 40 % quantile, the power should be 40 % of the time. In Figure 4.21 coverage-coverage presentation of the forecast data. Notice, that the measured quantiles are created by using the forecast model presented in equation (4.16), but the quantiles accuracy is analysed against the forecast data, which was created in chapter 4.5. The left hand side of the Figure 4.21 was created without using any modifications to the probability densities and on the right hand side of the figure the probability intervals were slightly modified. Coverage plots can be made for each look-ahead hour separately, instead of looking all of the look-ahead times in a one coverage plot. A closer analysis revealed that on look-ahead hours 3-13 the measured quantiles were too accurate, or too tight. Therefore, instead of using those quantiles, the quantiles from 7-17 were used in order to have a more wider quantiles. The results of this modification are on the right hand side of the Figure 4.21, where an improvement of coverages can be seen to the situation without any modifications (left hand figure). One could see from the right hand side of the Figure 4.21 that the coverages match quite well to the theoretical coverages. There is a 5 % offset on the 10 % coverage, which means that the 10 % quantile is too wide, or in other words too pessimistic. The gap between measured and theoretical quantiles start to diminish and the optimal coverage ratio is obtained on 60 % coverage. Gap between measured and theoretical coverages begin to increase after the 60 % coverage finally ending up 80 % coverage while the theoretical coverage should be 90%.

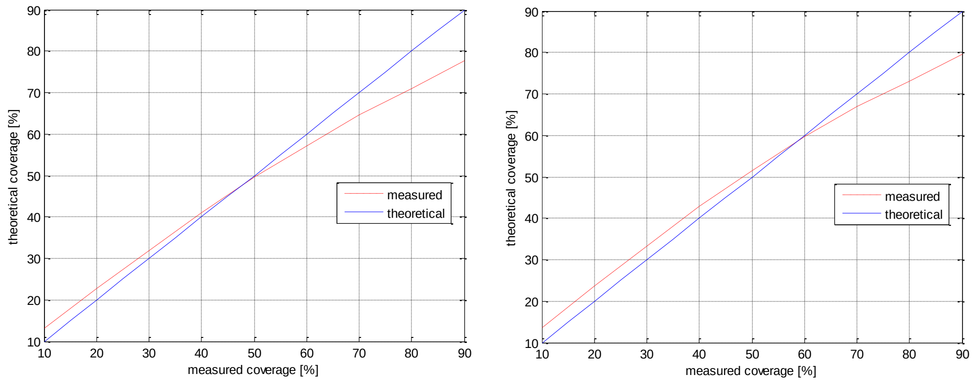


Figure 4.21 coverage-coverage presentation. Measured coverage is represented with the dashed line and the theoretical coverage is represented as a solid line.

The coverage-coverage diagram can only show information about the appearance of real power in different probability quantiles, but it does not provide any information about the shape of these probability densities. However, in this thesis it is assumed that the shape of the forecast error pdf is a good approximation, although it is mentioned in (Bludszuweit, 2008) that the forecast error pdf is not fat-tailed enough on some forecast hours, which leads to underestimation of larger prediction errors, as one could notice from the Figure 4.21. However, it seems that the beta-distributed probability distributions are accurate enough to have a better understanding of the uncertainty of a forecast on different look-ahead times.

4.8 Bidding strategies

On this chapter some of the assumptions that must be made on simulating market participating are presented. Also the idea of using probability information on bidding is presented

4.8.1 Assumptions in making the bids

When making bidding strategies and simulating market participating one must consider some assumptions. Assumptions must be made mostly about of the impact of trading wind generation to the market and its influence on the Spot and imbalance prices. It was shown that the large amount of wind power in the markets will affect the market price by lowering it (Jónsson, 2008). The study, which was made in western Denmark, where wind penetration is highest in the Nordic countries, shows that there is a clear correlation between system price and wind penetration. However, in this thesis where we use Finnish area prices and the wind penetration is less than 1 %. Hence it is sufficient to assume that the effects of wind generation to the market price can be neglected. Also the unit size of a wind farm is relatively small and in Finland the wind farms are spread into a wide geographical area. Thus it is safely to assume that the prediction error caused by the intermittent nature of wind energy affects a little to the formulation of balancing energy prices. Although, that is not entirely true since the volume of regulation would be much smaller without wind generation since conventional generation is much more controllable and the uncertainty lies only on the consumption estimation.

More importantly it is assumed that there is no subsidies on wind energy. Although, that in Finland subsidies are used, but usually the reason of subsidies is that subsidies are used for temporarily to lower marginal costs of wind generation manufacture, in order to increase the willing of market participants to buy wind generation. Therefore subsidies are used for a certain amount of time and afterwards the wind generation is supposed to function without any subsidies. Thus, this thesis is in particular use after the period of subsidies, when all the possible gain for wind power is needed.

