Optimal Bidding in day-ahead Spot Markets for Electricity

The Case of Wind Power in Norway

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NTNU
Det skapende universitet

MASTERKONTRAKT
- uttak av masteroppgave

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Electricity suppliers submit bids to the market based on estimated production and deviating amounts of delivered energy result in imbalance costs. For intermittent sources such as wind power, minimising the imbalance costs impose great challenges. The introduction of the Swedish-Norwegian Renewable Energy Certificate System is expected to stimulate further wind power development in Norway, highlighting the need for optimal bidding procedures.

The following topics will be studied:
1. Develop, implement and test a stochastic optimisation model giving optimal spot market bids for combinations of electricity producing technologies in a day-ahead market setting, taking scenarios of forecasted spot market prices, balancing market prices and production as input.
2. Generate scenarios for model input, taking correlation in probability of occurrence into account.
3. Develop and describe a routine that generates scenarios from given data and runs the model for optimal bidding.
4. Investigate the value of the model by using measures such as the Value of Stochastic Solution (VSS) and the Expected value of perfect information (EVPI).

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Student: Jeg erklærer herved at jeg har satt meg inn i gjeldende bestemmelser for mastergradsstudiet og at jeg oppfyller kravene for adgang til å påbegynne oppgaven, herunder eventuelle praksiskrav.

Partene er gjort kjent med avtalens vilkår, samt kapitlene i studiehåndboken om generelle regler og aktuell studieplan for masterstudiet.

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Preface

This report represents my Master's Thesis in Managerial Economics and Operations Research at the Department of Industrial Economics and Technology Management (IØT) at the Norwegian University of Science and Technology (NTNU).

The Master's Thesis exhibits original research summarising the knowledge acquired by students during their five years at university. At first this task seemed unobtainable, particularly when performed by one student alone. After five months, I nevertheless feel this Master's Thesis appropriately represents the learning outcomes of my cross-disciplinary programme of study in terms of technology, management and economics.

Abstract

Through the last decades, climate change and energy dependence concerns have gained increased attention. Renewable energy development has expanded, with wind power being the fastest growing technology. This thesis investigates the optimal interaction between an operational wind park and the Nordic power market. Wind power producers incur costs of imbalances resulting from deviations from their submitted production plans to the spot market. This report develop, implement and test a stochastic optimisation model giving optimal spot market bids for intermittent electricity producers in a day-ahead power market. The optimal bids are based on the evaluation of a large number of scenarios for the uncertain realisations of the wind forecasts, the balancing market prices and the spot market prices.

A case study is undertaken in order to evaluate model performance. Data is collected for specified dates at current and future wind power sites of a Norwegian company. The developed stochastic optimal bidding model is executed, once for each wind park individually and once for all wind parks jointly. The case study reveals that jointly use of the model gives expected revenues higher than both the sum of individual use and submission of bids equal expected production. The increase in expected revenues results from a risk-pooling effect of jointly bid submission and from the inclusion of price and production uncertainty. The risk-pooling effect also suggests that wind park owners would benefit from geographically diversifying their wind parks within the same price area.

Use of the developed model gives rather small increases in expected revenues and is likely to violate the *Balance Agreement*. However, investigations of model results give basis for further discussions. Examinations of the case study results show that perfect production forecasts would make the inclusion of uncertainty unnecessary, indicating that efforts should be made in order to reduce the uncertainty of the production forecasts, rather than on improving the price forecasts.

From a socio-economic point of view, the regulation costs incurred to wind power producers represents a reduction in value from introducing wind power to the power system. Some of the potential value of wind power is lost, through what can be seen as transaction costs of the current power market. It is suggested that delaying the spot market bid submission deadline, which in turn reduce the wind forecast lead-time and hence uncertainty, would increase the value of introducing wind power to the power system. Further research should be undertaken in order to investigate the optimal spot market bid submission deadline, minimising all costs related to this deadline.

Sammendrag - Abstract in Norwegian

I løpet av de siste tiårene har klimaendringer og spørsmål om energiforsyningssikkerhet fått økt oppmerksomhet. Fornybar energi er i stadig utvikling, med vindkraft som den raskest voksende teknologien. Denne oppgaven undersøker det optimale samspillet mellom en operativ vindpark og det nordiske kraftmarkedet. Vindkraftprodusenter påløper kostnader for ubalanser forårsaket av avvik fra innsendt produksjonsplan til spotmarkedet. Rapporten utvikler, implementerer og tester en stokastisk optimeringsmodell som gir optimale spotmarketsbud for uregelmessige kraftprodusenter i *day-ahead* kraftmarkeder. De optimale budene er basert på en evaluering av et stort antall scenarier for usikre realiseringer av vindprognoser, balansemarkedspriser og spotpriser.

En case-studie gjennomføres for å evaluere modellens ytelse. Data samles inn for angitte datoer for nåværende og fremtidige vindparker tilhørende et norsk selskap. Den utviklede stokastiske optimale budgivningsmodellen kjøres, en gang for hver vindpark individuelt og en gang for alle vindparker i fellesskap. Case-studiet viser at bruk av modellen i fellesskap gir forventede inntekter høyere enn både summen av individuell bruk og ved innlevering av bud lik forventet produksjon. Økningen i forventede inntekter er et resultat av akkumulering av risiko, *risk-pooling*, og som følge av inkludering av pris- og produksjons-usikkerhet. Effekten av *risk-pooling* antyder også at vindparkeiere vil være tjent med geografisk spredning av sine vindparker innenfor samme prisområde.

Bruk av den utviklede modellen gir relativt små økninger i forventede inntekter og bryter trolig *balanseavtalen*. Modellresultatene gir likevel grunnlag for videre diskusjoner. Resultatene fra case-studiet viser at perfekte produksjonsprognoser ville gjort inkludering av usikkerhet unødvendig, noe som indikerer at usikkerheten i produksjonsprognosene bør reduseres, snarere enn å forbedre prisprognosene.

Fra et samfunnsøkonomisk synspunkt, representerer vindparkenes reguleringskostnader en reduksjon i verdien ved å innføre vindkraft i kraftsystemet. Noe av den potensielle verdien av vindkraft går tapt, gjennom det som kan sees som transaksjonskostnader ved dagens kraftmarked. En utsettelse av innleveringsfristen for bud til spotmarkedet, som i sin tur reduserer vindprognosens ledetid og dermed usikkerhet, ville økt verdien av å introdusere vindkraft til kraftsystemet. Videre forskning bør utføres for å finne optimal innleveringsfrist av bud til spotmarkedet, ved å minimere alle kostnader knyttet til denne fristen.

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List of Abbreviations

ARIMA   AutoRegressive Integrated Moving-Average
ARMA   Autoregressive, moving-average
DFIG   Doubly-fed induction generator
EEC   European Economic Community, EØS in Norwegian
EES   Electrical Energy Storage
EVPI   Expected Value Of Perfect Information
GFS   Global Forecasting System
NTNU   Norwegian University of Science and Technology
OTC   Over The Counter
SS   Stochastic Solution
TSO   Transmission System Operator, Statnett in Norway
VSS   Value of Stochastic Solution
WS   Wait-and-See (Solution)

Nomenclature

A. Sets and indices

S ; s Set and index of Scenarios
H; h Set and index of Periods
L ; l Set and index of Locations
L_u; u Set and index of Used Locations, where $L_u \subset L$

B. Parameters

Π_{sh}^s Spot price in scenario s in period h [NOK/MWh]
Π_{sh}^{b+} Upwards regulated market price in scenario s in period h [NOK/MWh]
Π_{sh}^{b-} Downwards regulated market price in scenario s in period h [NOK/MWh]
G_l Installed capacity of wind farm at location l [MW]
F_{shl} Production in scenario s, period h and location l [MW]
P_s Probability of scenario s

C. Variables

g_{shl} Production in scenario s during period h by wind farm at location l [MWh]
g_{sh} Total Production in scenario s during period h [MWh]
x_h Bid to the day-ahead market for total production for period h [MWh]
Variables introduced for linearisation:
d_{sh}^+ Positive deviation between g_{sh} and x_h in scenario s during period h [MWh]
d_{sh}^- Negative deviation between g_{sh} and x_h in scenario s during period h [MWh]

1 Introduction

During the last decade, climate change and energy dependency concerns have gained increasing attention. Consequently, governments around the world consider introducing regulations encouraging the use of renewable energy. In the EU, the goal has been set that 20 % of all electricity should origin from renewable sources within the year of 2020. This rather ambitious goal gives massive challenges when it comes to developing new and existing technology as well as integrating these technologies with the current power systems.

Wind power has been the renewable technology with the largest growth. The Norwegian government is obligated to further develop renewable energy as a result of the Kyoto protocol and directive 2001/77/EC1 of the European Parliament which comes in force in Norway through the EEC. One of the actions taken by the government in order to increase the level of renewable energy, was the introduction of the Swedish-Norwegian Renewable Energy Certificate System. The certificate system will generate an extra revenue-stream to developers of new, renewable electricity production.

When new wind energy production sites are developed and operating, the produced energy must be sold. The majority of physical trades take place through the Nord Pool Spot power exchange auction. All electricity suppliers must submit their production plans to this spot market. Deviations from the bids submitted are usually associated with imbalance costs. For intermittent sources such as wind power, minimising the imbalance costs impose great challenges since the production cannot be known in advance.

This thesis will perform the following tasks:

- Develop, implement and test a stochastic optimisation model giving optimal spot market bids for combinations of electricity producing technologies in a day-ahead market setting, taking scenarios of forecasted spot market prices, balancing market prices and production as input.

- Develop and describe a routine generating scenarios from given data and runs the model for optimal bidding.

- Investigate the value of the model by using measures such as the Value of Stochastic Solution (VSS) and the Expected value of perfect information (EVPI).

A case study will be used in order to investigate the performance of the developed model. With support from the main topics, discussions regarding the socio-economic value of wind power will also be included. Finally, suggested further research topics regarding possible actions reducing the imbalance costs of intermittent sources and thereby the associate socio-economic losses are presented.

2 Literature Study

This chapter gives an introduction to the current literature governing the market interaction process for intermittent renewable energy production. Section 2.1 presents an overview of market interaction models describing the bidding process for renewable energy in day-ahead market settings. The bid sizes of renewable energy production to day-ahead markets depend on the forecasted production. Several methods exist in order to predict wind park production. Section 2.2 gives an overview of relevant literature concerning wind power prediction tools, Section 2.3 introduces spot price prognosis and Section 2.4 presents regulated power market price prognosis.

2.1 Optimal Market Interaction of Renewables

With the exponential growth of the renewable energy industry, attention has been given to the market interaction for producers selling energy to electricity markets. The attention is reflected by the numerous articles concerning optimal bidding and market interaction, mostly published during the last ten years. Most approaches are specialised cases, some include management of Energy Storage (ES) while others are adapted to market arrangements different to the Nordic system. This section will give an overview of the relevant literature concerning market interaction of renewable energy. It will do so by classifying the models used and pointing out both advantages and disadvantages of the chosen models.

An overview of the current research development concerning the use of optimisation algorithms in the field of renewable and sustainable energy is provided by Alcayde, Baños, Gil, Gómez, Manzano-Agugliaro and Montoya (2011) [4]. This study reviews over two hundred papers and serve as s a guide to relevant research in the field.The first conclusion of the study is that the use of optimisation methods to solve renewable energy problems has increased dramatically in recent years, specially for wind and solar. The second conclusion is that traditional approaches for modelling and solving still were in use at the same time as the number of articles using heuristic optimisation methods was growing. Frances and Kwon (2012) also make a review of optimisation based models for power producers in day-ahead electricity auction markets [28]. They present several relevant models, although limited attention is given to intermittent sources.

One of the models reviewed is written by Hildrum, Holen and Korpaas (2003) at NTNU, concerning operation and sizing of wind power plants with energy storage [24]. This article focuses on the energy storage and transmission constraints, and presents a deterministic model where spot prices, wind power production and balance prices are known in advance. The article concludes that introducing energy storage will increase wind farm revenues, but it is not investigated how much introduction of storage would create in revenues by itself. The energy storage used as example was pumped hydro storage, considering one day of operation. It is pointed out that water value consideration over a longer period would make the model more complete, although also more complex.

A stochastic model for optimisation of wind power with possibility to use

pumped storage is developed by Garcia-Gonzalez, Gonzalez, de la Muela and San-
tos (2008) [21]. They presents a two-stage stochastic problem with uncertainty in
spot prices as well as wind power output. The first stage decision is to decide what
volume to bid to the spot market, while the second stage discussion concerns how
much energy to actually deliver to the market, once the spot price and wind energy
are known. The Spanish market, being similar to the Nordic market, is considered.
The model simplifies the balancing market substantially, by assuming the balance
price always being a fixed fraction higher than the spot price. When modelling the
pumped-storage, one day is considered, thereby neglecting water values for coming
days. Nevertheless, it is shown that a joint market interaction increases the total
profits of the producers, compared to the profits when the producers interact with
the market individually. The study concludes that this is due to the fact that de-
viations from the volume bid to the spot market is calculated for both producers
combined. The pumped-storage proved to have flexibility of operation, reducing
the total imbalance costs. The wind farm owner was assumed risk-neutral.

The Master's Thesis at NTNU of Ravnaas (2009) considers optimal bidding
for a wind power park [52]. In connection with this thesis, Doorman, Farahmand
and Ravnaas (2010) published an article describing the Nordic power system in
great detail and implements this in a mathematical model [38]. The first stage and
recursive decisions are the same as in the paper from Garcia-Gonzalez, Gonzalez,
de la Muela and Santos (2008) [21], but uncertainty is now also included in the
balance market prices, as well as for wind power output and spot prices. The
balance market is described both using the 1-price and 2-price models. The article
concludes that the introduced 2-price system gives a wind farm producer incentives
for making bids equal to expected production and that expected profits are reduced
compared to the case of 1-price. Further work is suggested on the effects on the
balance market price in markets with higher wind penetration. From the master
thesis, data files for solving the mathematical model is obtained. The problem is
implemented in MATLAB and the solution algorithm is based on "trial and error"
approach with trying all possible bids, and then choosing the best one. The model
is only concerned about one actor interacting with the market.

Coordinated planning of wind and hydropower, when they are located in an
area with limited transmission capacity, is the focus of the Swedish article by
Matevosyan, Olsson and Söder (2009) [32]. They generate scenarios from uncer-
tainties arising from wind power production, spot prices and balance prices. The
article focuses on deciding the price that the wind power producer should pay the
hydropower plant in order to reduce the hydropower output when the capacity
limit of the transmission line is reached. The study concludes that coordination of
the wind and hydropower plant increases revenues for both actors, as they used the
available transmission capacity more efficient. In order to achieve this, the size of
the payments from the wind farm to the hydropower plant is described. The study
points out that the model used is a two stage stochastic model and that outcomes
of all stochastic variables were known when deciding the recursive variable. This
is not entirely correct, and future work is suggested to deal with implementing one
more stage into the model.

