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eeh power systems laboratory

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Optimal Wind Power Plant Bidding under Consideration of Storage

Master Thesis
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"Of all the forces of nature, I should think the wind contains the largest amount of motive power, that is, power to move things. Take any given space of the earth's surface, for instance, Illinois; and all the power exerted by all the men, and beasts, and running-water, and steam, over and upon it, shall not equal the one hundredth part of what is exerted by the blowing of the wind over and upon the same space.

. . . And as yet, the wind is an untamed, and unharnessed force; and quite possibly one of the greatest discoveries hereafter to be made, will be the taming, and harnessing of it."

ABRAHAM LINCOLN
First Lecture on *Discoveries and Inventions*,
April 6, 1858.

"On November 6, 2011 at 2 am, 59.6% of Spain's total power demand was supplied by wind power."

GLOBAL WIND REPORT
Global Wind Energy Council (GWEC),
March 2012.

Abstract

In this master thesis, a model is proposed to enable profitable market participation of wind power plants considering the availability of second-party owned energy storage. A novel concept of storage capacity reservations is presented using which the wind power producer hedges against wind outcomes which are unfavourable with respect to its day-ahead market bids. The idea that wind power producers need not to own storage devices is explored through decoupling of storage operation during actual energy production from the participation in day-ahead markets. Hence, the overall model is divided into two stages: *day-ahead scheduling* and *intra-day operation.*

In the *day-ahead scheduling* stage, profit maximizing bids for the day-ahead market are prepared while in the *intra-day operation* stage, the storage device owner assists the wind power producer in tracking its day-ahead market bids through suitable storage scheduling and through participation in intra-day adjustment markets. The day-ahead market bids are decided such that they are energy-neutral with respect to expected use of storage for imbalance mitigation. This allows the storage device owner to efficiently plan its operation schedule without worrying about overuse or under-utilization of storage capacity by the wind power producer.

The model is validated by comparing it with the participation of wind power plants in electricity markets on its own. The case study shows that even after considering the costs of storage reservations and storage operation, the proposed model leads to maximization of profits for the wind power plants while eliminating the profit variability.

Furthermore, the lost opportunity costs of having a joint wind-storage power plant is avoided through decoupling of the storage device from wind power producer. Mitigation of wind power imbalances can be seen as a secondary function for the storage device while it can still participate in the electricity markets on its own.

Kurzfassung

In der vorliegenden Masterarbeit wird ein Modell vorgeschlagen, welches eine profitable Marktteilnahme von Windkraftanlagen, unter Berücksichtigung der Verfügbarkeit von Energiespeichern im Besitz Dritter, ermöglicht. Ein neues Konzept im Hinblick auf die Speicherreservierung wird eingeführt um den Betreiber der Windkraftanlage bei ungünstigen Windverhältnissen in Bezug auf den Day-Ahead Markt abzusichern. Der Ansatz, dass die Betreiber der Windkraftanlagen die Speichersysteme nicht selbst besitzen müssen, ist durch die Entkopplung des Speicherbetriebes von der Teilnahme an den Day-Ahead Märkten während der Energieerzeugung der Windkraftanlagen gerechtfertigt. Daher wird das Gesamtmodell in zwei verschiedene Stufen unterteilt: *Day-Ahead Planung* und *Intra-Day Betrieb*.

In der *Day-Ahead Planung* werden Angebote zur Gewinnmaximierung für die Day-Ahead Märkte vorbereitet während im *Intra-Day Betrieb* der Betreiber des Energiespeichers den Erzeuger der Windkraft beim Erfüllen seiner Day-Ahead Angebote mittels passender Planung des Speicherbetriebes und Teilnahme am Intraday-Handel unterstützt. Die Day-Ahead-Angebote werden so definiert, dass sie in Bezug auf die erwartete Speichernutzung energieneutral sind um den Schaden durch Ungleichgewichte zu minimieren. Das erlaubt dem Besitzer des Energiespeichers eine effiziente Betriebsplanung ohne sich um über- oder Unterauslastung der Kapazität durch den Windkrafterzeuger Gedanken machen zu müssen.

Das Modell wird durch den Vergleich mit der alleinigen Teilnahme von Windkraftanlagen am Elektrizitätsmarkt validiert. Das Fallbeispiel zeigt, dass auch unter Berücksichtigung der Kosten für Speicherreservierung und Speicherung, das vorgeschlagene Modell zu einer Gewinnmaximierung der Windkraftanlage führt, während die Variabilität der Gewinne eliminiert wird.

Darüber hinaus werden durch die Entkopplung des Speichers vom Erzeugungssystem die Kosten eines kombinierten Wind-Speicher-Kraftwerkes vermieden. Der Ausgleich von Unregelmässigkeiten in der Windkrafterzeugung können, während der primären Teilnahme am Elektrizitätsmarkt auch als sekundäre Funktion des Energiespeichers gesehen werden.

Preface

This thesis is a result of research work done at the Power System Laboratory (PSL) of ETH Zurich during the last six months. Working on this thesis has been informative, insightful and challenging yet an enjoyable experience. This thesis concludes my Master's studies at ETH Zurich. Hence, it is opportune to thank people without whom I couldn't have made it so far.

Firstly, a special thanks goes to my supervisors Tobias Haring and Matthias Bucher for their guidance and for the numerous interesting conversations we have had in these months. I am also grateful to them for showing their confidence in me by allowing me much room to pursue my own ideas and explorations, while always being there whenever needed for critical discussions.

I would also like to express my gratitude to Prof. Dr. Göran Andersson for being my tutor in my Master's studies at ETH Zurich and for giving me the opportunity to write my thesis at PSL. I also thank other members of PSL for the welcoming atmosphere and for their valuable comments after my thesis presentation.

I would like to thank my colleagues and friends at PSL for the interesting chats we had during lunches and sunny summer afternoon coffee breaks. Those conversations made working on this thesis much enjoyable.

The last two years of my studies at ETH Zurich couldn't have been so wonderful without my friends whom I have met here. I am grateful for their support, inspiration and for the several fun-filled trips and outings we have had.

Special thanks goes to my parents and family members for their immense support and for their motivation through umpteen Skype conversations. To little *Arnav*, my eighteen month-old nephew, I dedicate this thesis. Though I haven't spent much time with you yet, holding you just after you were born is the best feeling I've had in my life so far.

Lastly, I am deeply grateful to the Swiss Government Excellence Scholarships program for supporting my post-graduate studies at ETH Zurich.

Anubhav Ratha
Zurich, November 21, 2013

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List of Acronyms

EWEA European Wind Energy Association

TSO Transmission System Operator

OTC Over-the-Counter

MPC Model Predictive Control

DP Dynamic Program

EPEX European Power Exchange

EEX The European Energy Exchange

pdf probability distribution function

cdf cumulative distribution function

NWP Numerical Weather Prediction

ANN Artificial Neural Networks

MCMC Markov Chain Monte Carlo

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Chapter 1

Introduction

1.1 Increasing Share of Wind Energy

Wind power installations in Europe have been supported by subsidies and incentives for over a decade now. These support schemes which include: feed-in tariffs, feed-in premiums and green certificates among others, have led to a steep rise in wind power installed capacity in Europe over the years, as described in detail in [1]. Fig. 1.1, published in a recent report [2] by European Wind Energy Association (EWEA), shows the growth trend for cumulative installed wind power capacity (MW) and net energy production (MWh) by off-shore and on-shore wind farms in Europe over the years. Forecasts for the future illustrate the continuing trend for growth of wind power installations in the future.

Integrating wind energy, characterised by its high variability and low predictability, in the power system is a big challenge for grid operators. This is because electric power system needs to be operated such that a balance between generation and consumption of energy is maintained at all instants. This challenge can be handled as long as the share of fluctuating energy in the electricity grid is small such that the fluctuations could be compensated for by the flexibility capabilities of conventional generators. With the boost from these financial support schemes, the share of fluctuating in-feed in general and wind power in particular is no longer marginal. Fig. 1.2, sourced from the EWEA report [2], predicts the continuing trend for increasing share of wind energy in the European electricity system, with an estimated share of 20-28% expected to be attained by the year 2030.