4.8.2 Using point prediction

Using a point prediction as a bid to the electricity trade is the best method for market participant, which does not have any other information about the future. The point prediction is usually made for each delivery hour at the time, and some cases if the prediction model creates predictions with interval that is less than one hour, then the power must be averaged to correspond one hour, since in Nord Pool electricity trade commodity is one hour energy delivery. Therefore, the trade is made with energy not with power, thus the energy delivery in one hour can be calculated from the one hour point forecast by using the following equation

$$E_{t+k} = P_{t+k} \cdot t_d, \tag{4.19}$$

where E_{t+k} is the energy of power, P_{t+k} in a time period, t_d, which is usually one hour. Notice that the power delivery is then assumed to be constant in time length, t_d although the power is fluctuating constantly. Then if the point forecast is wanted to use as a bid it can be formulated with a following manner:

$$E_{t+k}^{bid} = E_{t+k}, \tag{4.20}$$

where E_{t+k}^{bid} is the bid to the electricity market.

As mentioned before, point forecasts will minimize the prediction error and thus using the point forecasts as bids it will transform the prediction errors to regulation costs.

4.8.3 Theory based on bidding with probabilistic intervals

Instead of using point forecast as bids, one could take more probabilistic point of view on making bids, which allows to consider the uncertainty of a point forecast. The uncertainty is considered by assuming that around the point forecast there is a certain probability to have values around the point forecast, which means that there is a certain probability distribution around the point forecast. The methodology to create these probability distributions is illustrated in chapter 4.7. As said before, point forecasts, which aims to minimize prediction error, $e_{t+k/t}$ provides estimates of expectation value, $\bar{E}_{t+k}$ of the distribution of E_{t+k}. Notice, that the E_{t+k} is thus expected to be random variable with a probability distribution. It can be denoted that F_{t+k}^{E} is the pdf of a random variable E_{t+k}, which means that the expectation value of that random variable is:

$$\bar{E}_{t+k} = \int_{0}^{1} x \cdot F_{t+k}^{E} dx \tag{4.21}$$

Point forecast is thus linked to the expectation value by merely calculating an integral in equation (4.21). Now, if the actual energy at time *t+k* is assumed to be E_{t+k}^{act} then the error between contracted and actual energy is

$$d_{t+k}^{act} = E_{t+k}^{act} - E_{t+k}^{bid} \tag{4.22}$$

E_{t+k}^{bid} can be a bid for Elspot or Elbas and or either the Elbas and Elspot bids combined. However, in this thesis we concentrate on making bids in only in Elspot market since the modeling of bidding in both markets is not a trivial task, as it is shown in (Linnet, 2005) and the examination of bidding in one market will give enough information of functionality of the method. Thus the bid can be represented as bid for Elspot market

$$E_{t+k}^{bid} = E_{t+k}^{spot} \tag{4.23}$$

Notice that if the E_{t+k} is a random variable it will lead that the bid error, d_{t+k}^{bid} is also a random variable. In equation (4.24) the bid error.

$$d_{t+k} = E_{t+k} - E_{t+k}^{bid} \tag{4.24}$$

4.9 Formulating the regulation cost function

By using the theory of probabilistic bidding and assumptions, which are represented in chapter 4.8.1, it is now possible to create a regulation cost function, which is used for to optimize the revenue. It was shown in chapter 2.3 how the revenue function is possible to formulate if one wants to participate in Elspot markets. The function in equation (2.1) is valid when the regulation costs and volumes are known. However when forecasting two days ahead one cannot say, which are the regulation costs at that time, and also trading with wind energy where the participants have a little influence on how much power the turbines produces, it is really uncertain what the power is at the delivery hour. However, participant can influence on the sign of bid error if the participant is more sensitive for bid error to one direction than the other. In equation (4.25) loss expectation function, z_{t+k} for *k*- step ahead

$$z_{t+k} = \max_{E_{t+k}^{spot}} \int_0^1 \left(\pi_{t+k}^{spot} \cdot E_{t+k}^{act} - R\left(x - E_{t+k}^{spot}\right)\right) \cdot F_{t+k}^{E}(x)dx \tag{4.25}$$

It is possible to notice that equation (4.25) has an analogy with the equation (2.6), where in both equations the regulation energy costs are subtracted from maximum possible income. As a difference function in equation (4.25) takes into account the uncertainty of a forecast, which is paramount since we are dealing with wind after all. This transform the maximization of revenue to minimization of regulation costs, and thus therefore the optimization problem can be written as:

$$z_{t+k}^{reg} = \min_{E_{t+k}^{spot}} \int_0^1 R\left(x - E_{t+k}^{spot}\right) \cdot F_{t+k}^{E}(x)dx \tag{4.26}$$

where $R\left(x - E_{t+k}^{spot}\right)$ is depending on the prediction error with a following manner

$$R(d_{t+k}) = \begin{cases} d_{t+k} \cdot \pi_{t+k}^{ext+}, d_{t+k} \geq 0 \\ d_{t+k} \cdot \pi_{t+k}^{ext-}, d_{t+k} < 0 \end{cases} \tag{4.27}$$

In Figure 4.22 regulation losses in function of prediction error in January 2010. Regulation cost are mean regulation costs from January. Average down regulation cost is 16,44 €/MWh and up regulation cost is 8,92 €/MWh in that month. It is possible to see from the figure that down regulation costs are larger than the up regulation costs, since the larger the regulation cost is, the steeper the regulation loss curve will be.