Two articles developing models similar to this thesis became available during the spring of 2012. The first article was available online 17 March 2012 where Catalão, Mendes and Pousinho (2012) develop a model closely related to the model developed through this thesis [37]. The Portuguese market is considered and case studies is performed. The article concludes that using the stochastic model increases the expected profits and shows that wind power producers should not bid the expected production, given that reliable price forecasts are available. The second article is a pre-print submitted by Ávila, Hakvoort and Ramos to Elsevier 9 May 2012 [3]. The article is based on the doctoral thesis of two of the authors. The stochastic optimisation model introduced is very similar to the model developed in this master's thesis. The main difference is the market setting, where the doctoral thesis is based on the Dutch and German power markets with the possibility to exploit arbitrage opportunities when market prices are unequal.

A different approach to the bidding problem for intermittent power producers is possible when realising that choosing the optimal quantities submitted to the day-ahead market has the same properties as the *Newsboy* problem explained by Rudi and Pyke (2000) [40]. Adlakha, Nair and Wierman (2012) study the problem of conventional energy procurement in the presence of intermittent renewable resources [34]. The authors model the problem as a variant of the newsvendor problem, in which the presence of renewable resources induces supply side uncertainty, and in which conventional energy may be procured in three stages to balance supply and demand. The closed form expressions for the optimal energy procurement strategy is computed and the impact of increasing renewable penetration is investigated. Changes are proposed to the structure of electricity markets. A key insight from the results is that there is a separation between the impact of the stochastic nature of wind power aggregation, and the impact of market structure and forecast accuracy. It is shown that the optimal bids submitted to the day ahead market is expected to deviate from the expected production according to the cost of regulation. Additionally, the paper studies two proposed changes to the market structure, the addition and the placement of an intermediate market. It is show that addition of an intermediate market does not necessarily increase the efficiency of utilisation of renewable sources. Further, it is shown that the optimal placement of the intermediate market is insensitive to the level of renewable penetration.

Another example of using the Newsboy analogy is found in an essay by Rud (2009) called *"A Newsboy Model Perspective on the Power Market: The Case of a Wind Power Producer"* [39]. The essay focuses on the interaction between the day-ahead market and the real-time market, and discusses the optimal bidding and implications of a wind power producer who does not have the ability to predict with certainty his production, nor the ability to adjust production in real-time. The paper discusses how the problem may be interpreted within the classic newsboy model. In a setting of a day-ahead and a real-time market, the results indicate that the optimal sales bid of the wind power producer might diverge from the expected production. This aspect is also found in the context of market optimisation, where the uncertainty of the wind power production has direct implications for the optimal level of planned production by other producers.

2.2   Estimation of Wind Power Production

The use of weather prediction systems, more specifically wind forecasting methods, plays an important role when investigating the optimal market interaction of wind power. Forecasting methods can be divided into predictions of real-world realisations, *physical methods*, and implementations used when evaluating performance of optimisation models, *mathematical/statistical methods*. This section focuses on the the latter, which is work describing estimation methods of wind power production used when evaluating the performance of market interaction models.

A review on the forecasting of wind speed and generated power is provided by Lei, Shiyan, Chuanwen, Hongling and Yan (2009) [29]. Their article gives a bibliographical survey on the general background of research and developments in the fields of wind speed and wind power forecasting. ARMA models are discussed as the main type of conventional statistical methods. The article concludes that models all have their own characteristics. Some of them are good at short-term prediction while others perform better in long-term prediction; some are simple and widely used while other complex ones have more accurate results. Another article titled *A review on the young history of the wind power short-term prediction* by Costa, Crespo, Navarro, Lizcano, Madsen and Feitosaalso introduce relevant research in the field of wind forecasting used to predict wind turbine production (2008) [14].

Foley, Leahy, Marvuglia and McKeogh (2012) provide a practical approach to both physical and statistical methods [18]. They list common forecasting methods and discuss various measures used in order to determine and compare the performance of forecasting methods. The statistical and machine learning approach methods are detailed. Then the techniques used for benchmarking and uncertainty analysis of forecasts are overviewed, and the performance of various approaches over different forecast time horizons is examined.

Matevosyan and Söder (2006) use the statistical ARMA method when developing a model for minimisation of imbalance costs of trading wind power on the Nordic power market [31]. The model is similar to the model developed in this thesis, without taking uncertainty in prices into account.

An article comparing the performance of ARMA methods with quantile regression is written by Bertocchi, Innorta, Tomasgard and Vespucci (2010) [51]. This paper introduces a stochastic multi-stage linear model for the daily hydro-wind power system scheduling problem with scenarios on hourly wind power production. In order to study the influence of scenario generation on the optimal solution, two approaches for scenario generation was studied, the quantile regression and the autoregressive integrated moving average techniques. The article concludes from the value of stochastic solution that the quantile regression scenarios describe the uncertainty better than the ARIMA scenarios.

The general conclusions found in the literature are similar to what is stated by Foley, Leahy, Marvuglia and McKeogh (2012), namely that one of the ultimate goals of every wind power prediction model is to estimate the wind power output as early and as accurately as possible [18]. Wind power will become more attractive for system and market operators as weather prediction model accuracy improves and as

easier to use forecasting techniques are developed. Wind power prediction tools are invaluable because they enable better dispatch, scheduling and unit commitment of thermal generators, hydro plant and energy storage plant and more competitive market trading as wind power ramps up and down. Overall accurate wind power prediction reduces the financial and technical risk of uncertainty of wind power production for all electricity market participants.

2.3   Estimation of Spot Market Prices

At the submission time of production plans to the spot market, the future prices of this market are not known. This section introduce literature regarding methods used in order to generate forecast scenarios predicting next-day electricity prices in the spot market.

Contreras, Espinola, Nogales and Conejo (2003) investigate forecasts both for spot markets and long-term contracts, necessary to develop bidding strategies or negotiation skills in order to maximise benefit [13]. The paper provides a method to predict next-day electricity prices based on the ARIMA methodology. ARIMA techniques are used to analyse time series and been mainly used for load forecasting, due to their accuracy and mathematical soundness. The paper includes a detailed explanation of the ARIMA models and results from mainland Spain and Californian markets. The authors conclude that proper ARIMA models give reasonable errors, taking into account the complex nature of price time series and the results previously reported in the technical literature, in particular from Artificial Neural Networks.

Conejoa, Contrerasa, Espínolaa and Plazasb (2005) analyse different forecasting techniques to predict the market clearing prices of a day-ahead electric energy market [12]. The work concludes that time series techniques reveal themselves as more efficacious than wavelet-transform or neural network techniques. Among time series techniques, they find dynamic regression and transfer function algorithms more effective than ARIMA models.

A paper written by Zhou, Tesfatsion, and Liu (2009) develops a similar spot market forecasting method, based on an ARMA model [53]. The study proposes a two-stage approach for generating simulated price scenarios based on the available price data. Time series data from the Midwest ISO (MISO) are used as a test system to validate the proposed approach. The simulation results indicate that the proposed approach is able to generate price scenarios for distinct seasons with empirically realistic characteristics.

2.4 Estimation of Balance Market Prices

This thesis includes the uncertainty of the balance market prices. These prices are not known at the time of bidding to the spot market, and must therefore be forecasted. The literature has few articles concerning this topic, probably due to the fact that speculation of balance market prices might violate the regulations of the power market. Section 3.2.3 describe the applicable agreements in force at the Norwegian power system.

Jaehnert, Farahmand and Doorman (2009) presents work on modelling of prices using the volume in the Norwegian regulating power market [23]. The article develops a short term model based on a SARIMA process, and computes a forecast of future regulating states. With a statistical description of the regulating volumes, scenarios are generated that are the input to the long-term model resulting in regulation price scenarios.

Skytte (1999) performs an econometric analysis on the regulating power market in the Nordic power exchange [41]. The paper concludes that in order to buy regulating power one must pay a premium of readiness in addition to the spot price that is independent of the amount of regulation. For down-regulation the level of the premium of readiness is seen to be strongly influenced by the level of the spot price. On the other hand, the premium for up-regulation is less correlated to the spot price. Furthermore, it is seen that the amount of regulation more strongly affects the price of regulating power for up-regulation than for down-regulation. The disclosed cost of using the regulating power market is found to be a quadratic function of the amount of regulation. With the estimated relation a buyer or seller of electricity is able to optimise both his total bids on the spot and regulating power markets within his expectations of fluctuations of demand and supply.

3   Background

This chapter describes how wind turbines can be used in order to commercially generate electricity and discusses the functions of the electricity market where the produced energy is sold. Section 3.1 introduces the technology and economics of wind turbines while Section 3.2 describes the Nordic market for electricity.

3.1   Wind Power

Section 3.1.1 briefly elaborates on the main components of the wind turbine before it is explained in Section 3.1.2 how the wind turbine converts kinetic energy of moving air into electric energy that can be transmitted through the power grid. The measures of energy and efficiency are discussed in Section 3.1.3 and a short introduction to the economics of wind turbines are found in Section 3.1.4.

3.1.1   The Wind Turbine

Today, the wind turbines are considered one of the most mature renewable energy technologies. The horizontal axis turbine is the dominant type, although vertical axis turbines are gaining increasing interest because of its lower centre of gravity, an advantage in offshore installations [47]. The horizontal axis wind turbine consists of the main parts shown in Figure 1; rotor blades, nacelle, tower and foundation. Other core components are the generator and transformer. The majority of turbines also include a gear, while most directly driven turbines use permanent magnets. The gearbox is subject to frequent maintenance and failure, while directly driven turbines require heavy generators and expensive permanent magnets [36].
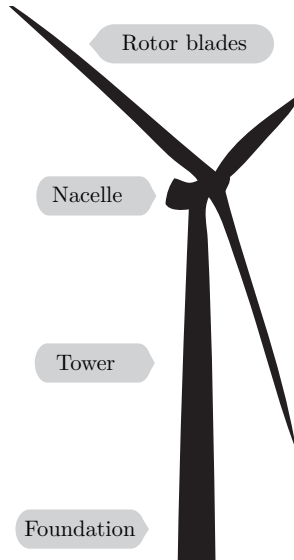
Figure 1: Main wind turbine components

The rotor blades use aerodynamic lift in order to convert kinetic energy into mechanical energy. This mechanical energy is then transferred through a shaft and often a gearbox to the generator, where the mechanical energy is transformed to electrical energy. The generator and gearbox, if present, are usually found inside the nacelle, which in turn is located on top of the tower. A higher tower means exposure to greater wind speeds, but also stronger dimensional forces. The tower can be fixed to the ground, or to a foundation sitting on the seabed. Floating turbines are currently under development and testing [10]. The electric energy output from the generator cannot be directly fed into the power grid. A transformer is therefore required in order to deliver the right power quality, meaning that frequency, voltage and other characteristics must satisfy the grid codes [50].

3.1.2   The Electrical System

The design of the electrical system for wind turbines differs from most conventional generators by the fact that the wind speed varies widely. Firstly, it must be decided whether a fixed-speed or variable-speed system is preferable. In a fixed-speed wind turbine the rotor speed is determined by the frequency of the power grid in combination with the gear ratio and the design of the generator. This means the rotor speed must be constant, regardless of wind speed [30]. Fixed-speed wind turbines are designed to reach maximum efficiency at a particular wind speed. The advantages of fixed-speed turbines are the simple, robust, reliable and well-proven technology with low cost electrical systems. The main disadvantages include uncontrollable reactive power, mechanical stresses and limited power quality control. Fixed-speed turbines are usually directly connected to the grid through a soft-starter and capacitor bank to reduce reactive power consumption. Being directly grid connected means that all wind speed fluctuations are transmitted to power fluctuations to the grid. In weak grids, or in systems with high penetration of wind power, such power fluctuations might become a serious issue [43]. The fixed-speed turbine was the dominant technology through the 1990s.

Due to increasing issues with the disadvantages of fixed-speed turbines, the variable-speed turbine is currently the dominant technology. Such turbines are connected to the power grid through a power converter. The fluctuations in wind speeds are absorbed in the rotor speed of the wind turbine. Variable-speed turbines are designed to maximise efficiency over a wide range of wind speeds. The power converter gives better control of power quality and mechanical stresses can be reduced. The challenges with variable-speed turbines are more complicated electrical systems leading to higher costs and also higher electrical losses.

Both fixed- and variable-speed turbines can be designed using different generator types, although most wind turbines use an asynchronous or induction generator having the advantages of mechanical simplicity and low price due to high production volumes. The main concern with such generators is the need for reactive magnetising current, which can be supplied from the grid, capacitor banks or modern power electronic converters. Another generator type is the doubly-fed induction generator (DFIG), which has the ability to control the flow of reactive power as well as providing voltage control. The DFIG gives a limited variable-

speed wind turbine, where the rotor speed is limited by the size of its variable rotor resistance.

Variable-speed turbines can also use synchronous generators, the dominant type in conventional electricity facilities. Synchronous generators do not need reactive magnetising current, but they are more expensive and mechanically more complicated than the other generator types described. Using a synchronous generator eliminates the need for a gearbox, but requires a full-scale frequency converter and leads to a large and heavy generator.

In order to reduce mechanical stress on components in the wind turbine as well as minimising power fluctuations, the aerodynamic forces on the turbine is controlled in different ways. Separation can be made between active and passive control mechanisms. Most recent turbines have active pitch control, where the angle of the rotor blades can be adjusted continuously according to the wind speed. At high wind speeds, the blades can be stalled in order to stop production and reduce forces on the wind turbine. Passive control means that the rotor blades are bolted to the hub at a fixed angle, designed to stall the blades at a certain predefined wind speed. Where passive control is cheap and simple, the active control system achieves greatest efficiency and low power fluctuations.

3.1.3   Energy and Efficiency

Only a fraction of the theoretical power in the wind can be utilised by Wind turbines. The theoretical power of the wind depends on the wind speed, v, the cross-section area considered, A, and the density of the air, ρ. The actual electrical output from a wind turbine also depends on rotor blade efficiency, mechanical losses and electrical losses. These losses are included in the power coefficient C_p. Equation (1) shows the formula for actual electrical output from a wind turbine.

$$P_{el} = C_p \cdot \frac{1}{2}\rho A v^3 \tag{1}$$

The power coefficient, C_p, is upwards limited by Betz's theorem [5] stating that the rotor blades at maximum can capture 59.26 % of the kinetic energy available in the wind. Wind turbines with C_p factors up to 50 % are commercially available.

Wind turbines operate from their cut-in wind speed to their cut-out wind speed, following a so-called *power curve*. Figure 2 shows individual power curves of two single turbines and the aggregated curve of a large wind park. Of the single turbines, one turbine is a low wind turbine while the other is designed for locations with strong winds. The Vestas V112-3.0 is chosen as the low wind turbine, while the Enercon E70-2.3 is chosen as high wind turbine. The 160 *MW* wind park consist of 80 individual turbines, including the wake effect, which is the effect of a slower airflow experienced by some of the turbines in the wind park due to disturbance from upstream turbines. When the wind speed exceeds the cut-out speed, production shuts down.
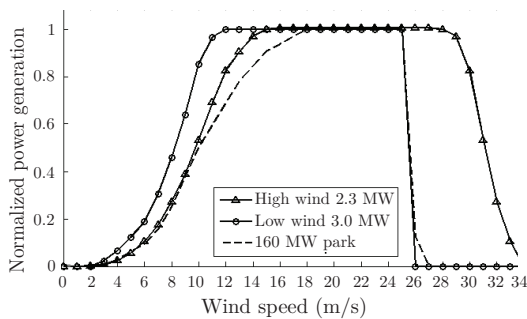
Figure 2: Power curves showing high wind, low wind and wind park production at different wind speeds.