On account of the intermittent nature of wind energy, integration of high shares of wind into the electricity grid is expected to result in higher costs of power system operation. These additional costs arise due to a variety of reasons as discussed in [3]. However, in the context of this thesis, the study in [4] is picked up for further discussion. It divides these additional costs into two categories:

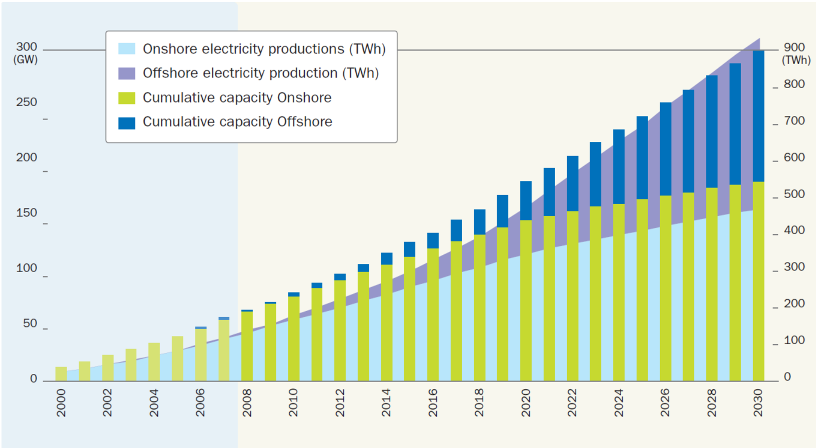


Figure 1.1: Past trends and future scenario for installed wind capacity (GW) and energy production (TWh) in Europe [2].

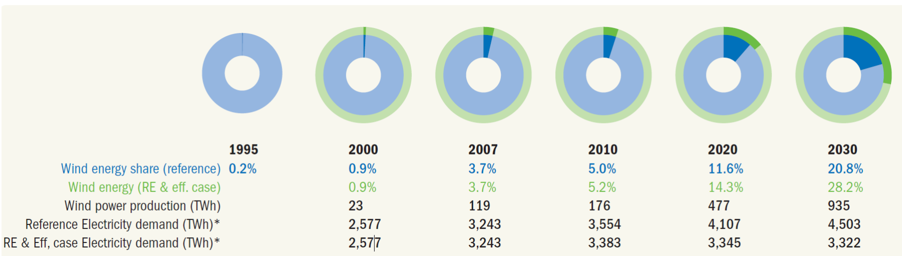


Figure 1.2: Past trends and future scenario for share of wind energy (%) in the European energy mix [2].

- **Balancing Costs** are short-term costs which arise from short-term adjustments, over the time period from minutes to hours, needed to manage the fluctuating in-feed from wind power plants.

- **Reliability Costs** are long-term costs which arise from the need for maintaining additional power on stand-by mode as operational reserves to ensure the supply-demand balance.

These short-term adjustments and operational reserves are usually provided by fast-acting thermal generators such as gas turbines. Besides being expensive to run, these thermal generators also offset, to the some extent, the planned benefits of reduction in carbon dioxide emissions by wind power plants.

In addition to the grid integration costs, with increasing shares of wind energy, the existing support mechanisms for wind power plants are expected to decrease. This can be foreseen to occur because wind power technology is expected to mature and achieve economies of scale. Furthermore, partial or complete withdrawal of support schemes would considerably ease the existing financial burden on governments. A very recent working document [5] released by the European Commission issues guidelines on redesign of renewable support schemes in European countries. The report stresses on the need for an overhaul in governmental support for renewable and for promoting market participation of renewable energy sources in general and wind energy in particular.

1.2 Motivation for the Thesis

The rising costs of grid integration and support mechanisms are expected to act as strong drivers for wind power plants to participate in the European electricity markets. However, the uncertainty in wind availability negatively influences the competitiveness of these power plants in electricity markets. As the current electricity market framework mandates submission of generation schedules in the form of energy bids prior to actual power generation, wind power plants face difficulties in matching their schedules due to imperfect wind forecasts. Given a real participation of wind farms in the electricity market, the differences between the contracted and actual production may lead to imbalance penalties, wherein wind power plants are penalized for the deviation from their scheduled generation plan. These penalties may result in a significant reduction in earnings of wind power plants in the electricity markets. Enabling profitable market participation of wind power plants is a necessity for efficient wind integration which needs to be addressed.

1.3 Focus and Goals

The focus of this thesis lies on addressing the challenge of profitable participation of wind power plants in short-term European electricity markets. The problem is approached considering the opportunity to use energy storage and participation in intra-day markets for mitigation of the variability in wind power generation.

A two-stage model is proposed in this thesis to optimize the market portfolio of a wind power producer. In the first stage, optimal hourly bids for the day-ahead market are prepared. A novel concept of storage capacity reservation contract, which acts as a hedging mechanism against unfavourable wind power realizations, is introduced. The second stage of the model involves operation of the storage device. The increase in accuracy of wind power forecasts as we move closer to actual production is utilized by employing a Model Predictive Control (MPC) framework. The MPC uses a *receding horizon control* strategy to schedule the operation of the storage device and to decide buying/selling bids for the intra-day adjustment markets.

The goals of this thesis are the following:

- Develop a model for strategic bidding of wind power plants to minimize the risk of imbalance penalties.
- Quantify the benefits of storage as compared to the situation when a wind power plant participates in electricity markets on its own.
- Estimate the incremental cost of using storage resources for mitigation of power imbalances in the electricity grid caused wind power plants.

The following assumptions are explored in this thesis:

- *Storage devices need not be owned by wind power plant.* This is realized by decoupling the day-ahead market bids from the operation of storage device. Instead, it is proposed that the wind power owner procures storage capacity (MW) from a second-party owned storage device in the form of storage reservation contracts.
- *Making best use of wind certainty gained over time.* The improvement in wind forecasts as we move from day-ahead to actual delivery period is used in the proposed model to make the best use of available information in the decision-making process during the second stage.

1.4 Report Outline

The report is structured as follows:

Chapter 2 contains a brief introduction to European electricity markets and presents an overview of some useful and interesting work previously done in addressing the challenge of profitable participation of wind power plants in markets. **Chapter 3** introduces the research questions which are dealt in this thesis and describes structure of the two-stage model developed. **Chapter 4** discusses day-ahead scheduling stage of the model in which bids for day-ahead market are decided along with storage reservation contracts. **Chapter 5** presents a detailed description of the intra-day operation stage of the model. **Chapter 6** describes the small case study performed to evaluate performance of the proposed model as compared to the participation of wind power plants in the electricity markets on their own. **Chapter 7** summarizes the main concepts presented in this thesis and discusses its findings in the light of their relevance in current market framework.

Chapter 2

Literature Review

This chapter presents an overview of some of the related work done to facilitate profitable market participation of wind power plants. In the first section, a brief introduction to European electricity markets is presented. The second section describes a selection of the literature on previous approaches in this field. The chapter ends with a brief summary discussing the key findings from literature.

2.1 European Electricity Markets

Since start of the deregulation process in early 1990's, European electricity industry has undergone several changes. The electricity markets are transitioning from vertically integrated monopolies into a liberalized market. In contrast to before, when power sector was not open to competition and electricity prices were fixed by regulators according to the cost of generation, transmission and distribution, prices are now determined by the equilibrium between supply and demand. In addition to traditional Over-the-Counter (OTC) bilateral electricity trading where prices and volumes are not made public, the share of electricity traded in power exchanges, where it is traded in an efficient and transparent manner just like any other commodity, is increasing. A comprehensive overview of the legal framework associated with electricity deregulation in Europe and a detailed note on the evolution of European electricity markets so far is presented in [6].