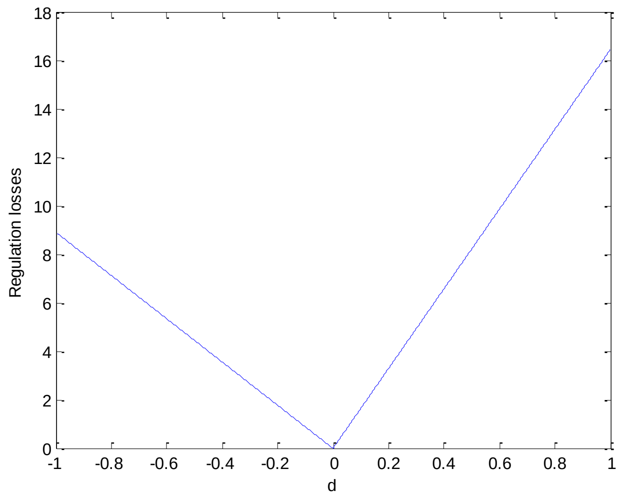


Figure 4.22 Regulation cost function. in the x-axis relative deviation from real power production and in the y- axis regulation losses in function of deviation.

It is possible to create other kind of regulation cost functions if the participant for instance wants to emphasise large or small prediction errors. However, the optimization process is not so straight forward and very likely it must be carried out with iterative numerical methods. In the next chapter optimization process for function in equation (4.26) is represented.

4.9.1 Optimal bid in day ahead market

In order to find the optimal bid equation (4.26) is needed to be solved in respect of optimal bid, E_{t+k}^{opt}. It is shown that there is a global solution for the optimum bid by solving equation (4.26) (Linnet, 2005). The optimum bid can be written as

$$E_{t+k}^{opt} = {G_{t+k}^{E}}^{-1}\left(\frac{\pi_{t+k}^{ext+}}{\pi_{t+k}^{ext+} + \pi_{t+k}^{ext-}}\right) \tag{4.28}$$

where G_{t+k}^{E} is the cumulative probability distribution function of random variable E_{t+k} and regulation costs π_{t+k}^{ext+} and π_{t+k}^{ext-} are estimates of real regulation costs. Therefore, it is necessary to predict regulation costs for about 36 hours ahead. Prediction of regulation costs is not a trivial task since it includes prediction of direction regulation need and its volume, also the prediction of market price is needed. However, the prediction of regulation cost is paramount in using this methodology since the only inputs to derive optimal bids are the regulation cost and methodology to derive probabilistic intervals.

It is possible to deduce form the equation (4.28) that if the regulation costs are equal, then the optimum bid can be found from the inverse of CDF function in value 0.5, which is in other words is the median of the random variable E_{t+k}. Therefore, if the regulation costs are equal there is no need for adjust the bid and point forecast must be used instead. However, this leads to a problem since the methodology, which was represented in chapter 4.7 creates probabilistic intervals centered around the distribution's mean, which differs from the distribution's median, since most of the distributions are fat tailed and thus non symmetric. Probabilistic distributions are centered around the mean value and since there is no closed form solution for beta distribution's median, some measures must be taken in order to create median centered distributions.

The problem is solved by dividing the power range into 100 equally sized power bins and creating probability intervals to each bins. Also for the each power bin the median of the probability density must be calculated. Then if the point forecast at time *t* is assumed to be p_{t+k} the absolute deviation for forecast bin *i* can be calculated with equation (4.29)

$$d_{t+k,i}^{median} = \left| p_{t+k} - p_{t+k,i}^{median} \right| \tag{4.29}$$

Deviations for each forecast bin from the point forecast must be calculated and find the minimum of the deviations, $d_{t+k,i}^{median,min}$. Thus, the probability interval of this median centered forecast can be found from the same bin, *i* as the minimum of deviation is located. This forecast bin and the corresponding pdf is then the median centered pdf for point forecast p_{t+k}. Afterwards the optimal bid can be calculated by using equation (4.28). This previously illustrated method allows one to use optimal bid without median centered probability intervals.

It can be seen from equation (4.28) that the optimal bid can be found from a certain quantile of the predictive distribution. The optimal quantile depends on the ratio of regulation costs. For instance in 2009 and 2010 optimal monthly and quarterly optimal bidding ratios are represented in Table 4.1. The ratios are calculated by calculating average up- and down regulation costs at the corresponding time windows.

Table 4.1 Optimal bidding ratios from CDF.

	2009		2010	
month	$G_{t+k}^{E,q}()$	$G_{t+k}^{E,m}()$	$G_{t+k}^{E,q}()$	$G_{t+k}^{E,m}()$
1		0.549		0.352
2	0.324	0.227	0.191	0.095
3		0.179		0.090
4		0.122		0.171
5	0.359	0.378	0.355	0.420
6		0.599		0.489
7		0.301		0.713
8	0.454	0.724	0.626	0.518
9		0.241		0.588
10		0.625		0.696
11	0.384	0.312	0.574	0.803
12		0.324		0.382

It can be noticed from the table above that the results are consistent with regulation cost presented in Table 2.2 and Table 2.3. Optimal ratios that are under 0.5 indicates that the optimal bid can be found underestimating the power production, since the down regulation cost prices are larger than the up regulation cost prices. In example June in 2009 when regulation prices ratio is 0.67, which indicates that up regulation is more expensive than the down regulation. By deducing from the price ratio the optimal bid must be found by overestimating the point forecast, since the ratio is larger than 0.5.