In order to reduce frequent start-ups and shut-downs, the turbine is not restarted until the wind speed drops 3 to 4 m/s below cut-out speed. This action is called the hysteresis loop, and can lead to significant loss of power in very short time. A passing storm can cause huge challenges for a power system with high wind power penetration when a large number of turbines enter hysteresis loops at almost the same time. Some turbines are equipped with technology intending to smoothen the cut-out and restart at high wind speeds. The chosen Enercon turbine has this feature, as can be seen on the right tail of the high wind turbine power curve in Figure 2.
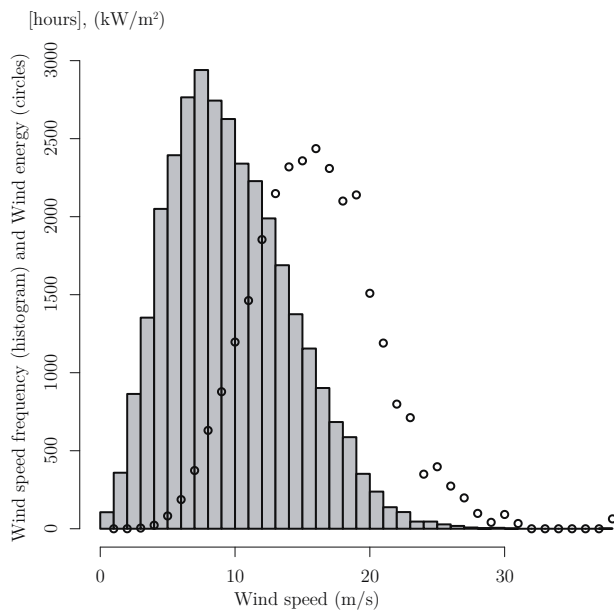
Figure 3: Wind speed and energy content distribution, from [27].

When designing and choosing among available turbines, the rated wind speed plays an important role. This is the wind speed at which the turbine output reaches rated capacity. The rated wind speed should be chosen close to the wind speed containing the most energy at the site chosen for installation. This does rarely match the most frequent wind speed, since the available power in the wind increases with the cube of the wind speed. The wind speed distribution graphed together with the energy content at different wind speeds for an example site at the west coast of Norway is shown in Figure 3. The histogram shows the number of hours at given wind speeds, while the circles show the energy content of a cross-section of the airflow in kW/m^2, also at given wind speeds.

3.1.4   Economics

In order to encourage companies to increase renewable energy production, several countries have support schemes that in different ways attract investments into wind energy development. Wind power is capital intensive compared to conventional power generation. Around 75 % of the total costs of wind energy are related to upfront capital costs [7]. The turbine and foundation make up for 80 % of this cost. Grid connection accounts for 10 % while land rent, electric installation, consultancy, financial costs, road construction and control systems fill the last 10 %. Cost of grid connection, foundation and electric installation are the most site dependent costs.

Operation and maintenance costs lie in the range of 1.5 % to 2 % of the initial investment. These costs include regular maintenance, repairs, insurance, spare parts and administration. Wind turbines are considered to have en expected lifetime of around 20 years. Lifetime expectancy depends highly on the site chosen, where turbulent locations reduce expected lifetime. Offshore locations have less turbulent airflows, but have challenges with salty conditions. Although wind energy is considered a green source of power, the rotor blades put forward great disposal challenges at the end of their lifetime.

Wind power projects have high risks due to the high initial investment costs. The revenue stream comes over the lifetime of the wind park and in order to give a positive net present value (NPV) of a project in total, the revenues must cover the initial investment, operation and maintenance costs in addition to giving return on the investment. The revenues are in turn highly dependent on the market prices, including the spot market, balance market and electricity certificate market prices. The future market prices are associated with a high degree of uncertainty, giving high risk to wind power projects. Even small changes in the predicted prices largely influence the NPV of a wind power project.

3.2   The Electricity Market

Electricity markets can be seen as a sequence of market arrangements that organise the interactions between the market players. The market arrangements have different timeframes from the long-term to short-term, until real time. Section 3.2.1 introduce the main market arrangements in the Nordic system before the spot and regulated power markets are discussed in more detail in Section 3.2.2 and Section 3.2.3, respectively. Lastly, Section 3.2.4 describes the market for electricity certificates.

3.2.1   Electricity Market Arrangements

This section describes the main characteristics of electricity markets in restructured or deregulated power systems. The market for electricity differs from most other markets due to characteristics of the commodity. Electricity cannot be stored on a large scale to competitive prices. When electricity is generated, it has to be used the same moment. These physical characteristics give the power market certain challenges and necessitate schemes that differentiate it from most other markets. One of these differences is the continuous need for balance between suddenly varying supply and demand. Another challenge is the pricing of electricity. Since electricity is consumed the same time it is produced, the pricing must happen either ahead of real time, *ex ante* or after real time, *ex post.*

Source   Generation   Transmission   Distribution   Retailing

Figure 4: The Value Chain of Electricity, adapted from [22].

The generalised value chain for electricity is shown in Figure 4. Electricity can be based on a large range of different energy *sources*, including renewable and non-renewable resources. Non-renewable resources are often transported long distances for use in centralised conversion facilities in order to generate electricity. In contrast, most renewable energy conversion takes place in generators at the location of the resource. *Generation* takes place at conversion facilities where energy from the original source is converted into electricity. The generated electricity is then brought to substations located close to end customers by the main *Transmission* network. *Distributors* are then responsible for carrying the electricity from the substations to end customers. Electricity *Retailers* are responsible for charging the end customers for the amount of electricity used. The Retailer is responsible for the terms of power delivery, including the price of electricity paid by the end consumer. When customers change electricity retailer, this will change the price and terms of delivery, but not the physical flow of electricity.

In 1991, the Norwegian market for electricity was deregulated. The other Nordic countries followed until the year of 2000 when Norway, Sweden, Finland and Denmark had a common market for electricity. Trading of electricity in this deregulated market consists of both physical deliveries and financial contracts. A representation of the nordic restructured power market is shown in Figure 5. This market has a clear separation between the *wholesale* and *retail* market ensuring that both power generation and sales are subject to competition.
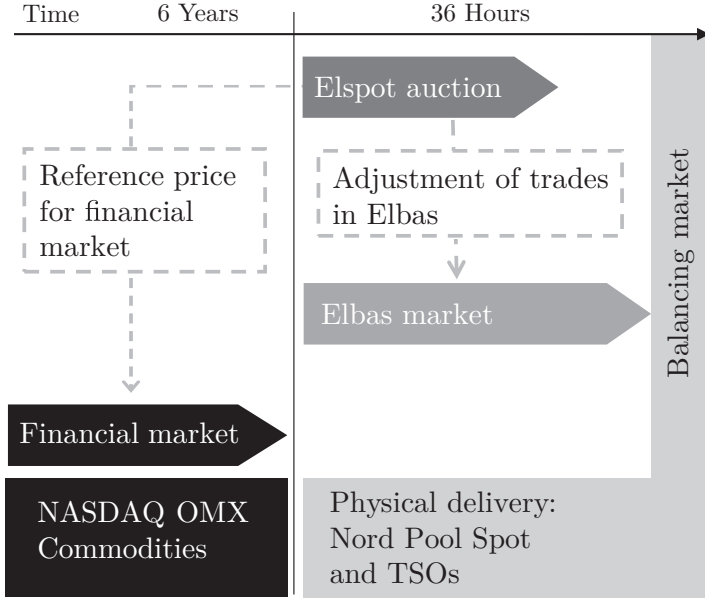
Figure 5: The Nordic electricity market, adapted from [44].

The *wholesale* market consists of trades between generators, grid owners and retailers both for short-term purposes and long-term deliveries. Wholesale trading takes place through brokers, Over-the-Counter (OTC) trades or through power exchanges. In the Nordic system, NASDAQ OMX is the financial power exchange while physical power exchange is traded at Nord Pool Spot through *elspot*. Section 3.2.2 describes the elspot market in more detail.

End customers buy electricity at the *retail* market. Here, retailers re-price electricity bought in the wholesale market before offering contracts to end customers. Retailers usually offer electricity at fixed-price, variable-price or spot contracts. Fixed price contracts require the customer to pay the same unit price during a given period, while variable-price contracts allows the retailer to change the price after a given customer notice time. Spot contracts follow the spot price with either a mark-up or fixed overhead. Customers can choose between retailers charging them for electricity, but not between distributers charging network tariff. The distributers are in a position of natural monopoly since building several distribution networks would not be socio-economic.

Figure 5 also shows the recently introduced intra-day market, *elbas*. Through this bilateral market, participants can trade expected imbalances close to real-time. By using elbas, actors can adjust their bids according to expected deviations close to real-time. So far, elbas has not proved to be a liquid marked over time in most areas in Norway [11], but this might change in some price areas because of the expected introduction of new, renewable energy production. Since elbas is a bilateral market, it requires that there is a buyer or seller willing to buy or sell volumes equal a participants expected imbalance.

During operational hours, system balance must be assured. In the Balancing market, shown at the far right of Figure 5, actual demand is compared with the *elspot* volumes, *elbas* trades taken into account. Assuring system balance and power quality are collective matters, and therefore a free market will fail to assure system balance and other ancillary services without proper regulations [8]. Consequently, the balancing responsible entities are often handled through natural monopolies, usually by the Transmission System Operator (TSO). Although the balancing responsibility is handled through a natural monopoly, market functions are often used also in the Regulated Power Market described in Section 3.2.3 [26].

In order to encourage further investments into the field of renewable energy, a common Swedish-Norwegian energy certificate market was recently launched. This market assigns an additional income to producers of renewable energy. The Energy certificate market is described in Section 3.2.4.

The optimal bidding problem can be solved independently from the financial market, the intra-day market elbas and the energy certificate market. These markets are therefore given less attention throughout this thesis. Financial contracts can secure energy sales and reduce the risk of operation, but will not influence the bids submitted to the spot market. Through elbas, participants can buy or sell expected imbalances. The *elbas* market gives the possibility to reduce the losses of deviation from bids submitted to elspot, but does not affect the optimal bids that are to be submitted to the spot market in the first place. The same argument goes for the electricity certificate market, which gives additional profits to wind parks without influencing the voice of optimal bid to the spot market.

3.2.2   The Spot Market

In the Nordic system, trading of more than 70 % of physical deliveries take place through Nord Pool Spot [44]. Nord Pool Spot has the responsibility for both the day-ahead market *elspot* and the intra-day market *elbas*. In the *elspot* market, several rules apply to the participating actors. Firstly, the bids must be submitted to the market by 12 noon. Secondly, bids must state preferred sold or bought quantities at distinct prices for each hour of the following day. Different bidding formats are possible through flexible bids, block bids and linked block bids. Since these other bidding possibilities are not relevant for wind power producers, they will not be described further here. Thirdly, the bids must be on the interval from zero to installed capacity, increasing by 0.1 MW. With increasing prices, the quantity of the submitted bids must be non-decreasing
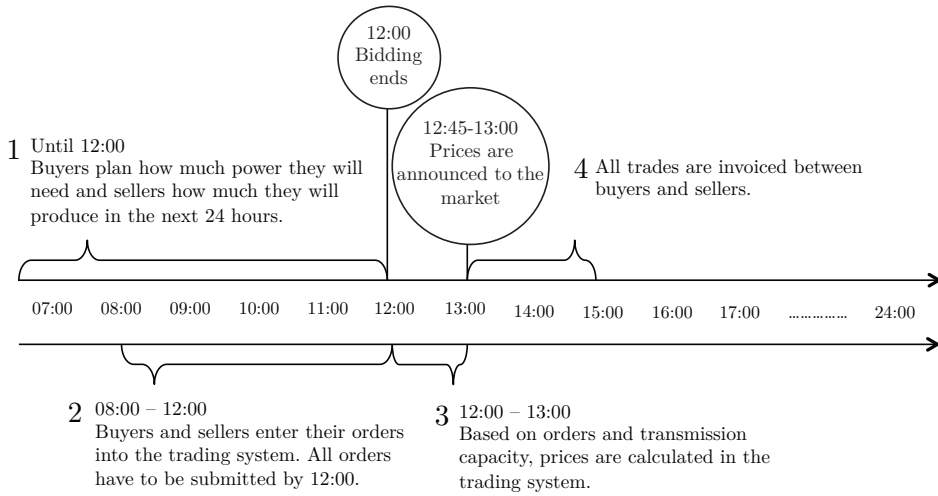
Figure 6: Daily Routines at Nord Pool Spot, adapted from [44].

The Nord Pool Spot elspot is a clearing market arranged as an auction with ex-ante pricing. Figure 6 shows the daily routines at Nord Pool Spot. Power supplying actors submit bids with their preferred production plans, creating the supply curve. The demand curve is partly created from bids from price sensitive power demanding actors and partly from retailers estimating household demand. Typical participants of this market are power utilities, retail companies, large industrial companies as well as broker firms. Figure 7 illustrates how the resulting supply and demand curves are used in order to find the market clearing price, also called the system price. Nord Pool Spot calculates the system price for each hour through the following day from bids submitted before 12 noon. The price can vary from hour to hour, but stays fixed for one hour at a time.

Price [EUR/MWh]
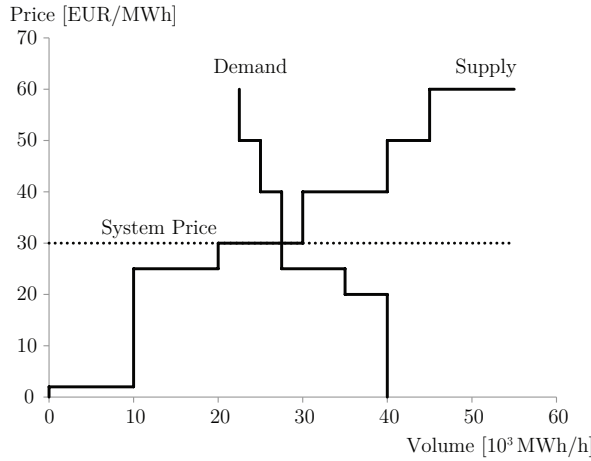
Figure 7: Example of market clearing process at Nord Pool Spot.

The calculation of the system price does not take into account transmission constraints. Such constraints may limit the possible physical delivery from where the electricity is supplied, to where it is demanded. In order to account for the transmission constraints, the Nordic system is divided into price areas called *elspot areas*. The TSO decides the bounds of these areas according to transmission limits. The areas may have prices that differ from the system price, depending on whether the maximum transmission capacities between the areas are reached. In areas with surplus supply, the price will be lower than the system price and vice versa. Transmission losses are also the reason why market participants are charged for point of connection tariffs based on marginal losses. Generators must pay a predetermined percentage times the spot price in order to account for marginal transmission system losses to the TSO. These costs are not considered in this thesis and an introduction can be found in literature [25].

It usually takes one hour from all bids are submitted until Nord Pool Spot has finished its calculations and released the prices for the following day. The price then tells the market participants how much energy they are obligated to purchase or sell during the various hours of the following day. These volumes are also forwarded to the TSO for use when settling the deviations for each market participant in the regulated power market.