Although several differences exist between the power exchanges within Europe in terms of regulations and functions, typically products are traded in a power exchange in the following markets:

Spot Markets These are markets associated with actual physical delivery of energy and usually involve two different sub-markets: *day-ahead markets* and adjustment or *intra-day markets*. In the day-ahead market, hourly contracts for supply and demand of electricity for the hours of the next day are traded. This market is usually cleared using an hourly auction mechanism. In this auction, the supply bids are stacked in increasing order of marginal costs of generation to obtain a so-called "merit order curve", which is then matched with the electricity demand curve to determine the price of electricity. Since there is quite a time difference between the clearing of day-ahead market (usually at or before noon on the day before actual delivery), market participants are provided with an opportunity to make short-term changes in the generation and consumption bids in a subsequent adjustment or intra-day market. Intra-day markets are usually cleared bilaterally, using continuous trading mechanism, wherein the bids may be submitted or changed close (usually until 45 minutes before) to delivery time. These bids are automatically matched and executed each hour at the clearing time and the prices, which are published publicly, are based on the supply and demand in that hour. The risk associated with continuous trading mechanism is that if the bid submitted is not complemented by a suitable counter-party, it is not executed at all.

Balancing Market Unlike other traded commodities, a balance between production and consumption of electricity at each instant has to be established to ensure secure and efficient operation of power systems. The balancing market or regulation market, managed by the Transmission System Operator (TSO), ensures that this balance between generation and load is maintained. Even though demand-side management practices are increasing, the load or consumption of electricity is largely inflexible as of today. Hence, power producers who participate in the market have to assist the TSO in its task of keeping power balance through participation in the balancing markets. Although the settling mechanism varies between countries in Europe, the primary motive of this market is the same. Power producers are penalized for positive or negative deviations from their production schedules established by the spot markets. In some countries, the power producer may be penalized or paid depending on whether the direction of deviation from its schedule supports the generation-load balance of the whole system or opposes it.

While [7], [8] and [9] provide a good overview on the functioning of European electricity markets, the following papers strengthen the understanding behind such a market design and highlight the effects that increasing participation of wind energy has on these market structures.

R. Green (2008) [10] This review article provides a comprehensive introduction to electricity market designs all over the world, specifically highlighting the salient features of and differences between the European and American markets. Furthermore, the implications on these markets of moving towards a power system with higher shares of wind energy are identified. These two market frameworks are then evaluated with regards to their adaptability to these changing needs.

Xie et al. [11] presents a detailed discussion on the challenges faced by present-day power systems as we move from negligible penetration of wind power towards a state with higher shares of wind. The focus is on identifying the impacts of integrating wind power on operational aspects of power systems such as scheduling and frequency regulation, which ultimately should be reflected in the prices for imbalance penalties.

C. Hiroux and M. Saguan (2009) [3] In this paper, the authors discuss the pertinence of current renewable support schemes and electricity market designs in handling higher shares of wind energy in the net generation pool. The question whether wind power producers should participate in electricity markets is weighed in terms of its benefits and risks. In their concluding remarks, the authors recommend the facilitation of increased participation of wind power plants in markets. This recommendation stems from their analysis which shows that positive effects of this on power systems through maximization of net social welfare outweighs the negative point of increased risks for these power plants, which could be mitigated with readjustment of support schemes and market designs.

2.2 Wind Power and Electricity Markets

The problem of financial losses arising from market participation of wind power has been dealt in the literature mainly through three different approaches.

2.2.1 Optimal Bidding using Stochastic Models

Stochastic programming, incorporating uncertain wind power forecasts and market prices as stochastic variables, is used in this approach to develop models which result in optimal bidding strategies for a wind power producer participating in electricity spot markets on its own. The following lists a selection of works which use this approach.

J. Morales, A. Conejo and J. Pérez-Ruiz (2010) [12] This paper presents a model for maximization of the profit expected from a wind power producer trading in a multi-stage electricity market consisting of day-ahead, adjustment and imbalance markets. The optimal bids are obtained by solving a stochastic linear program which provides a robust solution to a large number of scenarios. The scenarios are drawn using available forecasts for the uncertain parameters, namely, wind power availability and the prices in these three markets. Additionally, a suitable risk parameter introduces the trade-off between making bids to increase expected profits and the risk of incurring imbalances with such a market position.

P. Pinson, C. Chevallier and G. Kariniotakis (2007) [13] The authors in this paper solve a risk-averse robust optimization problem to obtain optimal market bids, taking probabilistic forecasts into consideration. Instead of using point forecasts for wind power, this approach considers wind forecasts to contain information on their uncertainty in the form of predictive distributions. Furthermore, the methodology also factors the sensitivity that a wind power producer may have towards prices in imbalance markets.

J. Matevosyan and L. Söder [14] presents a method for minimization of imbalance penalties for a wind power producer bidding in a single stage spot market. While considering the wind forecast errors to be a stochastic variable, the authors formulate a mixed-integer program taking into account the different cases for prices of imbalance penalties. This implies that imbalance price is a payment received if the TSO has an energy deficit and the wind power plant produces excess energy than its bid or if the TSO has a excess energy and the wind power plant produces less than its bid. In the other two cases, the imbalance price is a penalty which needs to be paid.

F. Bourry and G. Kariniotakis (2009) [15] In this paper, a model is developed in which the intra-day or adjustment markets are considered as a way to reduce imbalance penalties from participating in the day-ahead market. The intra-day market is considered to take place through a continuous trading mechanism such that suitable parameters are developed to model the probability that the submitted bids may or may not be accepted. The study showcases that participation in intra-day markets based upon the improved wind forecasts gained until their market clearing could possibly reduce imbalance penalties by up to 18%.

2.2.2 Hedging with Financial Instruments

In addition to the two markets described in Section 2.1, power exchanges also provide a platform for trading of structured financial products linked to the trades of electricity. In this platform, called *Futures* or *Derivatives Market*, financially-settled contracts are traded which may or may not be linked with physical delivery of electricity. Prices of the structured products or contracts traded in these markets (such as forwards, options, swaps, etc. collectively known as derivatives), are closely related to the price of electricity in the spot market. As a result, among other benefits, these contracts provide an opportunity for power sellers and buyers to manage their risk by hedging against unfavorable movements of prices in the spot market. A similar concept is applied to manage the risk of unfavorable wind realizations.

K. Hedman and G. Sheblé (2006) [16] While treating the uncertainty in wind power generation as an explicit risk involved in their market participation, the authors in this paper have proposed the use of options to hedge against unfavorable wind outcomes. It is argued that such options provide an opportunity to mitigate the risk involved with trading wind without the need for large investment in storage technologies. Comparing with storage operation, the paper demonstrates that such a method of purchasing options is financially competitive even if the capital investment for storage is not factored in the analysis. In their concluding remarks, however, the authors point out that on account of the lack of a complete and competitive options purchasing market for wind energy at the present time, more progress has to be achieved in this direction before the method becomes completely viable.

2.2.3 Using Energy Storage

The rationale behind the third approach is that once a commitment to the market is made in terms of energy bids, suitable operation of a storage device enables a wind power plant to stick to its schedule, thereby avoiding imbalance penalties. Selected papers based on work following this approach have been picked up for further discussion and are presented in the following.

E. Castronuovo and J. Peças Lopes (2004) [17] In this paper, the authors formulate a linear optimization problem for combined daily operation of a wind power plant with a small hydro generation/pumping facility. The uncertainty in wind power is reflected in a large number of wind power time-series scenarios generated from Monte Carlo simulations and optimal operation strategy is obtained for each of these scenarios. The goal is to identify the best operation strategy among all these solutions, for a combined wind-hydro power plant with little water storage capacity, considering the constraints and costs involved in the operation of storage device. However, the wind-hydro power plant considered in this paper does not participate in a a multi-stage market. Instead, the ensemble is remunerated in accordance with a previously known variable feed-in tariff, such that it is incentivized to produce more during peak hours. The results show that such a joint operation has a potential to reduce the need for maintaining reserves by the TSO.