One could now also see from the Table 4.1, which are the most important probability quantiles from the bidding point of view. One could see that most of the ratios are close to the median 0.5, which means that the probability quantlies close to the point forecast must be accurate. The Figure 4.23 also confirms this fact, where the deviation between optimal monthly and quarterly bidding ratios is taken from the median (ratio 0.5). In the figure quantiles can be seen as the area between negative and positive ratios, for example 20 % quantile is from 0.1 to -0.1 and 50 % quantile is from 0.25 to -0.25 and so on.

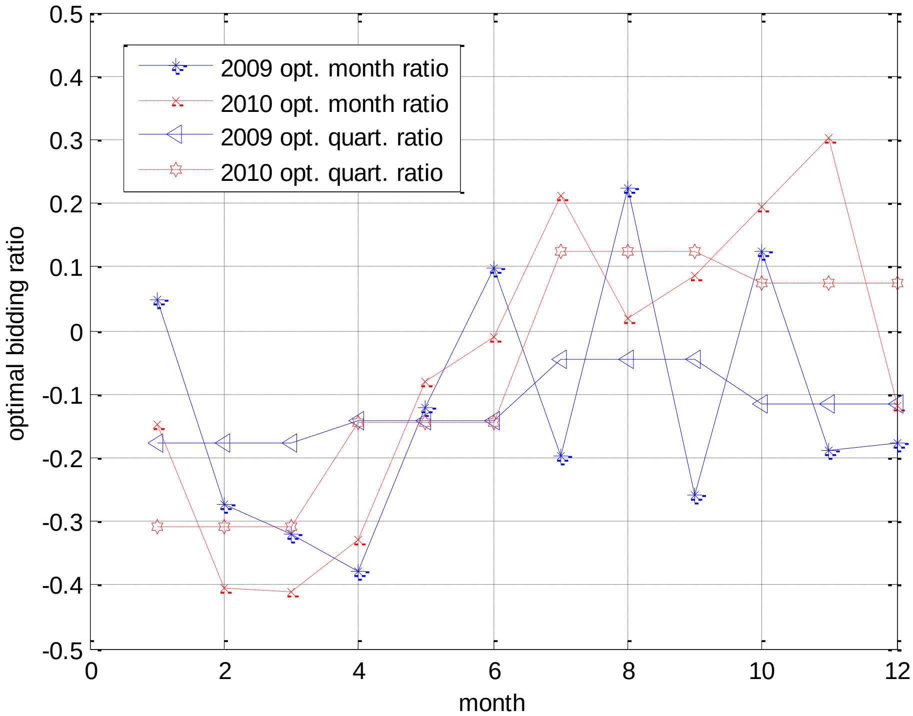


Figure 4.23 Deviation of the optimal bidding ratios from the median

The negative sign on the optimal bidding ratio tells that at that time it is more suitable to bid more than the point forecast and on positive sign, it is the contrary. It can be noticed that on months one to 12 the bidding ratios are clearly negative all the time, which suggest to bid more than the point-forecast suggests. However, on months six to 12 it is not so clear should one bid more or less than the point-forecast, since the data from 2009 and 2010 demand different kind of behavior. It is still clear that on summer months the point forecast might be a good compromise if one do not know certain what are the tomorrows regulation costs. One could also see that the most of the optimal bidding ratios are inside of the ratios ±0.3, which is the 60 % quantile. Therefore, the accuracy of quantiles, which are below 60 % is crucial in order to have accurate bids. The accuracy of those quantiles can be seen from the Figure 4.21 where the measured and theoretical coverage is presented. From the coverage point of view those quantilies are actually accurate enough to trust them.

4.10 Simulation of optimal bidding in Nord Pool

In this chapter some simulations are made with the real power and real market data. The simulations are made with a simulation model, which tries to represent a real life wind power participant behavior in Nord Pool. Thus, the idea is that only history data and the forecasted wind speed and direction made by FMI can be used. The assumption is that the participant will only participate in Elspot market and all of the imbalances will be dealt in the balance settlement. Forecast model that is represented in chapter 4.5 is used and the methodology to derive probability distributions can be found from the chapter 4.7. Some information of the characteristics of Nord Pool can be found from the chapter 0. The simulations are made for years 2009 and 2010 by using Finland's area prices and regulation prices.

The simulations are made every day as the participating to the Nord Pool requires – bids must be given to the market before 1 p.m., when the day-ahead market closes. Also the simulations are made with the same available information as the owner of Raahe's wind park has at that time. In order to compare different simulation result some indices must be used. In equation (4.30) the ratio between the maximum revenue and bid revenue.

$$\gamma = 1 - \frac{R_{max} - R_{bid}}{R_{max}} = 1 - \sum_{i=1}^{2*365} \sum_{k=1}^{24} \frac{\pi_{i,k}^{spot} \cdot E_{i,k}^{act} - \pi_{i,k}^{spot} E_{i,k}^{act} + IC^{*}(d_{i,k}^{act})}{\pi_{i,k}^{spot} \cdot E_{i,k}^{act}} \tag{4.30}$$

Main properties of the equation above is that it is bounded from $[-\infty, 1]$ and if the difference between maximum revenue and bid revenue is zero then the γ is one and the other limit is $-\infty$, which is not so likely outcome. In reality the lower limit is more likely zero. It is also possible that the index can be over 1 if participant is gaining money from the markets (negative regulation costs).