3.2.3   The Regulated Power Market

The main task given to the Transmission System Operator (TSO) is to facilitate the spot market by physically enabling the transport of electricity from sellers to buyers [46]. In Norway, the TSO is also ensuring system balance and power quality. This includes responsibility to account for sudden changes in supply or demand in order to keep the frequency of the system steady at 50 Hz. Changes in supply or demand occurs when market actors deviate from submitted plans to the spot market, or with the presence of faults on transmission lines or production facilities.

The TSO must make arrangements so adjustments can be made on short time scales. The arrangements are divided into primary, secondary and tertiary reserves [20]. The primary reserves are automatically activated by frequency deviations. Secondary reserves are in Norway manual and used in order to prepare for larger deviations than the primary reserves can handle. The tertiary reserves are manually activated and ensure that there is a buffer for the primary and secondary reserves. The tertiary reserves are partly solved by using a market mechanism called *the regulated power market* or often just *the balance market.*

In the regulated power market, balance participating entities bid the prices they require in order to alter production or consumption. Examples of such bids are shown in Figure 8. The bids are used by the TSO when imbalances arise in the power system in order to activate the options with lowest associated costs replacing the reserves used in order to restore system balance. Among the cheapest options, the option with the largest deviation from the spot price will set the regulated power market price for that particular hour.
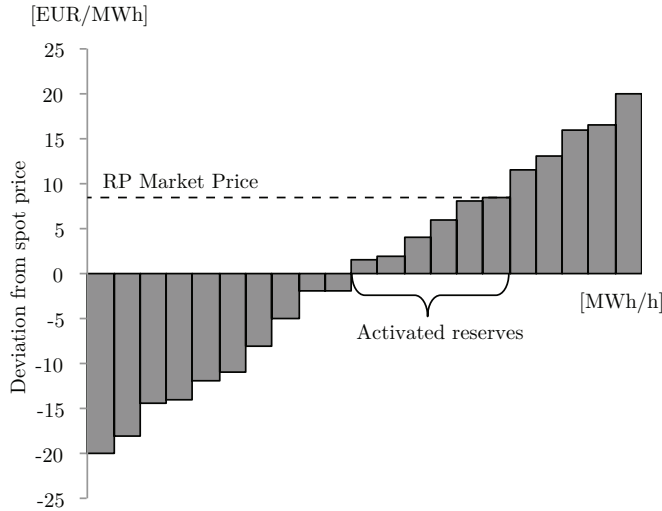
Figure 8: Regulated power market bids and price setting.

In order to enter the wholesale market for electricity, Norwegian participants must sign the *Balance Agreement* given by Statnett, the Norwegian TSO [45]. This agreement gives the TSO the right to settle the imbalances of all participants at the regulated power market prices. The agreement also refers to the laws and regulations governing the regulated power market [1]. Among other regulations, the agreement gives market participants the obligation to follow submitted plans and states that imbalances are settled inside every price area for each participant.

After operating hours, the TSO calculates the mismatch between actual and submitted volume. The TSO is given the submitted volumes from Nord Pool Spot, while the actual volumes are measured in the network. If the system in total has less supply than demand during a particular hour, the system is upwards regulated

for that hour and the balancing market price will usually be higher than the spot price. If the supply is greater than the demand, the system is downwards regulated during that hour. Similar, if demand is equal supply, the system is zero regulated. If a market participant is deviating from its submitted volume, this deviation is settled by the TSO in a process called the balance settlement.

The balance settlement is a way for the TSO to distribute the costs of regulation among balance responsible actors of the power market. According to the *Balance Agreement* and the associated regulations, all balance responsible actors pay or are getting paid for their deviations from submitted bids. For demand participants in the market, deviations are sold or bought at the regulated power market price. For supply participants this is also true for participants with less than 3 MW installed capacity. This is called the 1-price model. When installed capacity of supply participants exceeds 3 MW, deviations will be settled using the 2-price model. The 2-price model was introduced in order to make sure that producers never get better prices in the regulated power market than in the spot market and thereby encourage the producers to submit bids equal expected production [38].

Table 1: The six possible balance market cases and corresponding profits.

Case	System Regulation	$(g_{sh} - x_h)$	Profit (Loss)
1	Zero	$-$	$(g_{sh} - x_h)\Pi_{sh}^{s}$
2	Up	$-$	$(g_{sh} - x_h)\Pi_{sh}^{b+}$
3	Down	$-$	$(g_{sh} - x_h)\Pi_{sh}^{s}$
4	Zero	$+$	$(g_{sh} - x_h)\Pi_{sh}^{s}$
5	Up	$+$	$(g_{sh} - x_h)\Pi_{sh}^{s}$
6	Down	$+$	$(g_{sh} - x_h)\Pi_{sh}^{b-}$

In 2009 the 2-price model was introduced in Norway. A supplier with greater than 3 MW installed capacity will find itself within one of the six cases shown in Table 1:

1. If the system is zero regulated, volume bought in the balance market will be priced at the spot price, Π_{sh}^{s}.
2. If the system is upwards regulated, volume bought in the balance market will be priced at the upwards balance price, Π_{sh}^{b+}.
3. If the system is downwards regulated, volume bought in the balance market will be priced at the spot price, Π_{sh}^{s}.
4. If the system is zero regulated, volume sold in the balance market will be priced at the spot price, Π_{sh}^{s}.
5. If the system is upwards regulated, volume sold in the balance market will be priced at the spot price, Π_{sh}^{s}.
6. If the system is downwards regulated, volume sold in the balance market will be priced at the downwards balance price, Π_{sh}^{b-}

In cases where actual production equals submitted bid, $(g_{sh} - x_h) = 0$, there will be no regulation revenue or cost.

3.2.4   The Energy Certificate Market

The growing awareness of climate change and energy dependence concerns have created discussions in many countries whether renewable energy development should be encouraged by the governments. The European Union (EU) introduced the Directive on Electricity Production from Renewable Energy Sources (*RES Directive*) as one of many ways to encourage renewable energy development [16]. The *RES Directive* comes in force in Norway through the European Economic Community (*EEC*).

Since little new renewable energy production was initiated i Norway, the government decided to take action. Since 1 January 2012 Norway has been part of a Norwegian-Swedish electricity certificate market, encouraging increased development of renewable energy [2]. This bilateral certificate market is a support scheme for renewable energy, estimated to introduce 26.4 TWh of renewable production by 2020. The additional amount of energy corresponds to the power consumption of more than half of all Norwegian households. The new production capacity will be distributed between Norway and Sweden depending on investor views on profitability and complexity factors of obtaining concessions.

Producers of renewable energy that fulfil the given requirements [2], can sell electricity certificates in addition to the electricity they produce. The price of the certificates is given through the certificate market, where demand is created by requiring every market participant buying electricity to also buy electricity certificates. This way the government sets the volumes requested of new, renewable production while the market provides certificate prices [42].

The Energy Certificate Market will not affect how wind parks interact with the spot market. The certificate market is however likely to initiate a large-scale development of new wind parks, increasing the demand for methods to maximise revenues once the wind parks become operational.

4 Model Formulation

This chapter outlines the formulation of a mathematical stochastic optimisation model aiming to find optimal hourly bids to the day-ahead spot market for wind power. Section 4.1 introduces the characteristics of the problem, with a presentation of desired model output, necessary model input and how the model deals with uncertainty. Thereafter, model development is presented through Section 4.2.

4.1 Introduction

This section describes the characteristics of the bidding problem faced by a wind energy producer when interacting with the market for electricity. A setting similar to the Nordic power market is assumed, with the main characteristics previously described in Section 3.2.

The main component of the market interaction for owners of wind power in a day-ahead market is the bidding process. Section 3.2.2 described how this process takes place in the Nordic spot market. Conventional electricity producers use the possibility to bid different quantities at distinct prices in order to maximise expected long run profits [19]. In contrast, the bidding process for wind power will be a matter of quantity. This is due to the fact that wind power has close to zero marginal cost and usually no option of energy storage, both implying that production is beneficial whenever prices are above zero.

The actual production from wind parks will often differ from the bids initially made to the spot market. This deviation may in turn reduce the total profits due to regulation costs. Reducing the expected difference between the quantity bid to the spot market and the actual delivered quantity can therefore increase profits. The regulated power market and the possible losses when deviating from the submitted plan was discussed in Section 3.2.3.

Mathematical problems must be related to the underlying real world problems. In this thesis the methodology used is first to identify the desired model output in Section 4.1.1, before realising the necessary model input through Section 4.1.2. The use of scenarios in order to represent uncertainty is explained in Section 4.1.3.

4.1.1 Desired Model Output

When formulating an optimisation problem mathematically, it is necessary to first identify the real-life problem at hand [6]. Afterwards, a suitable mathematical model can be formulated, implemented and executed. The output of the optimisation model aims to help decision-makers take informed choices. In order to give this decision support, it is necessary to identify the decisions that are to be made as well as what additional information that might be useful to the decision-maker. In the case of optimal bidding in a day-ahead spot market for electricity, the main decision is choosing the size of hourly bids submitted to the spot market. Information supporting this decision include expected hourly wind farm production, expected daily revenues from the spot market as well as expected daily costs or revenues from the regulated power market.

4.1.2   Necessary Model Input

In order to produce useful results, a model must receive input data describing characteristics of the problem. For wind power, the production and hence the wind speed forecast for the twenty-four hours at the day of operation is of importance. Other required inputs include hourly spot prices as well as upwards and downwards regulated power market prices. The future always represents uncertainty, meaning that deterministic values of required input data cannot be known [6]. In order to describe the problem properly, this uncertainty is taken into account when describing the optimal bidding process.

4.1.3   Representation of Uncertainty

One way of dealing with uncertainty is by using the expected values in a deterministic model. This gives a simple and fast model, but is not likely to provide the best decision support [6]. Another way to deal with the uncertainty associated with future events is by introducing a stochastic programming model, where it is assumed that information regarding the distribution of the unknown parameters are known or can be estimated. Using such distributions, scenarios of parameter realisations can be made.
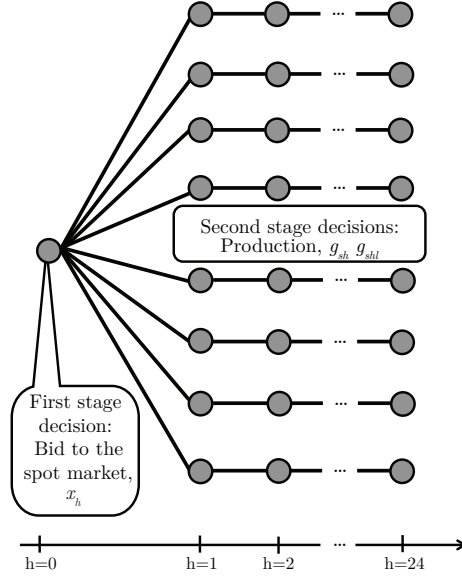
Figure 9: Scenario tree showing how uncertainty is handled in the model.

Each scenario will have a given probability, P_s, and every node in the second stage will have a given spot price, Π_{sh}^s, upwards regulated power market price, Π_{sh}^{b+}, downwards regulated power market price, Π_{sh}^{b-}, and predicted output for each wind park, F_{shl}. The problem has two stages and twenty-five time periods, as seen in Figure 9.

A sufficient number of scenarios are used as input to the two-stage stochastic model in order to represent uncertainty. The bid to the day ahead spot market, x_h, is the first stage decision, while the actual individual and total production in each scenario, g_{sh} and g_{shl}, are the recourse decisions. The first stage decision must be made initially, while the second stage decisions are to be made once nature has revealed the actual parameter realisations. The model has one time period for the first stage decision, settling what bids to submit to the spot market for each hour of the following day, and twenty-four time periods for the second stage decisions, resolving the actual production in each scenario.

4.2 The Optimal Bidding Model

This section describes the formulation of a model for the optimal bidding process for wind energy production. The uncertainty regarded in the bidding model for wind parks include the forecasting of production, spot prices and regulated power market prices. Section 4.2.1 formulates the revenue maximisation problem faced by either a single wind farm or several wind farms within the same price area, depending on model input. The complete model formulation is repeated in Section 4.2.2.

4.2.1 Formulating the Optimal Bidding Model

The revenue generated by a wind park can be split in three, one part from acting in the spot market and two parts from acting in the regulated power market. When actual production, g_{sh}, exceeds the bid submitted to the spot market, x_h, or contrary when actual production, x_h, is less than submitted bid, g_{sh}, market participant deviations are settled through the regulated power market as described in Section 3.2.3. Surplus production will be sold at the downwards regulated power market price, Π_{sh}^{b-}, while insufficient production must be accounted for with purchase of regulated power at the upwards regulated power market price, Π_{sh}^{b+}.

When several wind farms are included in the bidding process, only one bid is submitted for each hour of the following day to the day-ahead spot market [1]. As a consequence, imbalances are jointly settled meaning that the total imbalance is considered rather than the sum of the individual imbalances from each wind farm.

$$max \text{ Revenue} = \sum_{s \in S} \sum_{h \in H} P_s \cdot [\text{Spot}_{sh} + \text{RP Sale}_{sh} + \text{RP Purchase}_{sh}] \qquad (2)$$

The objective function of the linear stochastic optimisation problem shown in Equation (2) takes the sum over scenarios, s, and periods, h, of the scenario probability, P_s, multiplied by the sum of revenues from the spot market, Spot_{sh}, as well as regulated power market purchase and sale, RP Sale_{sh} and RP Purchase_{sh}.

$$\text{Spot}_{sh} = x_h \Pi_{sh}^s \qquad (3)$$

Equation (3) describes the revenue in each scenario, s, and period, h, from acting in the day ahead spot market, the scenario and period spot price Π_{sh}^s, times

the submitted bid for that hour x_h.

$$\text{RP Sale}_{sh} = \begin{cases} (g_{sh} - x_h)\Pi_{sh}^{b-} & | (g_{sh} - x_h) > 0, \text{RP Downwards} & (4a) \\ (g_{sh} - x_h)\Pi_{sh}^{s} & | (g_{sh} - x_h) > 0, \text{RP Upwards} & (4b) \end{cases}$$

Equation (4) shows that the revenue in a period where actual production is greater than submitted bid, depends on whether the market is upwards or downwards regulated. This follows the 2-price model described in Section 3.2.3. The regulated power market prices are given as both upwards and downwards prices for each hour. When the system is upwards regulated, the upwards price is greater than the spot price while the downwards price is equal to the spot price and vice versa. Because of this feature of the input data, the formulation can be simplified as shown in Equation (5).

$$\text{RP Sale}_{sh} = (g_{sh} - x_h)\Pi_{sh}^{b-} \qquad | (g_{sh} - x_h) > 0 \tag{5}$$

When the actual production is less than the submitted bid, the negative revenue from purchasing the corresponding amount of energy in the regulated power market can be described as shown by Equation (6).

$$\text{RP Purchase}_{sh} = (g_{sh} - x_h)\Pi_{sh}^{b+} \qquad | (g_{sh} - x_h) < 0 \tag{6}$$

When the system is zero regulated, the revenues from acting in the regulated power market will be the deviation between actual production and submitted bid, $(g_{sh} - x_h)$, times the spot price, Π_{sh}^{s}. Since the spot price and the regulated power market prices are equal when the system is zero regulated, the following holds; $(g_{sh} - x_h)\Pi_{sh}^{s} = (g_{sh} - x_h)\Pi_{sh}^{b+} = (g_{sh} - x_h)\Pi_{sh}^{b-}$. Periods with zero regulation can therefore be captured in Equation (5) or (6) for either upwards or downwards regulated market, and the term for the zero regulated balance market is hence not explicitly stated.