J. Angarita, J. Usola and J. Martínez-Crespo (2009) [18] Considering combined market participation of a wind-hydro ensemble, the authors present a stochastic optimization technique wherein intra-day market bids of the hydro generator are optimized such as that the expected revenue from joint operation is maximum. A key feature of this model is that the hydro power plant is interested in joint bid only if the avoided costs of imbalance penalty from mitigating wind deviations are higher than the reduction in its profits were it operating on its own. Therefore, it is shown that the cost of imbalance penalties, among other factors such as wind forecast horizon and size of the hydro reservoir, plays a crucial role in decision-making in such a joint operation case.

J. García-González, R. Muela, L. Santos and A. González(2008) [19] In this paper, a two-stage stochastic programming approach is followed for joint operation of wind generator and pumped-storage hydro power plants. The optimal bids for the day-ahead market are considered to be "here-and-now" decisions, that is they are not dependent on the realizations of uncertain parameters namely, wind outcome and market price. These uncertain parameters are dealt in the the form of discrete scenarios based on which second stage decisions on intra-day operation of the storage (pumped hydro) are taken.

L. Costa, F. Bourry, J. Juban and G. Kariniotakis (2008) [20] splits the problem into two phases: scheduling and operation. In the first stage, taking into account the limitations of the storage device, profit maximizing bids for the day-ahead market are calculated by solving a Dynamic Program (DP). In addition, a series of set-points are obtained which consist of expected power outputs from the storage device according to wind forecasts available at the closing of day-ahead market. In the operation stage which follows, any deviations from the expected wind outcome is compensated in real-time as far as possible by suitable storage operation.

In addition to the three approaches discussed above, some other novel methods to sell wind power profitably in electricity markets can be found in literature. One interesting study is performed recently by **Bitar et al. (2012)** [21], which proposes an alternative market where wind power producers sell electricity at various price-differentiated reliability levels of supply to flexible consumers who are willing to bear the risk of insufficient supply in exchange for lower prices. For example, a 95% reliable supply contract, which would be cheaper than a 100% reliable supply, has a condition that there exists a 5% probability that the supplier may not deliver the electricity. It is argued that such a *variable-reliability* market in place of present-day *firm* markets shifts the risk burden of uncertain wind in-feed from operating reserves to flexible customers, thereby eradicating the need for running expensive and carbon-intensive thermal generators as reserves.

2.3 Key Findings from Literature

After studying the approaches followed in previous works, important findings from the literature study is listed in the following.

- In the first among the three approaches identified in Section 2.2, the most prevalent method of solving stochastic optimization problems is to obtain a robust solution which fares well even with the worst among all the scenarios considered. Any excess wind is then traded in the intra-day markets, which usually involve continuous trading such that there exists a probability that the bid is not accepted. Due to the absence of storage, if intra-day selling bids are not accepted, forced curtailment of wind production is followed which leads to the costs of lost opportunity.

- The use of financial options for mitigating wind uncertainty, as suggested in [16] appears promising, but it is limited by the lack of liquidity in such contracts for wind power plants at present.

- The interesting alternative market proposed in [21] potentially eradicates the need for operational reserves. But it requires a significant change in the present market designs and coordinated demand-side management responses from consumers. The relevant infrastructure and know-how for operating such a *variable-reliability* market, though partially exist today, significant further research is required before it could be implemented.

- In the approach using energy storage devices, the study in [17] focusses more on the operational aspects of a wind-hydro ensemble rather than on market participation. In [18], an interesting combined bidding strategy is introduced for a similar wind-hydro joint power plant, albeit considering participation in intra-day markets only wherein the uncertainty in wind power outcome is considerably reduced.

- The studies following the energy storage approach have so far considered a joint wind-storage power plant. This assumption, in essence, makes the storage device a stand-by power plant, very similar to the existing operational reserves, except that it is operated by wind power plants themselves. However, unlike the traditional reserve power plants such as gas turbines which have high operational costs and are desired to be used only if needed, most energy storage devices have lower operation costs. Therefore, operating a storage as a stand-by for a wind power plant involves a great amount of lost opportunity costs for the storage device of earning revenues from participating in the electricity markets on its own.

- In addition, it has been assumed that the storage devices are owned by the wind power plants themselves. This requires a considerably large capital investment and adds to the financial burden of wind power plant owners.

Chapter 3

Model Overview

This chapter begins by highlighting the choice of storage consideration in this thesis and poses the research questions relevant in that context. The structure of the proposed model is presented in the subsequent section while the final section presents a discussion on wind uncertainty modeling adopted.

3.1 Research Questions

The problem of enabling profitable market participation for wind power plants can be approached in several ways, as illustrated in the previous chapter (Section 2.3). For a wind power producer without access to storage, as shown in Fig. 3.1, bidding higher than point forecasts involves the risk that actual wind production during delivery of the bids in the next day could be insufficient to meet the schedule. On the other hand, higher the amounts bid in the day-ahead market, higher is the earnings. Bidding with amounts lower than wind power forecast allows the flexibility to curtail wind production if it is in excess. But through curtailment, the wind power

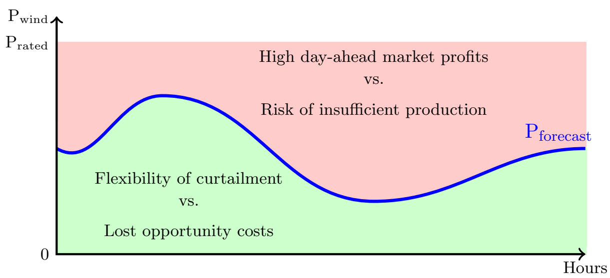


Figure 3.1: Illustration showing the regions for choice of day-ahead market bids for a wind power producer without storage. P_{rated} is the rated power (MW) of the wind power plant whereas $P_{forecast}$ is the wind power forecast (MW) for the hours shown.

producer incurs loss of opportunity costs of making profits in the day-ahead markets.

In this thesis, we consider the use of storage which has the potential to eliminate risks of insufficient wind production through discharging operation and to avoid curtailment losses through charging. The costs and risks shown in Fig. 3.1 in both the regions around the wind forecast could thus be eliminated with consideration of storage. Such an approach involving joint operation of a wind power plant and energy storage presents two interesting sub-challenges:

1. *How to choose optimal energy bids to be placed in the day-ahead market taking into account the wind and price uncertainty and the availability of storage?*

   For each hour of the day, one could place bids lower than the forecasts in day-ahead market to start with and then compensate the imbalances by operating a storage resource in real-time or by selling the excess wind generation in intra-day market to maximize profit opportunities. This could be possible because the accuracy of wind forecast is improved in the short-term, before the gate closure of intra-day markets. Otherwise, one could place bids higher than the forecasts in day-ahead market believing in optimistic wind outcomes and then compensate in real-time, as required, using storage operation or through buying bids in intra-day markets.

2. *How to operate the storage device during the delivery period when forecast errors of wind are reduced and the cleared prices of the day-ahead market are known?*

   As wind forecast improves when actual delivery period is approached, the plant operator has to make a decision whether to compensate for the imbalance (between the physical production from the wind power plant and day-ahead bids submitted) through the use of storage device or by placing buying and selling bids in the intra-day market.

3.2 Model Structure

A two-stage model developed in this thesis attempts to address the two research questions formulated in the previous section. While the first stage prepares optimal bids for the day-ahead market considering the availability of storage, the second stage optimizes the operation of storage device and the participation in intra-day markets through a predictive controller.