The main point of the simulation is to see whether the optimal bidding method give any extra profit compared to the point-forecast as a source of bid and what is the potential of this method.

4.10.1 Simulation using created forecast model

In this chapter the simulation is run by using persistence model and the created forecast model. The results are compared to the scenario where prediction errors are zero, perfect forecast. The simulation results are represented in the Table 4.2. The simulation starts first day of the January 2009 and ends on the 30.12.2010. In this simulation it assumed that the bid is simply the point-forecast, which the created forecast model can provide. Therefore, the results do not add any 'intelligence' to the bidding by considering the special characteristics of the Nord Pool.

Table 4.2 Simulation results for the persistence model, created forecast model and the perfect forecast

	Persist.	created for. model	perfect
Bid energy in Elspot [GWh]	47.33	40.76	46.04
Total up regulation [GWh]	21.28	14.51	0.00
Total down regulation [GWh]	22.56	9.23	0.00
Total regulation [GWh]	43.84	23.40	0.00
Down regulation cost [k€]	135.2	41.23	0.00
Up regulation cost [k€]	64.75	50.57	0.00
Total regulation losses [k€]	200.0	91.80	0.00
Av. down regulation cost unit [€/MWh]	4.84	5.72	0.00
Av. up regulation cost unit [€/MWh]	3.30	3.72	0.00
Average energy price [€/MWh]	42.20	44.55	46.54
Revenue [mil. €]	1.94	2.05	2.14
Revenue ratio, γ	0.91	0.96	1.00

First of all, it can be noticed from the table above that the need of regulation is nearly halved by using the advanced forecast model. Although, in advanced forecast model almost half of the energy flow goes via balance settlement as it is possible to see by comparing the rows 'Total regulation' and 'Bid energy in Elspot'. The up and down regulation need for advanced model is a bit biased to the up regulation, which means that the model underestimates the power production. This same conclusion can be seen from the Figure 4.15, where the systematic error is shown. The simulation was run with the bias corrected forecast but it did not show any improvements. The linear bias correction might not be the suitable method for this particular application.

In the persistence forecast the up and down regulation need is about an equal. However, an equal regulation need do not mean that the regulation costs are distributed evenly since the regulation prices are biased in Nord Pool, as it was shown in the Table 2.2 and Table 2.3. It is possible to see from the persistence model's up and down regulation costs that the down regulation costs are twice the size of down regulation costs, although the regulation need to both directions is equal. On the case of advanced prediction model there is not a similar behavior on the relations of regulation need and regulation cost. The up regulation costs are 50.57 k€ and the down regulation costs are 41.23 k€. The total regulation losses are thus 91 k€, which is more than two times lower than the persistence model's regulation losses. One conclusion in this point can be drawn that if one is using persistence model as a primary forecast model, the created forecast model saves in two years more than 100 k€. The average regulation costs unit describes the average regulation loss unit [€/MWh] what the participant has paid extra on the regulation compared to the Elspot price. It can be noticed that average regulation unit costs are slightly lower on the persistence forecast than the case of advanced forecast model. The real regulation costs in years 2009 and 2010 are represented in Table 2.2 and Table 2.3. The average regulation unit costs are quite similar in the case of created forecast model than the mean prices in on the tables. The average down regulation unit cost is 2 €/MW more expensive than the average up regulation unit cost.

The interesting fact is that if the if the average price of the produced energy is calculated, which can be seen from the Table 4.2, it shows how the regulation losses transfers directly to the price of wind energy what the participant gets, by lowering it. The average electricity price in Finland was 46.81 €/MWh in the simulation's time period, which means that even the perfect forecast cannot provide the mean electricity price as it is possible to see from the Table 4.2. This can be explained by the fluctuating nature of wind power - more power is sold when the price is low and less power is sold when the price is high ending up with a lower mean energy price. Even for the advanced prediction model the energy price is 2 €/MWh lover than it could be. This is an extra cost only for the energy sources, which are by nature intermittent. This is one of the reasons how the current market structure penalizes renewable sources, since they are difficult to control. The conventional generations, i.e. gas power are easy to control in the delivery hour thus these costs, which are caused by imbalances are diminished. This kind of cost will affect the profitability of wind power and thus difficult its position in electricity market. Of course, it is natural to allocate the costs of imbalances to the sources, but one could ask is 2 €/MWh difference too much.

The revenue by using the advanced model would give 96 % of the maximum revenue, which is quite good improvement if the revenue is compared to the revenue from persistence model, which is only 91 % what it could be. However there is still room for improvements, since the 4 % point improvement in revenue mean in actual revenue almost 100 k€ in two years.

4.10.2 Simulation using optimal bidding ratios

In this chapter simulation of wind power participant is studied by using the optimal bidding ratios on hourly, daily, monthly or quarterly level. The optimal bidding ratios are calculated by using two different scenarios. In the first scenario, the mean optimal bidding ratios are calculated by calculating first the mean of regulating costs and then using the results to calculate optimal bidding ratios with equation (4.28). Second scenario is that the mean optimal bidding ratios are calculated by using the hourly regulating costs and then taking the mean of the hourly regulation costs. In Figure 4.24 mean optimal bidding ratios are shown for quarterly and monthly bidding. It can be noticed that by using the optimal bidding ratios with mean regulation costs as an input suggests one to bid more aggressively than using the mean bidding ratios.