The simplified Equations (5) and (6) are dependent on whether $(g_{sh} - x_h)$ takes a positive or negative value. If this were to be implemented using a linear solver, it would have been necessary to introduce several new constraints [48]. Instead, the characteristics of the problem can be used by introducing two non-negative variables; d_{sh}^{+} and d_{sh}^{-}. These variables represent the positive or negative value of $(g_{sh} - x_h)$. For x_h fixed to zero, the relationship can be seen in Figure 10.

Only one of the variables d_{sh}^{+} and d_{sh}^{-} will differ from zero because of the objective function coefficients that are multiplied with them. These coefficients are the downwards and upwards regulated power market prices, Π_{sh}^{b-} and Π_{sh}^{b+} respectively. Attempts to give both d_{sh}^{+} and d_{sh}^{-} a positive value will always result in a more negative contribution to the objective function, as it either requires an actual production, g_{sh}, lower than possible production, F_{shl}, or a negative contribution in form of additional *RP Purchase*. The new variables d_{sh}^{+} and d_{sh}^{-} will be defined by the constraint shown in Equation (7).

$$(g_{sh} - x_h) - d_{sh}^{+} + d_{sh}^{-} = 0 \qquad \forall s \in S, h \in H \tag{7}$$
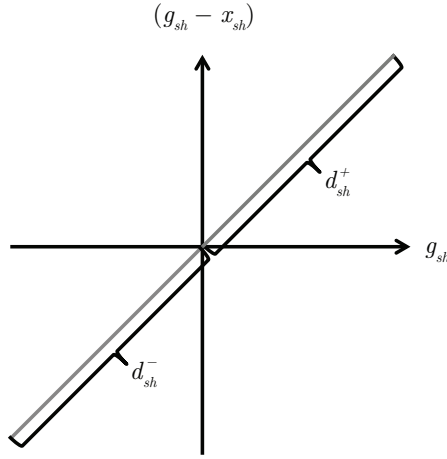
Figure 10: Representation of $(g_{sh} - x_h)$ shown with submitted bid, x_h, fixed to zero.

With the introduction of d_{sh}^+ and d_{sh}^- defined by Equation (7), the sales and purchases in the regulated power market seen in Equations (5) and (6), can now be expressed by Equations (8) and (9).

$$\text{RP Sale}_{sh} \quad = d_{sh}^+ \Pi_{sh}^{b-} \tag{8}$$

$$\text{RP Purchase}_{sh} = d_{sh}^- \Pi_{sh}^{b+} \tag{9}$$

In addition to Equation (7), the model constraints are shown in Equations (10) to (15). Constraint (10) defines the sum of the production from all the individual wind parks considered. Constraint (11) limits the production from each wind park by the maximum possible output of the wind park in every scenario and period. Constraint (12) makes sure that the bids submitted to the spot market fulfil the requirement of being less than total installed capacity as described in Section 3.2.2, while Constraints (13) to (15) make sure that all variables are non-negative.

$$g_{sh} = \sum_{l \in L_u} g_{shl} \quad \forall s \in S, h \in H \tag{10}$$

$$g_{shl} \leq F_{shl} \quad \forall s \in S, h \in H, l \in L_u \tag{11}$$

$$x_h \leq \sum_{l \in L_u} G_l \quad \forall h \in H \tag{12}$$

$$x_h \geq 0 \quad \forall h \in H \tag{13}$$

$$g_{sh}, d_{sh}^+, d_{sh}^- \geq 0 \quad \forall s \in S, h \in H \tag{14}$$

$$g_{shl} \geq 0 \quad \forall s \in S, h \in H, l \in L_u \tag{15}$$

The complete mathematical model formulation can be seen in Section 4.2.2.

4.2.2   Complete Mathematical Model Formulation

The complete resulting mathematical stochastic optimisation model for finding the optimal bidding procedure in a day-ahead spot market for electricity, taking into account the uncertainty in production, spot and regulated power market prices is shown in Equations (16) to (26).

Maximise

$$\text{Revenue} = \sum_{s \in S} \sum_{h \in H} P_s \cdot [\text{Spot}_{sh} + \text{RP Sale}_{sh} + \text{RP Purchase}_{sh}] \tag{16}$$

$$\text{Spot}_{sh} = x_h \Pi_{sh}^s \tag{17}$$

$$\text{RP Sale}_{sh} = \Pi_{sh}^{b-} d_{sh}^+ \tag{18}$$

$$\text{RP Purchase}_{sh} = -\Pi_{sh}^{b+} d_{sh}^- \tag{19}$$

Subject to

$$(g_{sh} - x_h) - d_{sh}^+ + d_{sh}^- = 0 \qquad \forall s \in S, h \in H \tag{20}$$

$$g_{sh} = \sum_{l \in L_u} g_{shl} \qquad \forall s \in S, h \in H \tag{21}$$

$$g_{shl} \leq F_{shl} \qquad \forall s \in S, h \in H, l \in L_u \tag{22}$$

$$x_h \leq \sum_{l \in L_u} G_l \qquad \forall h \in H \tag{23}$$

$$x_h \geq 0 \qquad \forall h \in H \tag{24}$$

$$g_{sh}, d_{sh}^+, d_{sh}^- \geq 0 \qquad \forall s \in S, h \in H \tag{25}$$

$$g_{shl} \geq 0 \qquad \forall s \in S, h \in H, l \in L_u \tag{26}$$

5   Model Implementation

This chapter implements the model formulated through Section 4 using suitable software and methods. Section 5.1 explains the implementation of the uncertain input data, before Section 5.2 briefly shows the software used when implementing the mathematical optimisation problem. Lastly, Section 5.3 explains the usage of the developed user interface and the file structure containing the complete model implementation.

5.1   Input Data

The optimal bidding model gives results highly dependent on input data. The bidding procedure suggested by the developed model can never be of higher accuracy than the input data itself.

   The model can be used for two fundamentally different purposes. When used during operation of an installed wind park, the purpose is to maximise revenues and the main importance becomes having input data accurately describing the surroundings for the actual moments in time. The other purpose is testing the model performance on a general basis. When the focus is general model performance, the main importance becomes representing input data according to correct parameter realisation distributions. In other words, during operation it is desirable to predict the outcome of the parameters by minimising the forecast errors compared to actual realisation. When testing model performance, the forecasts for production, spot and balance price does not necessarily predict the corresponding realised values. Instead, the forecast should follow the distribution of likely realisations.

   One method used in order to generate statistically correct forecast scenarios following known, normal distributed error terms is the ARMA forecasting method described in Section 5.1.1. The implementation of the production, spot price and balance price forecasts are described in Sections 5.1.2, 5.1.3 and 5.1.4, respectively.

5.1.1   ARMA Forecasting Method

The ARMA model will be described briefly here, while a thorough description of the model is found in [13]. The ARMA model consists of two parts, one being the *AutoRegressive* and the other being the *Moving-Average*. The model is usually notated ARMA(p, q) where p and q are the number of autoregressive and moving-average terms, respectively. ARMA models are widely used in order to represent an univariate time series and the general formulation is shown in Equations (27) to (29).

$$X_h = C + \sum_{i=1}^{p} \alpha_i X_{h-i} + \sum_{i=1}^{q} \beta_i \varepsilon_{h-i} + \varepsilon_h \tag{27}$$

$$|\alpha_i| \geq 0 \quad \forall i = 1, 2, .., p \tag{28}$$

$$\varepsilon_h \sim N(0, \sigma_\varepsilon) \quad \forall h \in H \tag{29}$$

X_h is the forecasted value of parameter X in time period h. ε_h is the forecast error, assumed to be randomly drawn from a normal distribution with expected value of zero and standard deviation of the forecast error, σ_ε. The constant parameters, α_i, are autoregressive parameters deciding the impact given by previous values of X to the forecasted value of X. β_i are moving-average parameters giving the connection between the forecast errors, ε_h, of this and previous periods. C is a constant describing the intercept when $h = 0$.

The numbers p and q indicate the number of previous periods that are considered when generating the forecast for a particular period. The p and q should in general be chosen large enough to describe the statistical properties of the data and give an acceptable error term, while at the same time be small enough to give an efficient model [9].

5.1.2   Production Forecast

In order to estimate future production from a wind farm, several steps are necessary. First, a forecast of wind speeds must be obtained. Then this forecast must be converted to wind park output. When a wind park has been in operation for some time, it is possible to gather information on actual production compared to corresponding wind speeds and directions. The conversion from wind speed to park effect then takes into account wake effects and wind direction effects. It can then be assumed that the conversion from wind speed and direction to wind park output is certain and that uncertainty is included in the wind speed forecast.

For the purpose of investigating model performance, several assumptions can be made. A simplified method is to use a wind speed forecast in order to calculate output from a single wind turbine using the power curve of the installed turbines. Example power curves were discussed in Section 3.1.3. Multiplying the resulting turbine output with the total number of installed turbines gives an approximation to the total wind park output.

The literature study in Section 2 revealed that most studies use either ARMA or ARIMA models in order to generate forecast scenarios of wind speed errors with desired statistical properties. When using an ARMA model to forecast wind speeds, the procedure is to model error terms and then add these error terms to a given forecast. This can be explained by the fact that actual wind speed equals the sum of forecasted wind speed and the forecast error as seen in Equations (30) and (31).

$$Error = True\ Wind\ Speed - Forecast \tag{30}$$
$$\Rightarrow True\ Wind\ Speed = Forecast + Error \tag{31}$$

Adding the forecasted wind speed to a given number of wind speed error scenarios and then using the power curve on the resulting wind speeds can generate several scenarios for the wind park output.

In the spot market, the bidding takes place 12 hours before the first hour of operation. This means that it is necessary to forecast the wind speeds and the

power output 12 to 36 hours ahead of time. Most forecasting models are run only a few times a day due to their large size and long run times. The Norwegian Meteorological Institute finishes model runs twice daily at approximately 06:00 and 18:30. At the time before 12:00, the 06:00 forecast as well as currently realised wind speeds are known.
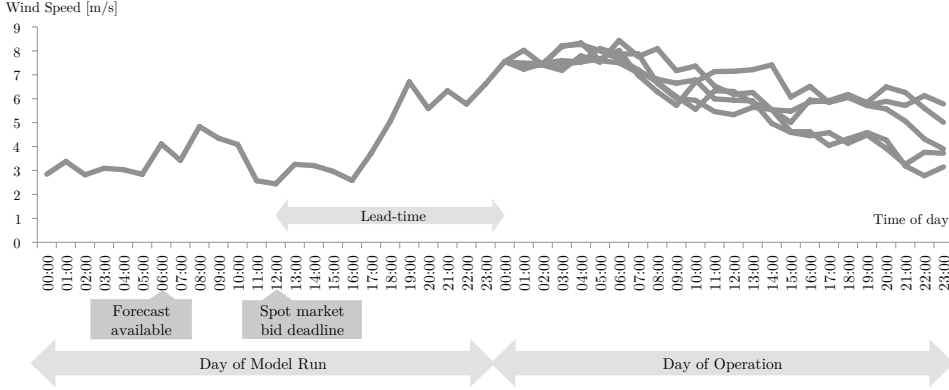
Figure 11: Example wind speed scenarios with twelve hours lead-time.

When creating scenarios of wind park production estimates, the error terms can be added to the deterministic forecast starting at the day of operation. Figure 11 illustrates this situation on a limited number of example scenarios. When adding error scenarios starting the day of operation, the resulting scenarios will have twelve hours lead-time on the forecasts errors.
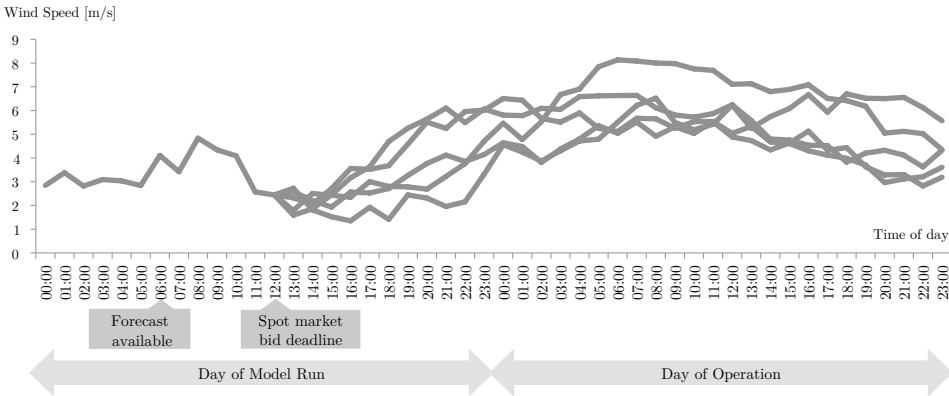
Figure 12: Example wind speed scenarios with no lead-time.

In order to remove the lead-time, error terms must be added to the forecast starting at the first period after the last measured wind speed. This will include

the uncertainty of the forecast between the last known measurement and the first hour of operation. Example scenarios without lead-time are shown in Figure 12.

The variance of the wind speed scenarios seen in Figure 12 was not changing much over time. When creating forecasts of the future, the difficulties of predicting outcomes are generally increasing with time into the future. The example scenarios in Figure 11 and Figure 12 are generated using constant standard deviation of the wind speed forecast error. Using a standard deviation varying with the lead-time of the forecast will generally result in forecast scenarios with increasing variance over time. A simple example of variable standard deviation is shown in Figure 13.
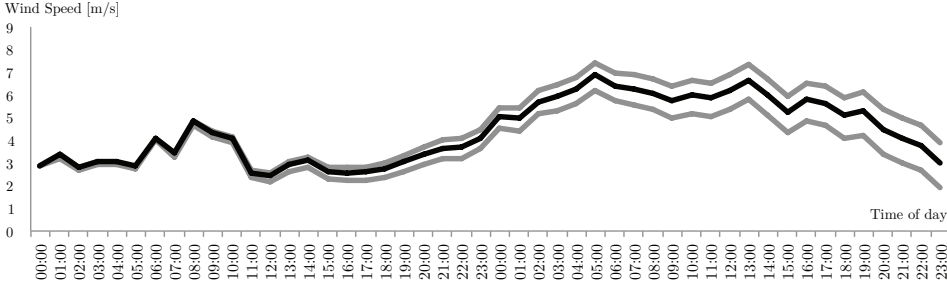
Figure 13: Example wind speed scenarios with variable standard deviation.

The implementation of wind park output scenario generation is done by including the twelve-hour lead-time. Since the model currently is used only in order to investigate theoretical model performance rather than real-life performance. This is not expected to significantly influence the results. The forecast errors are generated using an ARMA model on the time-series of actual forecast errors calculated from forecasted wind speeds minus the actual observed wind speed. The ARMA parameters found, was treated as constants for all hours during the day of operation. Using constant input parameters to the ARMA model and hence using a constant standard deviation might affect the model results.

An Excel file is to be filled with the wind speed forecast for the coming day, as well as updated observations. A macro described in Section 5.3 will use these values when generating a given number of wind park output scenarios based on scenarios of wind speeds.