Fig. 3.2 shows a flowchart for the two stages and illustrates the relationship between them and their interactions with power markets and the electricity grid. The chart is divided into four blocks: *Power markets*, *Electricity grid* and the two stages *Day-ahead scheduling* and *Intra-day operation.*

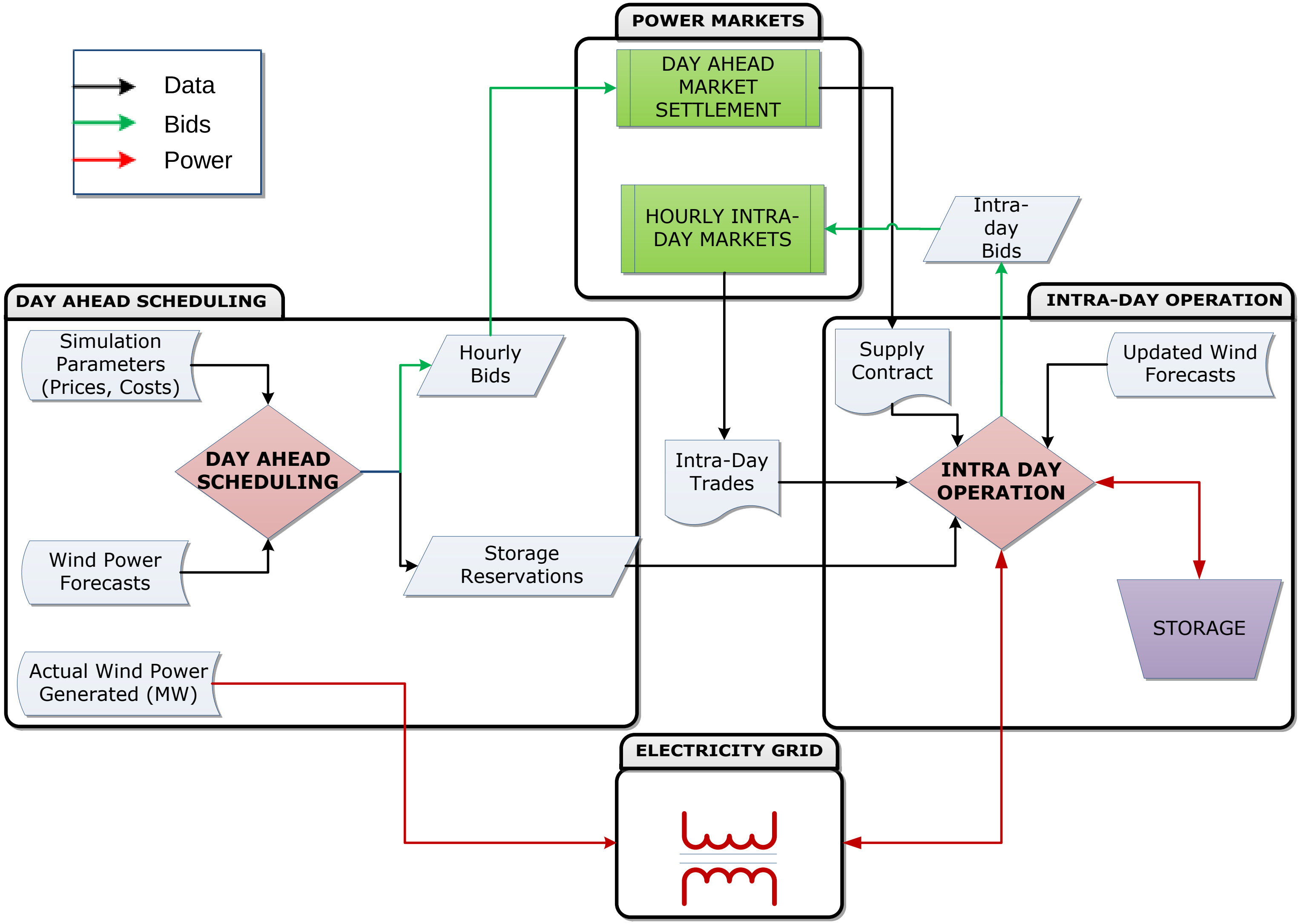


Figure 3.2: Flowchart of the developed model showing the four blocks comprising it.

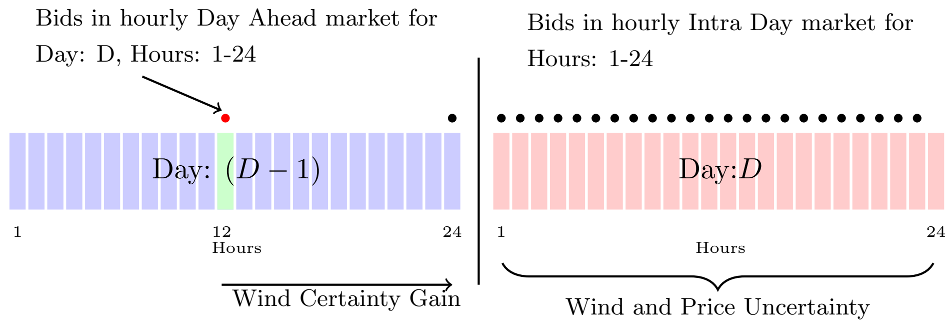


Figure 3.3: Time-line of the two-stage market showing the uncertain parameters. The (•) represents market clearing for the Day-ahead market for Day D and each (•) represents a market clearing point for the hourly intra-day markets.

Power markets A time-line of the market structure considered in this thesis is presented in Fig. 3.3. The power markets comprise an auction-based day-ahead market (cleared at 12 PM on the previous day) and hourly continuous intra-day market with bidding allowed until 45 minutes prior to the start of each hour. This market structure is modeled after the functioning of European Power Exchange (EPEX) Spot Market and has already been discussed in detail in Chapter 2. As shown in Fig. 3.3, while bidding in the day-ahead markets at 12 PM in Day $(D-1)$, the wind power producer must consider the uncertain wind power outcomes lying 12 to 36 hours ahead. Participating in the intra-day market allows the wind power producer to take advantage of the certainty gained as delivery period is approached. The separation of the problem into two stages, shown in Fig. 3.2 as Day-Ahead Scheduling and Intra-Day Operation blocks, allows the incorporation of updated wind forecasts into the modeling.

Day-Ahead Scheduling As shown in Fig. 3.2, available forecasts for wind power and electricity market prices for the next day are used as inputs to calculate profit maximizing bids for the day-ahead markets. In addition to the hourly bids, a sequence of hourly storage capacity reservations (MW) is determined. As shown in the illustration in Fig. 3.4, reserved capacity of storage device provides a band around the bid such that mismatches occurring within it can be handled using proper storage operation. It can be observed that mismatches where actual wind generation outcome is higher than day-ahead bids are covered by charging reservation. On the contrary, mismatches occurring in the other direction are covered by the discharging reservation.

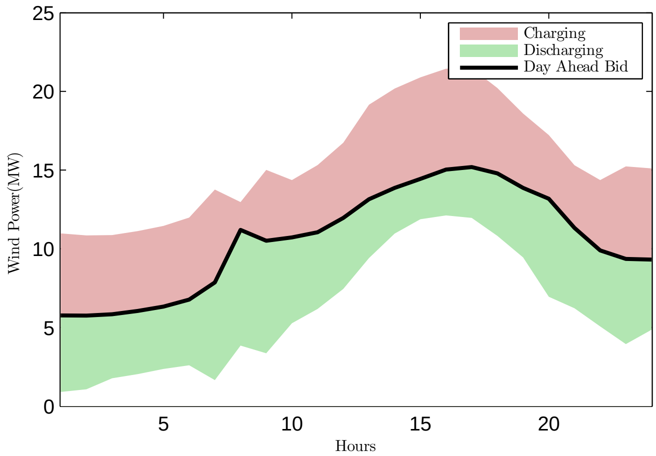


Figure 3.4: Illustration for the concept of charging and discharging reservations for a sample day.