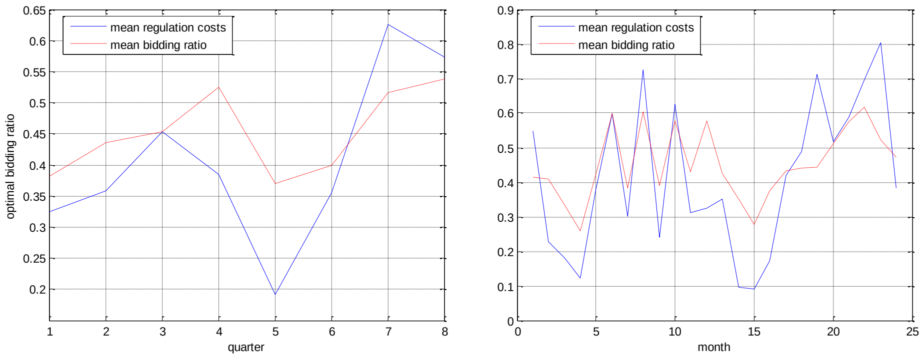


Figure 4.24 Optimal bidding ratios on monthly or quarterly level by using mean regulation costs as an input or mean optimal bidding ratio.

The both of the scenarios required that the regulation costs are known. Therefore, this simulation assumes that the participant have a perfect regulation costs prediction model and thus the simulation results are best possible scenarios, which is, like always, too optimistic. This simulation will give some valuable knowledge what is the potential of optimal bidding, or in other words, how much the revenue can be increased if the up and down regulation unit costs are known. In the Table 4.3 and Table 4.4 simulation results are represented by using the two previously mentioned scenarios.

Table 4.3 Scenario one: Simulation results by using optimal bidding ratios by calculating first the mean regulation costs and then the mean bidding ratios

	Daily	Monthly	Quarterly
Bid energy in Elspot [GWh]	9.73	35.11	33.22
Total up regulation [GWh]	36.72	20.24	19.37
Total down regulation [GWh]	4.211	9.31	6.55
Total regulation [GWh]	37.15	29.55	25.92
Down regulation cost [k€]	2.12	34.35	24.36
Up regulation cost [k€]	117.42	56.36	64.66
Total regulation losses [k€]	119.54	91.80	89.02
Av. down regulation cost unit [€/MWh]	5.72	4.69	4.97
Av. up regulation cost unit [€/MWh]	3.86	3.88	3.38
Average energy price [€/MWh]	43.95	44.57	44.61
Revenue [mil. €]	2.04	2.05	2.05
Revenue ratio, γ	0.94	0.96	0.96

It is possible to see from the Table 4.3 that the revenue is surprisingly low when the daily optimal ratios were used. The revenue is even lower than the revenue by using the advanced forecast model. The reason behind this is that the optimal bidding ratios by using daily mean prices suggest a participant to bid more aggressively than using mean bidding ratios. Therefore, if there is a regulation hour to another direction than the mean daily bidding ratio suggest it is possible to end up with huge losses. By comparing the simulation results from Table 4.3 and Table 4.4 one could see that using the mean bidding ratios, without calculating them from the mean regulation costs provide a better revenue on every time horizon.

Table 4.4 Scenario two: Simulation results by using optimal bidding ratios by calculating the optimal bidding ratios on hourly

	Hourly	Daily	Monthly	Quarterly
Bid energy in Elspot [GWh]	77.22	41.12	37.32	36.90
Total up regulation [GWh]	23.46	19.29	16.70	16.67
Total down regulation [GWh]	54.64	14.37	7.98	7.53
Total regulation [GWh]	78.10	33.66	24.68	24.20
Down regulation cost [k€]	-41.35	18.40	31..79	31.23
Up regulation cost [k€]	-30.20	24.98	52.95	56.62
Total regulation losses [k€]	-71.54	43.37	84.74	87.91
Av. down regulation cost unit [€/MWh]	0.99	4.31	5.66	5.71
Av. up regulation cost unit [€/MWh]	0.95	2.45	3.60	3.54
Average energy price [€/MWh]	48.10	45.55	44.70	44.63
Revenue [mil. €]	2.14	2.10	2.06	2.06
Revenue ratio, γ	1.03	0.98	0.96	0.96

The interesting thing by using the hourly regulation costs is that one could actually get more revenue than the perfect forecasting can yield. The reason behind his is quite natural since the regulation costs can sometimes be negative, which means that the participant can actually gain money from the imbalances. Ideally market is not constructed with a manner, which allows one to gain from imbalances but is not a rare phenomenon in the market, as it was mentioned in the chapter 2.2.1. Using of the hourly optimal bidding ratios is not recommended for the electricity market point of view since if the up or down regulation cost are negative or really close to zero it causes a situation where market participant must bid all or nothing to the market. One could have already noticed from the equation (4.28) that if the up regulation cost is zero, from the optimization point of view participant should not bid anything and buy all of the energy via balancing settlement thus avoiding the risk of down regulation costs. On the contrary, if the down regulation cost is zero then the participant must bid as much as the nominal power of the wind farm is. This behavior causes a binary choice to the electricity grid, which would definitely affect to the regulation prizes. However, in the simulation it is assumed that the behavior of the participant do not affect to the regulation prizes and thus this kind of behavior is allowed.