5.1.3   Spot Price Forecast

The hourly spot market prices for the next twenty-four hours are not known at the time of bidding. It is therefore necessary to forecast these prices. In order to represent the uncertainty, the spot price forecast should not only estimate the expected prices, but also give a description of the error distribution. Several price forecasting methods satisfy this requirement and an overview is given in [12], where it is concluded that time series techniques reveal themselves among the most efficient solutions, with ARMA models being one of them.

When forecasting next-day spot market prices, it is suggested that an ARMA(1,1)

model sufficiently describes the statistical properties of the time-series [19]. Then only one α and β is to be decided. Several algorithms are able to find best possible values for the α and β. At the time spot price forecasts are made, the spot prices are known for the current day. In contrast to the estimated production output, values are known until the day of operation. This means that prices for the current day are used in order to forecast the day of operation and adding error terms to this forecast gives scenarios for model input with no lead-time.

5.1.4 Balance Price Forecast

There is uncertainty regarding both the future regulated market prices, as well as what direction the system will be regulated. The balance price shows low correlation with the system price, but depends strongly on balancing volumes [23]. A balance price forecast based on the spot price is therefore likely to have a larger error than a forecast based on the balance volume. A forecast using an ARMA model based on historical balancing prices can also be used, giving less accuracy compared to a model based on volumes, but better accuracy than a model based on spot market prices [38]. The current model implementation is for general testing purposes and scenarios with possible realisations, having the right statistical properties, are therefore sufficient.

At the time of scenario generation, the prices in the regulated power market are usually known up until hour six of the current day. Prices up to this time are used in order to forecast the day of operation. Error terms are added to the forecast giving scenarios for model input. The upwards and downwards regulated power market prices are found separately. All regulated power market prices in the final scenarios are compared with the spot market price of the same scenario, making sure the upwards regulated power market prices always are greater or equal the spot prices and the downwards regulated power market prices are less or equal the spot market prices.

5.2 Optimisation Problem

The mathematical optimisation problem formulated in Section 4.2.2 was implemented using the FICO® Xpress Optimization Suite.
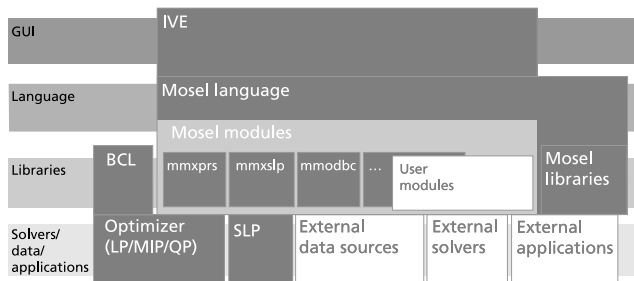
Figure 14: The Xpress product Suite, from [17].

It can be seen from Figure 14 that this Suite contains a graphical user interface (GUI) called Xpress-IVE. Through this interface, optimisation problems can be formulated using the Mosel language. The Xpress Optimization Suite then solves the problems using the Xpress-Optimizers. The implementation of the optimal bidding problem will only solve on computers with a licensed full version of this program, due to the number of constraints and variables. The problem is formulated so all input data enters the problem by reading given Microsoft Excel files. The problem is also implemented in a way making it possible to call it from Microsoft Excel using Visual Basic Macros.

5.3   User Interface

The model is implemented in order to easily enable users to run the model. In addition to a working version of the FICO® Xpress Optimization Suite described in Section 5.2, the file system included in the Appendices must be copied to the computer where the model is to be run. This file system with included files and folders are shown in Figure 15.
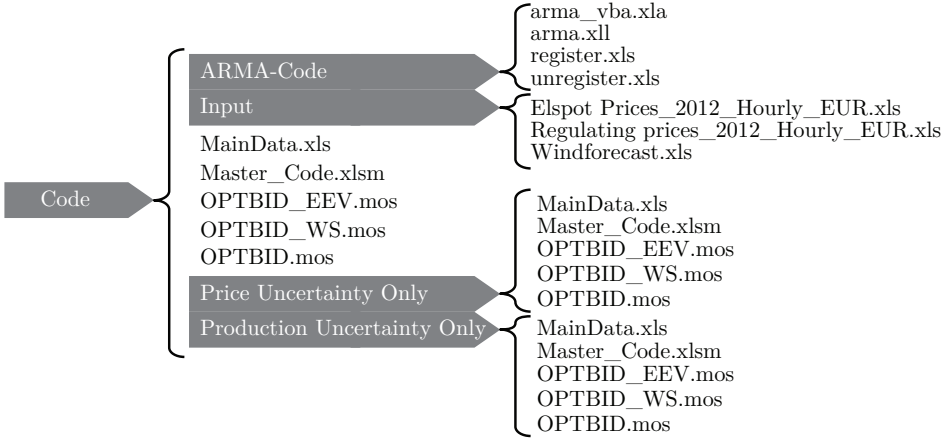
Figure 15: Structure of the relevant model implementation files.

Before running the model the first time, the *register.xls* in the *ARMA-Code* folder must be opened. This file enables the *arma.xll* program required by several other macro functions. When the ARMA-module is loaded, it can be used on the same computer without the need to load it again. The *MainData.xls"* file in the *Code* folder contain both data needed to be entered before the first model run, as well as values updated by the model during model runs. Before running the model the first time, the user must enter into *MainData.xls* the preferred number of scenarios to be generated, the number of operational periods, the number of locations considered and finally the installed capacity of the wind parks at each location.

After the first-run settings are completed, the user must open *MasterCode.xlsm*. When choosing the *Input* Sheet of this workbook, the user will see the graphical interface shown in Figure 16. The user can now enter the date of the forecasted period, choose the correct price area and tick the locations that are to be included when running the model. When ready, pressing the *Find optimal bids* runs the macro functions that generate scenarios and runs the optimal bidding model. If the model is to be run again for the same date but for different wind parks, pressing the *Same date, new locations* will run the model again using the previously generated scenarios.

Figure 16: The user interface found in the *MasterCode.xlsm* file.

When the model has finished running, choosing the *results* sheet of *MasterCode.xlsm* reveals the optimal bids and expected revenues found by the model. An example of such results is shown in Figure 17.

Date: 2012-03-16
Price Area: NO3
Wind farms: 1 2 3 4

											Optimal bids [MWh/h]												
											Period												
1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
10	13,1	20,3	25,2	49,5	31,8	37,2	50,4	57,2	58,1	77,6	95,1	96,5	114,6	113,5	112,5	136,2	160,8	141,2	119,2	106	111,3	117,8	80

Expected spot market revenue   85 603,72 [EUR]

Expected balance market sales revenue   7 995,74 [EUR]
Expected balance market purchase revenue   -21 521,41 [EUR]
Expected balance market revenue   -13 525,66 [EUR]

Expected total daily revenue: 72 078,06 [EUR]

Figure 17: Example of the *Results* sheet of *MasterCode.xlsm* after model runs.

The macro functions and subroutines included in *MasterCode.xlsm* and their main tasks are shown in Table 2.

Table 2: Descriptions of macro functions and subroutines in *MasterCode.xlsm.*

Macro Name	Main purpose
Sub getnScenarios()	Creates global variable of number of scenarios given by user in MainData.xls.
Function FullPath()	Returns the full path of the current Spreadsheet.
Sub Writelocations()	Enters the locations chosen in MasterCode.xlsm into MainData.xls.
Sub WriteScenprob()	Writes the scenario probabilities in MainData.xls.
Sub FindSpotARMA()	Reads spot prices from the Elspot Prices_2012_Hourly_EUR.xls in the Input folder and runs the ARMA program both in order to find a forecast and forecast error. Resulting scenarios are saved to MainData.xls.
Sub FindRKUpARMA()	Reads the upwards regulated power market prices from Regulating prices_2012_Hourly_EUR.xls in the Input folder and runs the ARMA program both in order to find a forecast and forecast error. Resulting scenarios are saved to MainData.xls.
Sub FindRKDownARMA()	Same as Sub FindRKUpARMA(), but for downwards regulated power market prices.
Sub FindOutputforecast()	Reads the wind speed forecast and historical forecast error from Windforecast.xls in the input folder and runs the ARMA program on the foreast error. The scenarios of wind speeds are then calculated into wind park output using the power curve. Resulting scenarios are saved to MainData.xls.
Sub OPTBID()	Calls the run_mosel function that runs the model using Fico Xpress and the OPTBID.mos file, taking input from the MainData.xls file.
Sub Main()	Calls all subroutines necessary for finding optimal bids; getnScenarios, Writelocations, WriteScenprob, FindSpotARMA, FindRKUPARMA, FindRKDownARMA and OPTBID.
Sub Main2()	Calls the subroutines necessary to run the model when only locations have changed, getnScenarios, Writelocations and OPTBID.

6 Model Performance with Case Study

This chapter will evaluate the model by performing a case study and calculating the VSS and EVPI measures. Firstly, Section 6.1 describes the case study. Then Sections 6.2 and 6.3 give short introductions to the VSS and EVPI measures, correspondingly. Lastly, Results of the case study is presented and briefly discussed in Section 6.4.

6.1 Case Description

Background information on the case study is presented, with Section 6.1.1 presenting the case study location, Section 6.1.2 the chosen dates and Section 6.1.3 the data collection process undertaken.

6.1.1 Location

The case study is carried out based on current and future wind park sites of the company TrønderEnergi in the area of Sør-Trøndelag, Norway. The wind parks at Valsneset and Bessakerfjellet are already in operation, while the Frøya and Engvikfjellet sites are under development. Wind power already accounts for approximately 10 % of the total yearly energy generation of the company and is becoming an increasingly important part of the production portfolio [49]. All four wind parks and their locations are shown in Figure 18.
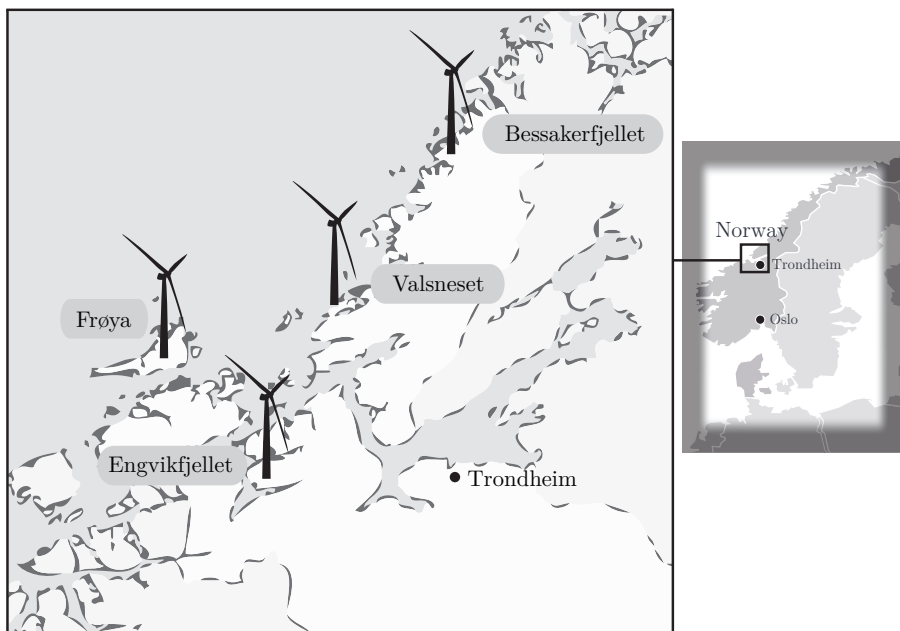

Figure 18: Wind park locations used in the case study.

At Valsneset five turbines with installed capacity of 2.3 MW each, have been in operation since 2006. The turbines were delivered by the German company Enercon [15]. Each turbine tower has a height of 64 meters, with rotor diameter of 71 meters. In 2008, all 25 turbines at the mountain of Bessakerfjellet were in operation. The turbines are the same type as the ones at Valsneset. The application for a concession to develop Frøya wind park was submitted in 2004. During this case study, it is assumed that all the 86 turbines the company applied for are of the same type as Valsneset and that they already are in operation. When it comes to Engvikfjellet, it is also assumed that all 43 turbines already are producing electricity.

6.1.2   Dates

The model performance depends on the scenarios used for model input. The model is formulated and implemented ensuring the possibility for model runs each day in order to find the optimal bidding procedure for the upcoming twenty-four hours. Different time periods will have unlike price and production scenarios. In order to identify general trends in the model performance, two dates with various price and production prognosis are selected.

Table 3: Dates chosen for case study.

17 March	2012
18 April	2012

The dates shown in Table 3 represents the dates of which the twenty-four hour of optimal bids are to be decided. The model is also tested for 16 March and 17 April, giving similar results. When stating 17 March 2012, this means the model was run 16 March 2012, finding the optimal bids for the subsequent day.

6.1.3   Data Collection

Spot prices and regulated power market prices are publicly available for download at the Nord Pool Spot website [44]. Spread sheets containing the relevant prices are downloaded at 11:00 the day preceding the twenty-four hour periods of the days of operation shown in Table 3. When it comes to wind speed forecasts, publicly available data for each site from The Norwegian Meteorological Institute are used [33]. The files are named and arranged according to Figure 15 described in Section 5.3.

6.2   Value of Stochastic Solution - VSS

The Value of Stochastic Solution (VSS) measures the value of including uncertainty in the model. Equation (32) shows the VSS calculated as the difference between the solution of the stochastic problem (SS) and the expected result of using the expected value (EV) solution, called EEV [6].

$$VSS = SS - EEV \tag{32}$$

The value of the SS comes from the original problem, while the EEV solution is the expected result when using the EV solutions as model input. The EV solutions are found by replacing all uncertain parameters in the original formulation with their corresponding expected values. This means including only the expected values as one scenario for production, spot price and balance price forecasts. The results of total energy bid to the day-ahead market for each period, x_h, and energy produced during each period, g_{shl}, must be stored. Then the declaration of the original problem is modified to become the EEV problem, by changing the declaration of the variables x_h and g_{shl} to the new parameters X_h and G_{shl}. The stored results are now assigned to these parameters, X_h and G_{shl}, and used as input to the EEV problem, where the full set of scenarios are included.

Due to the way the optimal bidding problem is formulated, unexpected results of the EEV might occur since solving the model with the EV can cause extreme resulting bids. The EV solution includes only the deterministic spot and regulated power market prices. The model can therefore choose to bid total installed capacity when the system is known to be downwards regulated and likewise suggest bids of zero when the system is upwards regulated. The model will be indifferent between such extreme bids and the expected production whenever there is zero cost of regulation. Using these extreme values when calculating the EEV gives very large costs of regulation and hence an unrealistically high VSS. In order to account for this, the expected production can be used directly when finding the EEV solution. The production forecast is already given and is also representing the bids a decision-maker is likely to submit to the market when not considering uncertainty.

6.3 Expected Value of Perfect Information - EVPI

The future cannot be predicted with absolute accuracy. It is however often possible to reduce the uncertainty of future events and this usually comes at a certain cost. The Expected Value of Perfect Information ($EVPI$) is a theoretical measure of how much a decision maker would be willing to pay in order to eliminate all uncertainty [6]. The numerical value of the $EVPI$ for a maximisation problem is found using Equation (33). For minimisation problems, the right hand side is reversed.

$$EVPI = WS - SS \tag{33}$$

The *wait-and-see* (WS) solution represents the solution if we could wait for the realisations of all random parameters before making any decisions. SS is the stochastic solution of the original problem. The WS solution is a way of imitating perfect forecasts of wind park production, spot and regulating power prices. A perfect wind park output forecast implies that both numerical weather prediction and methodology to convert wind speeds into total wind park production is absolutely correct. Even though this never can happen in reality, $EVPI$ is still a useful measure of the distance between the best solution of our original problem,

SS, and the theoretical maximum, WS. In order to find the WS solution, the declaration of x_h in the original problem must be changed to x_{sh}. This modification enables the model to choose individual bids to the spot market for each scenario and period. Since the WS problem is not stochastic, original problems containing non-anticipativity constraints can relax these.