Intra-Day Operation In the intra-day operation stage, as shown in Fig. 3.2, a supply contract is received after the day-ahead market settlement is complete. In this stage, a Model Predictive Control (MPC) based framework uses the updated wind forecasts to determine a minimum cost optimal control strategy for the storage device such that the supply contract is met as closely as possible. Additionally, as shown in the figure, bids for participating in the intra-day markets are also prepared in this stage.

Electricity Grid During physical delivery period in Day D, the wind power plant feeds the generated wind power to the grid. Suitable balancing power is supplied from the storage device such that deviations from the bids made in the day-ahead markets are minimized. As indicated by the bidirectional arrows in Fig. 3.2, it is assumed that the point of grid-coupling for the storage device allows bidirectional power flow. This enables the mitigation of both deficit and excess of actual wind generation as compared to the day-ahead supply contract.

3.3 Modeling Assumptions

For simplifications in modelling, the following assumptions are made throughout this thesis:

1. The prices of electricity in spot markets are assumed to be perfectly known. This assumption eliminates the price uncertainty which is one of the two uncertainties faced by the wind power producer, shown in Fig. 3.3.

2. In the day-ahead scheduling stage, the wind power producer is allowed to make only selling bids for the auction in day-ahead market.

3. The wind power producer in both day-ahead markets and intra-day markets is assumed to be a “price-taker”. This assumption is based on grounds that the wind power producer is supposed to be small in size and therefore has no influence on the market prices. However, with increasing shares of wind energy in the net generation mix, hours with high wind generation result in lower electricity market prices. This is because as of today, wind power plants place their bids in the day-ahead markets at zero marginal cost. Hence, higher amounts of energy from wind are reflected by a shifting of the aggregated supply curve towards the right. Considering the demand to be inflexible, this leads to a market settlement at a lower price than expected. The reader is directed to [22] for a detailed analysis of the interaction between the amounts of wind energy generated and electricity prices.

4. In contrast to some European power market mechanisms (as mentioned in Section 2.1), the imbalance settlements are assumed to involve penalties for deviation from the day-ahead schedule, regardless of the its direction and whether the overall system is in power excess or deficit.

3.4 Wind Power Uncertainty Modeling

As shown in Fig. 3.3, while deciding bids for day-ahead market, the wind power producer faces an uncertainty in wind power outcome with a look ahead time of 12 to 36 hours. This uncertainty needs to be suitably considered in modeling.

The hourly wind power output of a wind farm is considered a random variable X with a continuous probability distribution function (pdf), $P(X)$, such that:

$$P(X) = f(\mu, \sigma, \rho, \cdots), \tag{3.1}$$

where μ, σ, ρ, $\cdots$ represent the parameters of the distribution namely, expected value, standard deviation, skewness and so on.

This modeling allows the use of any continuous probability distribution for characterizing the uncertainty in wind power forecasts, provided,

- its probability distribution function (pdf) and cumulative distribution function (cdf) can be expressed analytically, and
- the inverse cdf or quantile function exists.

The wind power point forecast (W) obtained from forecasting tools is chosen as the expected value (μ) for the probability distribution.

A variety of tools have been proposed in the literature to predict wind power in the form of point forecasts. Numerical Weather Prediction (NWP) models, statistical models based on historical data and models based on Artificial Neural Networks (ANN) are some of the most commonly used tools for forecasting wind power. Since a detailed analysis of forecasting techniques is out of scope of this thesis, interested readers are directed to [23] which provides a comprehensive review of prevalent wind power forecasting methods.

Other parameters ($\sigma, \rho, \cdots$) defining the probability distribution $P(X)$ can be estimated analytically using expressions similar to Eq. 3.2, where standard deviation (σ) of the distribution $P(X)$ is expressed as a function g of the ratio between point forecast value (W) and the rated capacity of the wind power plant. Such modeling of σ however, needs correct identification of the underlying function g through rigorous analysis of historical data.

$$\text{Standard Deviation}, \sigma = g\left(\frac{\text{Wind Point Forecast (W) [MW]}}{\text{Rated Plant Capacity [MW]}}\right) \tag{3.2}$$

Curve fitting techniques provide a simple yet effective method for estimation of these parameters. For instance, Fig. 3.5 shows fitting of the historical day-ahead forecast errors in wind power to a standard normal distribution, $\mathcal{N}(0, \sigma)$. From this fitting, the standard deviation, σ for the distribution can be estimated. In [24], wind power forecasting error distributions are studied in detail and standard normal distribution is identified to be suitable for fitting errors occurring in short-term wind forecasting.

From this simplified modeling of the wind power forecast errors, it follows that wind power realizations can be expressed in the form of a random variable X having a normal pdf $P(X)$, centered around the point forecast value, W and with a standard deviation σ estimated from curve fitting techniques. Fig. 3.6 illustrates the modeling of uncertain wind availability as the random variable X.

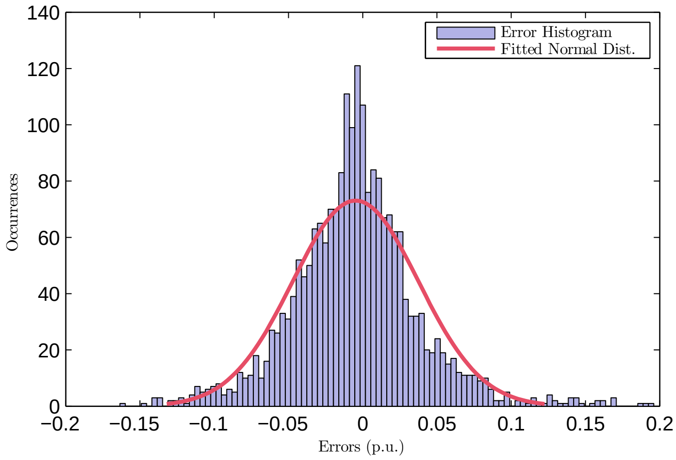


Figure 3.5: An example for curve fitting of errors in historical day-ahead wind forecasts to a standard normal distribution for estimating the standard deviation, σ of the distribution $P(X)$.

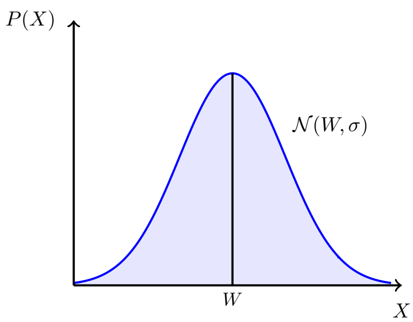


Figure 3.6: Modeling of wind uncertainty as a normally distributed random variable X.

Chapter 4

Day-Ahead Scheduling

This chapter discusses the optimization problem which is solved to obtain optimal bids for the day-ahead markets.

4.1 Problem Formulation

As discussed in Chapter 3, wind power forecasts and electricity market prices are used in the day-ahead scheduling stage to solve an optimization problem for computing profit maximizing bids for the day-ahead market.

The assumptions taken in deciding bids for the day-ahead market are listed in the following.

- At this stage it is possible to undertake an unconstrained optimization with respect to the capacity (MW) limits of the storage device. This should, in principle, allow the wind power producer to sell the contract for supply of balancing power to one or more storage asset owner(s) in the market, as required.
- As described in the previous chapter (Section 3.2), the uncertainty in wind power values is characterized in the form of hourly probability distributions, with the point forecasts as the expected value. The prices for the day-ahead market are assumed to be deterministic.

The objective function in the optimization problem $P1$ used in this stage comprises two terms which are related to each other:

- The bids for day-ahead market are decided based on a trade-off between the expected revenues from the day-ahead market ($\lambda^{DA} \cdot B$) and the costs associated with it. These costs include the storage capacity reservation costs (λ^{C_u} and λ^{C_d}) and imbalances penalties (λ^{I}). Storage capacity reservations (C_h^u and C_h^d) act as a hedging mechanism against unfavourable wind power realizations for the wind power plant owner for which he has to pay a certain premium (reservation costs).