One could see from the tables above how the different time horizon reflects to the need of regulation. While the time horizon is increased, where the optimal bidding ratio is calculated, more stable the bidding becomes. From the Figure 4.24 one could see that monthly bidding ratios varies from 0.1 – 0.8, whereas the quarterly bidding ratios varies between 0.25 – 0.65. This directly transfers to the need of regulation since the bid, since the bid which minimizes the need of regulation can be found from the bidding ratio of 0.5. For the scenario two, one could see how the average energy price is decreased when the averaged time horizon is increased, which suggest to use bidding ratios, hourly or daily level. The regulation losses will nearly double (37 k€ ->85 k€) when using the optimal monthly bidding ratio instead of daily bidding ratio.

However, the scenario two can provide an improved revenue in every time horizon than the advanced prediction model. Even the bidding ratio that is averaged on quarterly basis provided a better revenue than the advanced prediction model. If one is comparing those revenues to the revenue from persistence model, the different on regulation losses is 112 k€ by using the quarterly bidding ratios, which is the worst revenue from the studied optimal bidding ratios.

As the results from using mean optimal bidding ratios shows that the revenue can be increased by considering the special characteristics of the Nord Pool. Thus, the creation of probability intervals is not vain if the gain from imbalances of regulation costs are exploited to the fullest. The remaining question is now how to predict regulation costs or optimal bidding ratios, since the model needs as an input a bidding ratio.

4.10.3 Simulations with different bidding strategies

Now that the capability of using probability information as a base of bidding is proved, couple of real life bidding scenarios are simulated. In this study no advanced regulation cost prediction model were used, which could improve the results by far. However, it is possible to see from the Figure 4.24 that there is clearly some periodically in the optimal bidding ratios on monthly and yearly level. Therefore, simulation was made for year 2010 by using bidding ratios from year 2009.

The balance settlement usually takes time, which means that the regulation prices of day before the bidding day are unknown. Thus the market participant cannot use the day before information as an aid for making the bids today. In this simulation optimal bidding ratios were used on monthly and quarterly basis. In the Table 4.5 simulation results by using the optimal bidding ratios of 2009 on 2010

Table 4.5 Simulation results on year 2010 by using optimal bidding ratios of year 2010

	Adv. Pred. model	Monthly	Quarterly	Perf. prediction
Bid energy in Elspot [GWh]	20.19	18.53	18.32	22.81
Total up regulation [GWh]	7.29	8.54	8.31	0
Total down regulation [GWh]	4.67	4.26	3.82	0
Total regulation [GWh]	11.96	12.80	12.13	0
Down regulation cost [k€]	26.74	22.44	19.98	0
Up regulation cost [k€]	30.48	35.40	32.97	0
Total regulation losses [k€]	56.96	55.72	52.95	0
Av. down regulation cost unit [€/MWh]	7.20	7.32	7.16	0
Av. up regulation cost unit [€/MWh]	4.83	4.87	4.71	0
Average energy price [€/MWh]	52.06	52.12	52.24	54.56
Revenue [mil. €]	1.19	1.19	1.19	1.24
Revenue ratio, γ	0.95	0.95	0.96	1.00

It can be seen from the table above that by using the previously year optimal bidding ratios, it is possible to decrease the costs of regulation by a little. The biggest revenue can be obtained by using the quarterly bidding ratios of 2009. The regulation losses are diminished with 4 k€ if the revenue is compared to the advanced prediction model. The difference is not a big, but by using the quarterly averaged optimal bidding ratios it makes it possible to distribute the regulation risk, since the regulation costs behaves in a same manner on quarterly basis. The variation within the years on monthly averaged optimal bidding ratios is much greater, as it is possible to see from the Figure 4.24, and the revenue is not as big as on quarterly averaged bidding ratios. The average regulation costs units are lowered by using the quarterly averaged bidding ratios, as it is possible to see from the Table 4.5.

The main idea is still valid by using a real life solution: The best possible revenue cannot be obtained by minimizing the regulating power, but instead minimizing the regulation costs. In Table 4.5 it can be seen that the minimum of regulating power is obtained by using the advanced prediction model, but still the revenue is smallest of the three simulated scenarios. By using this method with more advanced regulation cost prediction model, the benefits would be even greater. The Figure 4.25 can be seen as an example of quantile forecast, where the different probability quantlies can be seen as different colors of green. It can be noticed that the probability intervals varies depending what is the forecasted power and what is the look-ahead hour.