6.4   Results

This section will present the results of model runs using the case data, including uncertainty in spot market prices, regulated power market prices and expected production. The stability of the stochastic solution is elaborated on by Section 6.4.1 before Sections 6.4.2 and 6.4.3 present the case study results from 17 March 2012 and 18 April 2012, correspondingly. A discussion on the effects of price versus production uncertainty is included in Section 6.4.4, while overall discussions are found in Chapter 7.

6.4.1   Stability of Stochastic Solution

The scenario generation process use random numbers. Randomness is a prerequisite for stochastic models, but too large fluctuations will give results of little use [35]. All uncertain parameters of the model have zero expected forecast error, meaning that including an unlimited number of scenarios would produce identical results of every model run. Implementing unlimited number of scenarios is not possible in reality, which means repeated model runs are expected to produce different results. The stability of the solution to the optimal bidding model is investigated by running the model ten times and comparing the model results. The optimal bids from the ten model runs are shown in Figure 19.
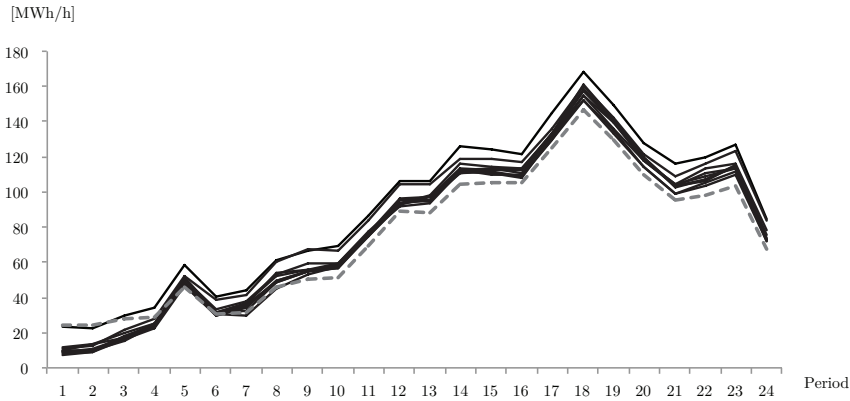

Figure 19: Optimal bids from ten model runs with data input for 18 April 2012. Dotted line: expected production, solid lines: the ten model runs.

The expected revenues from the ten model runs reveals that all results were within a range of 4.2 % from the average revenue. The bidding procedures shown

in Figure 19 also indicate that all ten model runs follow the same tendency, with bids lower than expected production during the first hours and then bids higher than expected production for the remaining periods. A discussion of this tendency is included in Section 6.4.3. Increasing the number of scenarios is expected to reduce the variance of the results. In the following Sections, 6.4.2, 6.4.3 and 6.4.4, the model is run once with the number of scenarios fixed at one thousand.

6.4.2   Case Study Results - 17 March 2012

The optimal bidding model is run for 17 March 2012, once with all wind farms included and once for each wind farm individually. The headings of Table 4 states the time period considered, *Period*, the optimal bids when considering all wind parks together, *Joint*, the sum of the optimal bids when adding the result of model runs for each park, *Sum Individual*, the expected production from the forecast, *Expected production*, the difference between joint consideration and sum of individual bids in per cent, *Joint less Individual* and the difference in per cent between joint optimal bid and forecasted production, *Joint less Expected*.

Table 4: Results of optimal bidding model run, 17 March 2012.

Period	Joint [MWh/h]	Sum Individual [MWh/h]	Expected Production [MWh/h]	Joint less Individual %	Joint less Expected %
1	244.1	244.5	242.6	0%	1%
2	250.1	250.8	249.3	0%	0%
3	251.1	252.0	249.9	0%	0%
4	62.4	63.6	61.6	-2%	1%
5	81.6	82.8	80.7	-1%	1%
6	103.6	105.0	102.0	-1%	2%
7	315.8	327.0	310.1	-3%	2%
8	318.4	318.2	316.8	0%	1%
9	335.0	346.2	330.2	-3%	1%
10	255.1	254.0	254.5	0%	0%
11	183.6	185.9	185.9	-1%	-1%
12	115.3	116.5	114.4	-1%	1%
13	90.1	88.4	93.4	2%	-4%
14	56.1	47.6	60.6	18%	-7%
15	34.9	24.8	38.9	41%	-10%
16	20.6	11.5	24.4	79%	-15%
17	14.7	1.6	20.4	819%	-28%
18	1.1	0.0	10.5	inf	-90%
19	0.0	0.0	9.1	inf	-100%
20	6.6	0.0	18.0	inf	-63%
21	21.4	17.4	30.6	23%	-30%
22	27.3	18.4	35.0	48%	-22%
23	28.1	16.8	37.1	67%	-24%
24	46.7	38.2	52.7	22%	-11%

It can be seen from Table 4 that the *Joint less Individual* difference is in the range from - 3 % and up to infinite because of periods with *Sum Individual* bids of no volume. The *Joint less Expected* reveals deviations ranging from - 100 % to

2 %. The graphical representation of the same bidding schemes shown in Figure 20 reveals a large dip in production based around period four and five. During these periods, strong winds are expected to cause several of the wind parks to shut down production. The largest variations in bid size from the different bidding procedures are seen at the end of the period, where production is expected to be low. When expecting wind speeds barely to low for production, small forecast errors can cause relatively large deviations in actual production. This is true for wind speeds both close to the upwards and downwards slope of the power curve of the wind park. Wind turbine and wind park power curves were discussed in Section 3.1.3.
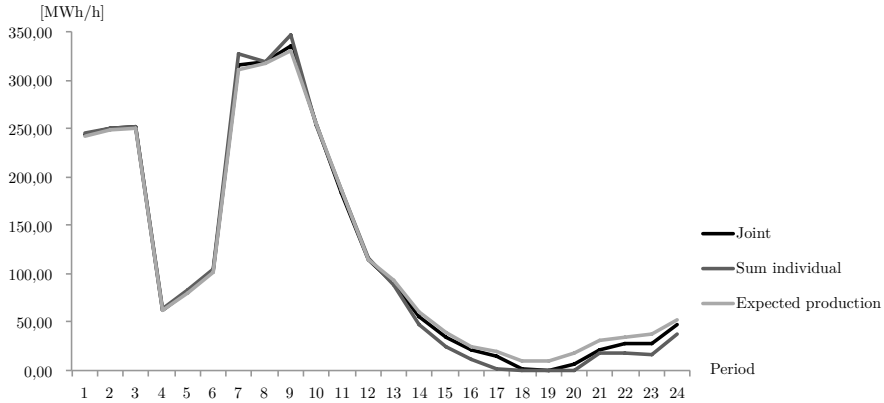
Figure 20: Graphical illustration of different bidding procedures, 17 March 2012.

The joint optimal bids deviate from the sum of the individual optimal bids in several periods because of a risk-pooling effect due to diminishing correlation in production uncertainty. If there is high probability that a greater production than expected will occur at a majority of the wind parks, then the joint optimal bid will be greater than the expected volume. Contrary, when the majority of the scenarios representing the production uncertainty of several parks tend to represent a lower production than the expected value, the joint model will find an optimal bid smaller than the expected production. The incentives for co-location and joint market interaction of renewable energy are thoroughly discussed in [27].

The deviation between joint optimal bids and the expected bids are caused by both the risk-pooling effect and by the forecasted prices in the spot and regulated power markets. The individual optimal bids for each wind park take these prices into consideration, the expected production does not. If an upwards regulated hour is expected, it is beneficial to submit a bid lower than expected production, since excess production will be sold at the spot market price anyhow. A higher bid than expected production would result in the risk of having to buy the unfulfilled amount at the upwards regulated power market price which is greater than the spot price. The effect of forecasted prices are more clearly evident for 18 April 2012 and is therefore discussed in more detail in Section 6.4.3.

Table 5 shows resulting revenues from the model run for the *Joint* and *Sum*

Individual cases, as well as the *Wait-and-See* and *EEV* revenues to be used when assessing the value of the model. *Spot* represents the revenues from bids submitted to the spot market. *RP Sale* shows the revenues from selling excess energy in the regulated power market, meaning that actual production during a particular hour is greater than submitted bid to the spot market. *RP purchase* shows the total cost of purchasing power in the regulated power market when submitted bid is greater than actual production.

Table 5: Resulting revenues of different bidding schemes, 17 March 2012.

Expected Revenues	Joint [EUR]	Sum Individual [EUR]	Wait-and-See [EUR]	EEV [EUR]
Spot	75 653.70	74 359.47	83 114.20	77 348.30
RP Sale	5 784.56	8 428.61	25 61.67	5 168.16
RP Purchase	-5 962.24	-8 086.30	-8 323.76	-7 089.59
RP Total	-177.68	342.31	-5 762.09	-1 921.43
Total	75 476.02	73 43.81	77 352.11	75 426.87

By using Table 5 it can be calculated that total joint revenues is 1.0 % larger than the sum of the individual park revenues. The VSS is found to be EUR 49.15. The small value of the VSS in this case means submitting bids based on the expected production would lead to a small expected loss of revenue, compared to using the optimal bids found by the model. In other words, the expected value of using the stochastic model developed at this day is less than 0.01 % of the *Joint* revenues. The $EVPI$ introduced in Section 6.3 is also found from Table 5 to be EUR 1 876,09. According to this $EVPI$, owners of the wind parks should be willing to pay up to 2.5 % of the *Joint* revenues in order to eliminate all uncertainty. Section 6.4.4 will investigate further whether production or price uncertainty takes up the majority of this value.

6.4.3   Case Study Results - 18 April 2012

Model performance is also investigated using input data for 18 April 2012. Again the model is run once with all wind farms included and once for each wind farm individually. Table 6 shows the resulting bidding strategies and how much they differ from each other.

It can be seen from Table 6 and the graphical representation in Figure 21 that the *Joint less Individual* difference is in the range from - 5 % to 12 %, while the *Joint less Expected* reveals deviations ranging from - 21 % to 25 %. Section 6.4.2 stated that the joint optimal bids are deviating from the expected bids as a result of both the risk-pooling effect and as a result of forecasted prices in the spot and regulated power market. The individual optimal bids for each wind park take these prices into consideration, the expected production does not. This can explain the larger deviations in *Joint less Expected* than *Joint less Individual* observed.

Table 6: Results of optimal bidding model run, 18 April 2012.

Period	Joint [MWh/h]	Sum Individual [MWh/h]	Expected Production [MWh/h]	Joint less Individual %	Joint less Expected %
1	23.7	21.60	24.2	10%	-2%
2	22.4	20.20	24.4	11%	-8%
3	29.5	26.30	27.5	12%	7%
4	34.0	30.80	28.6	10%	19%
5	58.1	56.50	46.0	3%	26%
6	40.7	38.30	30.3	6%	35%
7	44.5	42.40	31.8	5%	40%
8	60.9	55.30	46.0	10%	32%
9	67.0	66.50	50.0	1%	34%
10	69.0	69.00	51.7	0%	33%
11	86.6	87.90	68.9	-1%	26%
12	105.8	103.70	89.1	2%	19%
13	106.5	105.80	88.3	1%	21%
14	126.2	118.00	104.7	7%	21%
15	123.8	118.50	105.3	4%	18%
16	121.1	116.90	105.4	4%	15%
17	144.9	140.10	125.3	3%	16%
18	168.4	167.70	146.6	0%	15%
19	149.5	149.00	130.0	0%	15%
20	128.0	127.60	110.1	0%	16%
21	115.8	115.20	95.4	1%	21%
22	119.8	124.70	98.5	-4%	22%
23	126.9	133.30	103.6	-5%	23%
24	84.8	87.30	67.6	-3%	25%

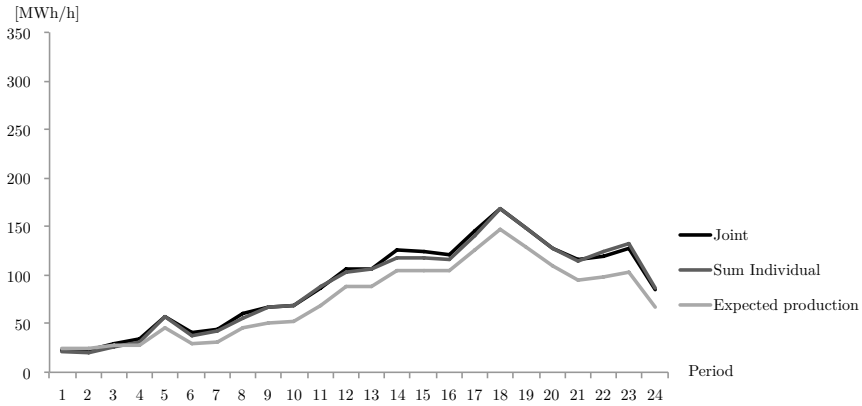Figure 21: Graphical illustration of different bidding procedures, 18 April 2012.

If an upwards regulated hour is expected, it is beneficial to submit a bid that is lower than expected production, since excess production will be sold at the spot market price anyhow. A higher bid than expected production would result in the risk of having to buy the unfulfilled amount at the upwards regulated power

market price which is greater than the spot price. This effect can be illustrated by the example scenario shown in Figure 22 where it can be seen that the Regulated Power market purchase price, *RP UP*, is higher than the spot price, *Spot*, during periods 1 to 6. The Regulated Power market sales price, *RP Down*, is lower than the spot price from period 14 to 24.

Considering only the scenario seen in Figure 22, total revenue will be unchanged as long as bids less or equal expected production are submitted during periods 1 to 6 and bids greater or equal expected production are submitted for the periods after hour 14. This means that submitting bids of zero production during the first hours and bids with installed capacity for the later periods would give equal revenues to submitting expected production. When including enough scenarios, this effect will not be this extreme. Instead, the model will tend to increase the bids in periods with high probability of being upwards regulated and tend to reduce the bids in periods with high probability of being downwards regulated.
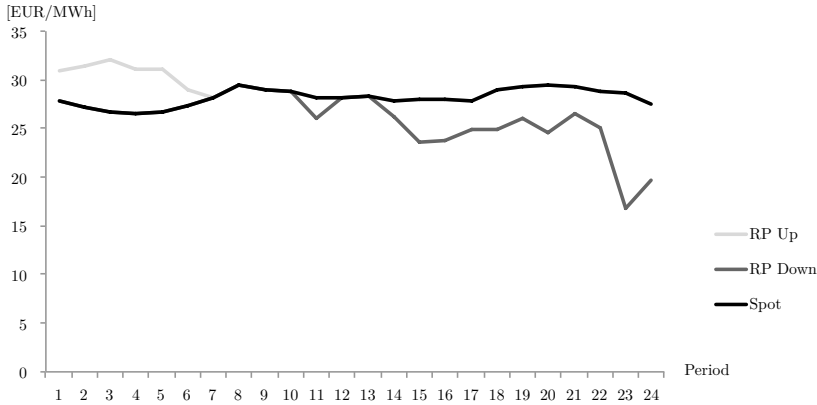
Figure 22: Example scenario of spot and regulated power market prices.