- In addition to the above trade-off, the second term in the objective function ($|\sum_{h=1}^{24}(\lambda_h^{\mathrm{S}} S_h)|$) incentivizes energy-neutrality of the bids during the day. This term relates bids in the day-ahead market to the realistic operation of storage device during the next day. It implies that the net energy expected to be used for charging the storage device in the next day should be as close as possible to the net energy expected to be discharged. This ensures that the difference between energy content of the storage device at the start of the day and that at the end of the day is minimized. This is a crucial consideration for achieving the decoupling of storage device from the wind power plant, which is a goal of this thesis.

The parameter $\rho \in [0, 1]$, which relates the two terms of the objective function, can be used as a weight for the energy neutrality criteria and is specified beforehand. If ρ is chosen equal to 1, the energy neutrality term is eliminated from the optimization problem.

The optimization problem $P1$ is stated in the following:

Optimization Problem ($P1$)

$$\max_{(z,\alpha,S)\forall h} \quad \rho \sum_{h=1}^{24} (\Lambda_h^{\mathrm{T}} z_h) - (1-\rho) \left| \sum_{h=1}^{24} (\lambda_h^{\mathrm{S}} S_h) \right|$$

subject to, $\forall h$,

$$z_h = \begin{bmatrix} B_h & C_h^u & C_h^d & R_h & (I_h^u + I_h^d) \end{bmatrix} \tag{4.1}$$

$$0 \le \alpha_h < 1 \tag{4.2}$$

$$b_h^u = \Phi^{-1}\left(\frac{1+\alpha_h}{2}\right) \tag{4.3}$$

$$b_h^d = \Phi^{-1}\left(\frac{1-\alpha_h}{2}\right) \tag{4.4}$$

$$b_h^d \le B_h \le b_h^u \tag{4.5}$$

$$C_h^u = (b_h^u - B_h) \tag{4.6}$$

$$C_h^d = (B_h - b_h^d) \tag{4.7}$$

$$R_h = \begin{cases} \frac{|-(B_1)^2|}{2\delta} , & \forall h = 1 \\ \frac{|(B_{h-1})^2 - (B_h)^2|}{2\delta} , & \forall h \neq 1 \end{cases} \tag{4.8}$$

$$I_h^u = \mathbb{E}(X \mid X_h > b_h^u) - b_h^u \tag{4.9}$$

$$I_h^d = b_h^d - \mathbb{E}(X \mid X_h < b_h^d) \tag{4.10}$$

$$S_h = (B_h - W_h) \tag{4.11}$$

Variables

h	:	Hours of the day (1,2,$\cdots$,24).
X_h	:	Random variable for wind power (MW) outcome in hour h.
W_h	:	Available point forecast for wind power (MW) in hour h.
B_h	:	Bid (MW) in day ahead market in hour h.
α_h	:	Dynamically selected risk tolerance factor which decides the position of bounds in hour h, such that $\alpha_h \in [0, 1)$.
b_h^u, b_h^d	:	Upper and lower bounds (MW) for day-ahead market bid B_h in hour h.
C_h^u, C_h^d	:	Up (charge) and down (discharge) storage capacity reservation (MW) in hour h.
R_h	:	Ramping energy (MWh) spent between hours $(h-1)$ and h.
I_h^u, I_h^d	:	Expected imbalances (MW) occurring in hour h.
S_h	:	Expected use of storage (MW) in hour h.

Functions

$P(X)$	:	Probability distribution of wind power random variable X.
$\lvert \bullet \rvert$	:	Absolute value function.
Φ^{-1}	:	Quantile function or inverse cumulative distribution function (cdf) for the probability distribution $P(X)$.
$\mathbb{E}$	:	Expected value function for a part of the probability distribution $P(X)$, truncated as defined in the domain.

Parameters

ρ	:	Fixed parameter to control the strictness of energy-neutrality requirement in day-ahead bids.
δ	:	Maximum change in bids allowed in bids between subsequent hours (MW/hour).

Costs and Rewards

λ_h^{DA}	:	Day-ahead market price (€/MW) forecast in hour h.
$\lambda_h^{\mathrm{C}_u}, \lambda_h^{\mathrm{C}_d}$	:	Storage reservation costs (€/MW) in the up (charging) and down (discharging) directions for the hour h.
λ_h^R	:	Penalty for ramping energy (€/MWh) in the hour h.
λ_h^{I}	:	Penalty for imbalances (€/MW) in the hour h.
Λ_h	:	Cost vector for hour h,$(-\begin{bmatrix} -\lambda_h^{\mathrm{DA}} & \lambda_h^{\mathrm{C}_u} & \lambda_h^{\mathrm{C}_d} & \lambda_h^{\mathrm{R}} & \lambda_h^{\mathrm{I}} \end{bmatrix})$.
λ_h^{S}	:	Cost for storage operation (€/MW) in the hour h.

4.1.1 Explanation of Constraints

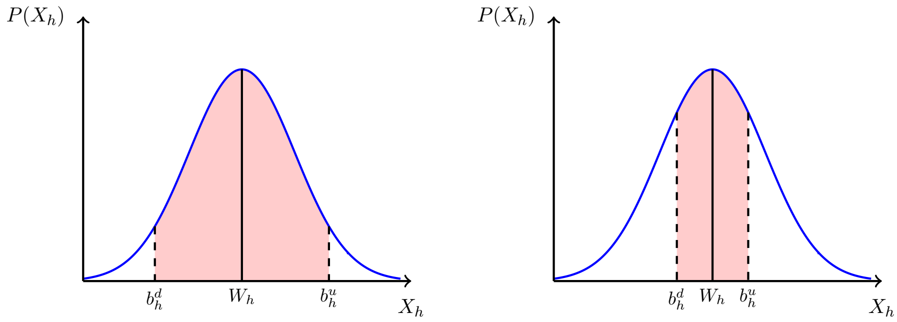
The constraints involved in the problem $P1$, given by Eqns. (4.2)-(4.11), are explained in detail in the following.

1. The constraint in Eq. (4.2) provides bounds for the choice of α_h. The decision variable α_h is a dynamically selected parameter which indicates the preference to place bids (B_h) different from the point forecast of the hour (W_h) if economical storage resources are available. Since W_h represents the expected value for the wind power realization random variable (X_h), there is implicit risk involved with bidding in markets with volumes different from W_h. However, as the availability of storage reservations is incorporated, it is possible to tolerate some risk in this respect and bid strategically in order to maximize profits. α_h defines an interval for the bounds $[b_h^d,\ b_h^u]$, within which the bid for the hour (B_h) is chosen. In the absence of storage or if the cost of storage is very high, the optimizer chooses α_h close to zero and the bounds are very close to the point forecast W_h. In that case, the bids are placed very close to the point forecast (W_h) for the hour. The reason for choosing a left-closed, right open interval [0,1) for the choice of α_h in the constraint in (4.2) is elaborated in the next paragraph.

2. The bounds b_h^d and b_h^u, defined in equality constraints in Eqns. (4.3) and (4.4), are calculated from the inverse cumulative distribution function (cdf) or quantile function of the probability distribution of random variable X_h for a chosen value of α_h. The bounds may or may not be symmetrical about the mean value W_h depending on whether the probability distribution $P(X_h)$ is symmetrical about W_h or not. If $P(X_h)$ is considered as a Normal distribution, Fig. 4.1 demonstrates the change in position of bounds b_h^d and b_h^u with respect to change in α_h. It can be observed that if α_h is chosen by the optimizer to be 0.9, the bounds b_h^d and b_h^u are chosen such that 90% of outcomes of random variable (X_h) lie within the interval $[b_h^d,\ b_h^u]$, with 5% of the realizations lying outside the bounds on either sides. On the other hand, if the optimizer chooses α_h to be 0.5, the interval $[b_h^d,\ b_h^u]$ moves closer to the expected value W_h and only 50% of wind outcomes (X_h) now lie within the bounds. From the definition for the bounds, it follows that $\alpha_h = 1$ makes the interval $[b_h^d,\ b_h^u]$, unbounded as $(-\infty, \infty)$. Hence, the value 1 is excluded from the choice space for the variable α_h, as expressed in Eq. (4.2).