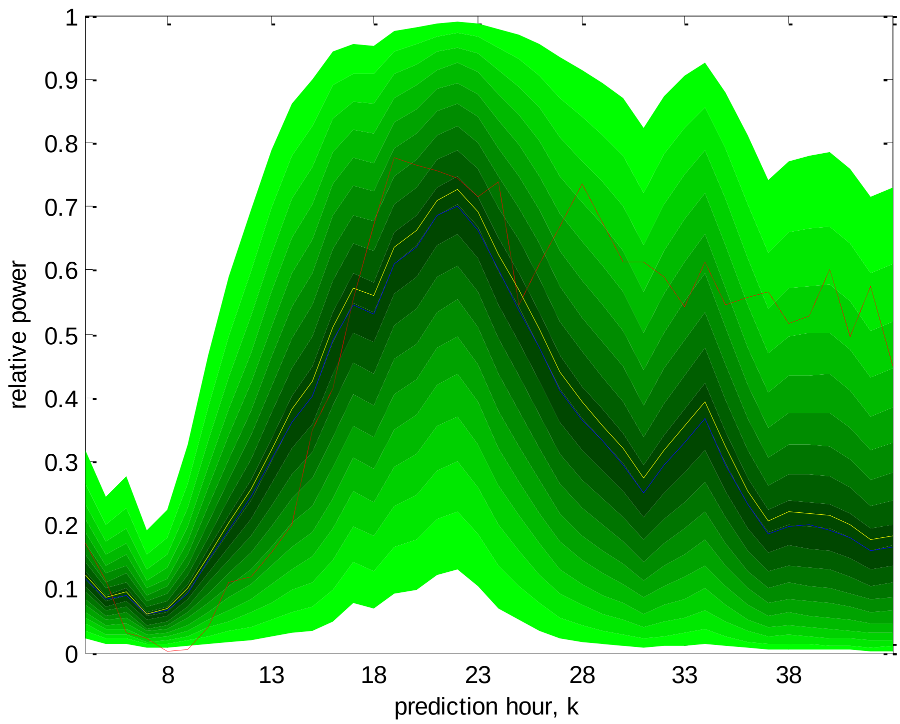


Figure 4.25 Quantile forecast. White line is the optimal bidding forecast, red line is the actual power, blue line is the point forecast. The different colours of green are the probability quantiles from 10 % to 90 %

5 Conclusion

The purpose of this thesis was to show that there is a way to reduce the regulation losses by adjusting the bids in the electricity market. In order to prove the previous statement a simple forecast model was created. The created forecast model's performance was analyzed against the reference model, which was persistence model, and it was showed that the forecast model outperforms the reference model in every look-ahead hour. The created forecast model also performed rather well against the five different forecast models, which performance was studied in (Pinson, 2006), although the performances of the created model and the five different forecast models are not straightly interpret, since the performance of a forecast model depend on the location where the forecast is made. However, as a result the created forecast model's performance was seen to fulfill the requirements, which were given to it.

The theory behind the optimal bidding method was studied in (Linnet, 2005) and the results of that study worked as a foundation to derive optimal bids in this thesis. The theory requires that the optimal bid can be found from a certain probability quantile of a probability distribution. Therefore, probability distributions of forecast error was created. The probability distributions were created with the method introduced in (Bludszuweit, 2008). It assumes that the forecast error distribution is beta distributed, which provides forecast error distributions with a sufficient accuracy, as it was shown in the thesis. However, there are better ways to create probabilistic distributions and since the accuracy of probability is the most important input in the optimal bidding, by using more advanced methods to derive probability distribution the method would function more accurately and thus the market participant's revenue would increase.

In order to see whether the optimal bidding method really improve the wind power participant's revenue and does the created forecast model and probability error distribution function in a real life case, some simulations were made from a Finnish market participant perspective. The simulations proved that there is a huge potential in optimal bidding method, which improves the market participant's revenue instead of using a point-forecast as a bid. Simulations were made by using the optimal regulation costs, which are the inputs to the model, and also using the history of regulation costs. The optimal regulation cost ratios were calculated on hourly, daily, monthly and quarterly basis, which means that the actual regulation prices and Elspot-prices were know at the bidding moment. Of course, a perfect regulation price and Elspot-price model is hard to create, but using these optimal regulation costs it was possible to analyze the potential of optimal bidding method.

In this thesis the weight was more given to the potential of optimal bidding and to see is there any potential for a market participant to use it. Therefore, advanced forecast model for regulation prices and Elspot-prices was not studied, although the method only needs up and down regulation costs as an input, and by using the ratio between those prices the optimum quantile can be found. However, it was important to see how the method would work in a real life situation. It was noticed that there were correlation in regulation cost ratios on yearly level and thus the simulations were made on 2010 by using the regulation cost ratios lagged with one year. Surprisingly, without having a forecast model for regulation cost ratios, the revenue was higher than just using point forecasts as bids.

The ratio between regulation costs and Elspot prices is quite low in Nord Pool, which means that the electricity price is much higher than the cost that the imbalances induces to the market participant. This leads to the situation that the regulation losses are relatively much smaller than the revenue from Spot trade. Of course, from a market participant point of view this does not matter since the losses are always taken from the market participant's pocket. However, the benefits of optimal bidding would be much clearer if the cost of regulation and Elspot-prices would be closer to each other. Therefore, making this study for other electricity market could lead to different results. For instance, a similar study in a Dutch electricity market resulted much clearer gain by using the optimal bidding method instead of using point forecast as a bid (Pinson, 2006).

The most important areas of further study would be to create a forecast model for regulation price and Elspot price, or if it would be possible to create a model to forecast directly optimal bidding ratios. Also it would be important to create more accurate probability intervals, which would improve the accuracy of optimal bids. In this thesis it was only studied bidding in day ahead market, Elspot. In real world it would be possible to bid also in Elbas market, which could also reduce the regulation costs. Therefore, bidding in the day ahead market and the intraday market would be a interesting step forward from this study.

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