Table 7 shows resulting revenues from the model run for *Joint* and *Sum Individual* cases, as well as the *Wait-and-See* and *EEV* revenues to be used for evaluating the value of the model. *Spot* represents the revenues from bids submitted to the spot market. *RP Sale* shows the revenues from selling excess energy in the regulated power market, meaning that actual production during a particular hour is greater than submitted bid to the spot market. *RP purchase* shows the total cost of purchasing power in the regulated power market when submitted bid is greater than actual production.

Using Table 7 it can be calculated that total joint revenues are 5.1 % larger than the sum of the individual park profits. The *VSS* amounts to EUR 2 342.38 corresponding to 3.3 % of the total joint revenues. In other words, the expected value of using the stochastic model developed is EUR 2 342.38 for 18 April 2012. The *EVPI* introduced in Section 6.3 is found to be EUR 8 674.52 also by using Table 7. The owners of the wind parks should according to this measure be willing to pay an amount corresponding to 12.3 % of the *Joint* revenues in order to elimin-

Table 7: Resulting revenues of different bidding schemes, 18 April 2012.

Expected Revenues	Joint [EUR]	Sum Individual [EUR]	Wait-and-See [EUR]	EEV [EUR]
Spot	95 050.79	93 579.04	16 5825.00	70 063.80
RP Sale	4 090.94	6 929.36	173.72	10 052.50
RP Purchase	-28 660.85	-33 421.89	-86 843.80	-11 977.90
RP Total	-24 569.91	-26 492.54	-86 670.09	-1 925.40
Total	70 480.88	67 086.51	79 155.40	68 138.50

ate all uncertainty. Section 6.4.4 will investigate further whether decision-makers should focus on reducing production or price uncertainty.

6.4.4   Effects of Uncertainty

Sections 6.4.2 and 6.4.3 presented the general results from the model runs and discussed some of the findings. Among the results were the VSS and $EVPI$ measures and questions were raised whether these values were connected to the uncertainty in production or prices. This Section will enlighten these questions by first presenting results from model runs including only wind park production uncertainty and then model runs including only spot and regulated power market price uncertainty. Thereafter, a general discussion is included.

Table 8: Results when including production uncertainty only, 17 March 2012.

Expected Revenues	Joint [EUR]	WS [EUR]	EEV [EUR]
Spot	75 866.80	77 348.30	77 348.30
RP Sale	5 663.49	0.00	5 139.99
RP Purchase	-6 070.32	0.00	-7 071.31
RP Total	-406.83	0.00	-1 931.32
Total	75 459.97	77 348.30	75 416.98

Table 8 shows the expected revenues from spot sales, regulated power purchase and sale as well as total expected revenue for the *Joint*, *wait-and-see* and *EEV* cases. It can be seen that the *wait-and-see* solution contains no regulation costs. Only production uncertainty was included, meaning that the *wait-and-see* solution, making separate bids for each scenario, will bid the expected production of each scenario.

When production was assumed certain and the prices uncertain, the model gave results shown in Table 9. Here it can be seen that all expected total revenues are equal. For the *Joint* case, this can be understood by the fact that production is known and submitting corresponding bids to the spot market will result in no regulation. The *wait-and-see* solution has the same total expected revenue, but a different distribution. The optimisation model must in this case have had several

Table 9: Results when including price uncertainty only, 17 March 2012

Expected Revenues	Joint [EUR]	WS [EUR]	EEV [EUR]
Spot	77 348.30	83 190.00	77 348.30
RP Sale	0.00	2 367.39	0.00
RP Purchase	0.00	-8 209.12	0.00
RP Total	0.00	-5 841.73	0.00
Total	77 348.30	77 348.30	77 348.30

optimal solutions, since bidding the expected production for all scenarios in the same period would also have given the same total revenue.

Table 10: Uncertainty measures of the 17 March and 18 April 2012 model runs.

		Joint	Joint, uncertain production	Joint, uncertain prices
17 March 2012				
Total Revenues	[EUR]	75 476.02	75 459.97	77 348.30
VSS	[EUR]	49.15	42.99	0.00
EVPI	[EUR]	1 876.09	1 888.33	0.00
18 April 2012				
Total Revenues	[EUR]	70 480.88	70 447.53	79 119.30
VSS	[EUR]	2 342.38	976.72	0.00
EVPI	[EUR]	8 674.52	8 671.77	0.00

   The model evaluation measures are presented in Table 10. The same procedure was done with data for 18 April 2012, and the corresponding evaluation measures are also shown in Table 10. Results from 18 April coincide with the results from 17 March. Both results show that when reducing the uncertainty of the model, a decrease in the VSS and $EVPI$ can be observed. It was also revealed that the VSS and $EVPI$ measures are zero in the case of uncertain prices only. This does not mean it is only beneficial to take uncertainty in production into account. When including all uncertainty, the uncertainty in prices and production are both influencing the resulting optimal bids. This can be exemplified using a scenario where there is an upwards regulated period at the same time that actual production is less than expected production. The optimal bid will now be pushed upwards by the prices, but downwards by the production in this particular scenario. Other scenarios might have prices and productions affecting the solution in the same direction. The total of the scenarios give the global optimal solution to the bidding problem.

   The VSS and $EVPI$ measures of zero does however reveal that a perfect production forecast would make the use of stochastic model superfluous, contrary to perfect price forecast. This result indicate that attention should be given to improve production estimation methods, rather than price forecasting techniques.

7   Discussions

The case study revealed that using the developed optimal bidding model increased the expected operational revenues from wind parks. The model had short solving times, only a few seconds for the optimisation problem and a few minutes for the complete implementation in visual basics including scenario generation. The case study revealed that jointly submitting bids for wind parks, rather than individually, increased expected profits. The results were in line with previous studies in the literature, also those using the newsboy approach. An overview of relevant research was given by the Literature Study in Section 2.

The increase in expected profits was explained by risk-pooling, meaning that correlation of errors are reduced with increasing numbers of wind parks considered. This result indicates that wind park owners will benefit by geographically diversifying their wind parks within the same price area, consistent with current literature [34]. It also suggested that companies should submit bids to the spot market jointly for the complete generation portfolio, including hydropower, coal, gas or other production available.

Risk-pooling could encourage wind power park owners to initiate agreements in order to jointly bid their production. Such agreements would reduce the total expected costs of regulation, but would also introduce three new challenges. One of the new problems would be distributing the costs of regulation between the companies working together. Another challenge would be to persuade the companies to reveal their production plans to each other, since production plans usually are related to a high degree of confidentiality. The last question raised would be whether the jointly bidding arrangement would violate governmental collusion regulations, realising that the collaborating firms would be in a situation similar to a monopoly with the possibility to manipulate spot prices and balance market prices.

Section 6.4.4 discussed whether price or production uncertainty was the main driver for the VSS and $EVPI$ measures. It was explained that the combination of both uncertainties gave the value of the stochastic optimal bidding model. With perfect production forecasts, it would be unnecessary to include uncertainty altogether. The same was not true with perfect forecasts of the prices, which only reduced the value of including uncertainty.

The inclusion of price uncertainty might be seen as market speculation. All producers must accept the *Balance Agreement* described in Section 3.2.3 in order to access the wholesale market for electricity. Through the *Balance Agreement*, producers commit to attempt following their submitted production plans. The Norwegian TSO Statnett would argue that submitting bids not equal to the expected production would be violating the *Balance Agreement*. Due to the uncertain nature of wind park output, it would however be hard to recognise producers not submitting expected production.

The aspects discussed so far all have in common that due to the uncertainty of production, the value of introducing new wind power to the power system is reduced. In order to maximise the value of introducing new wind power, the uncertainty must be decreased. Less uncertainty can be achieved by improving the forecasting systems, both when it comes to the wind forecasting and when it comes

to the conversion from wind speed and direction to park output. Some companies specialise in very specific forecasts and research is done on improving the general forecasting methods [18].

Conversion from wind speed and direction to park output is also in focus of many companies operating wind power production. Instead of general simplifications, wind speeds and directions can be measured at each wind turbine. Then, actual wind speed and direction can be compared with the forecasted values as well as actual production. This would give accurate descriptions of the forecast errors as well as individual, location specific power curves for every turbine.

Even with the improvements of wind park output prediction systems, considerable uncertainty would still be present due to the long lead-time of the wind forecasts. Even without the improvement of forecast methods, better forecast would be found if the forecast lead-time was reduced. Reducing the lead-time could be achieved by ending the spot market bidding closer to the day of operation. Delaying the spot market bid submission deadline would increase the value of wind power in the power system, but would also affect other market participants.

Calculation of the system price takes less than one hour, giving a lower limit to the time between deadline of submitting bids and operational periods. It must be investigated how much time the TSO would require in order to maintain ancillary services such as system balancing at a satisfactory level. Other parties might also have points of view regarding the time of spot price announcement.

The current design of the power system originate from the historical conditions with production facilities with easy scheduling such as hydropower, combined heat and power (CHP), coal and gas plants. In order to ensure fulfilment of the entire value of new intermittent sources such as wind power, the power system design must be challenged. Reducing the lead-time of wind forecast by delaying the deadline of submitting the spot market bids is likely to have a significant impact. When first considering a change of the power system design, it should be investigated whether system prices should be calculated more than once for each period of operation, with each time being close to each particular period of operation. This means the bidding deadline could be individual for each time period of the day of operation, meaning that the lead-time would be equal for all periods. The optimal period duration should also be investigated.

From a socio-economic perspective, the spot market deadline should be adjusted in order to maximise socio-economic surplus. Delaying the deadline would increase the value of new, intermittent power production such as wind power, but might reduce the value of conventional power generation. The traditional sources generally have long start-up and shutdown times with high associated costs. Ramping up or down production also requires time and usually comes at given costs. The renewable sources would in general benefit from having a deadline as late as possible, while conventional generators would prefer early deadlines giving the possibility for production planning. The optimal spot market deadline would be found by minimising all relevant costs related to the spot market deadline. This exercise should be performed using the current generation mix in the Nordic market, as well as using the expected generation mixes for given times in the future.

8   Conclusions

The majority of renewable energy sources have some degree of intermittency in their production output. In the Nordic spot market for electricity, participants must submit their production plans at noon the day prior to operation. Deviations from submitted production plans usually introduce regulation costs. With focus on wind power, a stochastic optimisation model aiming to find the optimal spot market bids was developed, taking into account the uncertainty in spot market prices, regulated power market prices and expected production. A routine generating scenarios and running the developed optimisation model was created and described. The value of the optimal bidding model was investigated by performing a case study and by calculating the VSS and $EVPI$ measures. Based on the case study results, general discussions regarding the socio-economic value of introducing wind power to the power system were included.

Section 8.1 lists the main findings, Section 8.2 summarises the contributions of this Master's Thesis while Section 8.3 points out the limitations of the results before Section 8.4 suggest topics for further research.

8.1   Main Findings

- Use of the developed stochastic optimisation model increased the expected revenues compared to bidding expected production for the dates chosen for the case study. The increase in expected profits was explained by both the risk-pooling effect when jointly submitting bids and by the model inclusion of price and production uncertainty.

- Wind park owners would benefit from geographically diversifying their wind parks within the same price area. Submitting bids to the market including the complete production portfolio could also increase the risk-pooling effect.

- The Nordic electricity market currently has incentives for market participants to jointly submit their bids to the spot market. Due to confidential production plans and collusion regulations, such collaborative bidding are not likely to occur.

- Perfect production forecasts would make the stochastic model unnecessary, implying efforts should be given in order to reduce the uncertainty of production forecasts, rather than of price predictions.

- Although not easily recognisable, including price uncertainty in the planning process in order to find optimal bids might violate the Balance Agreement.

- Uncertainty of the production from wind parks reduces the value of introducing wind power to the power system. Increasing the value of introduced wind power can be obtained by improved wind forecasts, better wind speed and direction to turbine output conversions or by delaying the deadline for bid submission to the spot market.

8.2   Summary of Contributions

This Master's thesis has developed, implemented and tested a stochastic optimisation model giving optimal spot market bids for intermittent electricity producing technologies in a day-ahead market setting, taking into account the uncertainty in prices and production forecasts. The model formulation presented provided the advantage of including uncertainty also in the regulated power marked prices. The formulation and implementation of the model provided short solving times, enabling several model runs or, with a few modifications, operational use.

The report has presented a realistic application of the developed model to a Norwegian case, considering real market data and generated power production scenarios from existing and future wind parks.

Routines generating scenarios and running the model were created, enabling the possibility to perform case studies other than the ones presented here. The implementation code is made available for other researchers wanting to perform similar case studies or wanting to modify the model.

8.3   Limitations

The validity of the developed model, as well as the case study results with corresponding discussions are limited by the assumptions and implementation choices made.

When converting the wind forecast to wind park production scenarios, the general power curve was used without taking into account wake losses or other losses connected to individual turbine locations. The effects of wind direction on actual production was disregarded. The wind speed to wind park output conversion was implemented by creating output scenarios with desired statistical properties useful when assessing expected model performance. In order to be useful for actual operational planning, the implementation of the conversion from wind forecast to wind park production must be improved.

Wind power producers were considered risk-neutral. Other risk attitudes might change the optimal bids in order to alter the variance of the expected revenues.

Most wind speed forecasts can be provided with an uncertainty distribution. During this thesis, the uncertainty distribution of the wind forecast from the forecast provider was not considered. When it comes to the standard deviation of the wind forecast errors, they were considered constant, rather than variable.

In terms of forecasting the uncertain parameters and their errors, the effects of using methods alternative to the ARMA model were not investigated. It was neither explored whether the error terms of the forecasts were unbiased estimators.

Marginal loss tariffs were not considered. Including this point-of-connection fee could occasionally make it preferable to stop production before prices drop below zero.

The numerical results of the case study might not represent the true values due to these limitations. However, the main discussions and conclusions should be valid.

8.4   Further Research

The optimal bidding model could be used in order to perform other case studies. The implementations should be improved, according to the limitations described in Section 8.3.

The optimal time of spot market deadline should be investigated further. The socio-economic value of the power system should be maximised. This can be done by finding the optimal spot market bid submission deadline or several deadlines, when minimising all costs related to this deadline. Examples of such costs are the regulation costs for intermittent sources, ramping and startup costs for conventional sources, costs of ancillary services, labour hour costs and other costs related to the deadline of the spot market.

Ultimately, the main socio-economic question regarding the power system is how and where generators, particularly renewables, should be allowed to interact with electricity markets. Hopefully, by building on the current research results from this thesis and other literature, the most efficient manner for renewable energy to interact with the electricity markets can be identified.

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Appendices

Implementation files including the model code and case study data described in Section 5.3 are submitted together with the Master's Thesis to the DAIM (Digital Arkivering og Innlevering av Masteroppgaver) database used by NTNU for storage and submission of Master's theses. The attachments can be found by searching the database using the tile of this thesis.

The contents include, but are not limited to the files shown in Figure 15:

- Spreadsheets with the input data used in the case study.

- VBA codes presented in Figure 2.

- Fico Xpress model code with implementation of the market interaction models and code fore evaluating the performance measures.