3. The upper and lower bounds for choosing the bid B_h is defined by the constraint in Eq. (4.5). The bid is chosen from the interval $[b_h^d, b_h^u]$ as demonstrated in Fig. 4.1.

4. The constraints in Eqns. (4.6) and (4.7) determine the storage capacity (MW) to be reserved in both charging (up) and discharging (down) directions. The storage capacity reservations for the hour (C_h^u and C_h^d) are given by the distance of the bid B_h from the corresponding upper bound b_h^u and lower bound b_h^d, respectively.



(a) b_h^d and b_h^u for $\alpha_h = 0.9$ (b) b_h^d and b_h^u for $\alpha_h = 0.5$

Figure 4.1: Change in position of bounds, b_h^d and b_h^u for hour h with α_h. The bid, B_h, is chosen from the interval $[b_h^d, b_h^u]$.

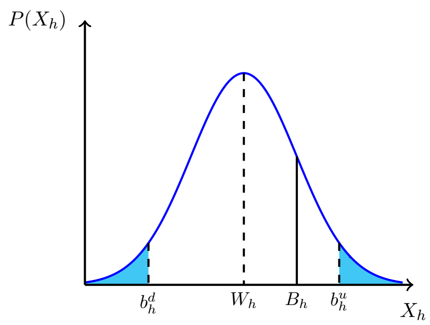


Figure 4.2: Region for imbalance penalty for a given reserved storage capacity. Imbalances are expected for wind power realizations X_h lying outside the interval $[b_h^d, b_h^u]$.

5. On moving towards very high shares of wind energy, flexible thermal units in the power systems may need to accommodate frequent changes to their scheduled production. This leads to the higher costs involved with frequent ramping in thermal units. Consequently, it can be foreseen that the grid operator or the Transmission System Operator (TSO) may opt to impose restrictions on wind power producers in regards to changes between subsequent hourly bids. The formulation in the constraint in Eq. (4.8) penalizes extreme changes in the bids between subsequent hours. This modeling of ramping costs in the form of energy lost during ramping follows from the minimum cost thermal unit ramping model proposed in [25], where it is described in detail.

6. The constraints in Eqns. (4.9) and (4.10) allow the penalization of expected imbalances. As highlighted in Fig. 4.2, imbalances are expected

only for wind power realizations which lie outside the interval $[b_h^d, b_h^u]$, where the reserved storage capacities is not enough to accommodate the difference between bid B_h and wind outcome random variable X_h.

7. According to the modeling adopted in this thesis, at the time of making bids for the day-ahead market, wind power point forecast W_h is the best guess available for possible wind power realizations. The equality constraint in Eq. (4.11) defines the expected storage use for each hour during the actual production in the next day. When the bid B_h is higher than point forecast W_h, the value of S_h is positive implying that the storage device is more likely to be charged than discharged and vice-versa. This expected use of storage is then optimized over the entire day such that energy neutrality during the day, as described previously, can be maintained.

4.2 Choice of Optimal Solution

Fig. 4.3 demonstrates the trade-offs in the optimization problem $P1$ and the choice of optimal bid B_h within the bounds defined by b_h^d and b_h^u for the hour h. As indicated by direction of the arrows, the cost for imbalance penalty (λ_h^{I}) provides an incentive for α_h to be high and correspondingly, the bounds to be farther apart, thereby reducing the region for imbalances shown in Figure 4.2. On the other hand, the costs for storage use (λ_h^{S}) push α_h and correspondingly the bounds interval $[b_h^d, b_h^u]$ to be as small as possible to minimize expected storage use. An optimal trade-off is reached depending on the values of these costs and a suitable value for α_h is chosen by the optimizer. It can be seen that the value of optimal bid B_h is chosen from the sample space of all values within the interval $[b_h^d,\ b_h^u]$, depending upon the trade-off between the reward from day-ahead market $(\lambda_h^{\mathrm{DA}})$ and the costs of storage reservations ($\lambda_h^{\mathrm{C}_d}$ and $\lambda_h^{\mathrm{C}_u}$).

The outputs of interest from the solution of the optimization problem $P1$, which are used in the intra-day operation stage of the model, are listed in the following.

1. *Day-ahead market bids, B* (MW), which contain a series of hourly bids to be placed in the day-ahead market for the next day.

2. *Storage capacity reservations, C^d and C^u* (MW), each of which contain hourly values of reserved storage capacity for discharging and charging operation respectively.

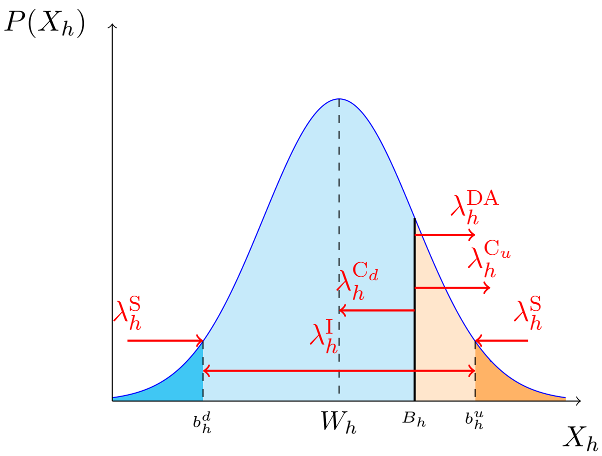


Figure 4.3: Trade-offs in optimization problem $P1$ and factors influencing the choice of optimal bid B_h to be placed in day-ahead market for the hour h.

4.3 Implementation

The problem in the day ahead scheduling stage ($P1$) is a constrained non-linear optimization problem. YALMIP [26] toolbox for MATLAB is used to formulate the problem.

Chapter 5

Intra-Day Operation

In this chapter, scheduling of the storage device operation and participation in intra-day markets are discussed. The receding horizon control strategy adopted in this stage of the model is described in detail.

5.1 Objectives

The objectives of the intra-day operation stage are listed in the following.

- Contracted production schedule received from day-ahead market clearing should be tracked as closely as feasible, such that imbalance penalties are minimized.

- Storage device should be operated within the limits of reserved capacity obtained from the results of day-ahead scheduling stage.

- Suitable buying and selling bids for the intra-day markets should be prepared.

These intra-day market bids are expected to serve two purposes as mentioned in the following.

1. Buying bids in the intra-day market should be made to mitigate the imbalances occurring in the hours when the power reservations for storage (MW) or the energy content of the storage device (MWh) are not sufficient.

2. Bids should be made in the intra-day market to buy and sell energy in order to maintain the daily energy neutrality (discussed in Section 4.1) of the storage device. This ensures that the energy content (MWh) of storage device at the end of the day doesn't deviate from the value at the start of day.

As discussed in Chapter 3, an intra-day market with continuous trading framework is considered in this thesis. Therefore, the risk that bids in hourly intra-day market may not be cleared on grounds of lacking a suitable counter-party should be reflected in terms of higher costs associated with bids in this market. This provides a preference for operating the storage, whenever feasible, over participating in the intra-day markets.

5.2 Introduction to Model Predictive Control

A Model Predictive Control (MPC) based operation framework is used to achieve the objectives of intra-day operation stage stated in the previous section. MPC is a broad term for any control formulation where an optimal control trajectory for a given system is obtained through solving a constrained or unconstrained cost minimization problem. The first step involved in MPC is the mathematical modeling of underlying system. The chosen model should be capable of capturing the process dynamics in order to precisely predict the future outputs, whilst being simple enough to be efficiently implemented. State space models are most commonly used for this purpose on account of their simplicity and flexibility. The reader is directed to [27] for a detailed discussion on designing aspects of MPC systems and their implementation in MATLAB.

Even though in practice MPC can be implemented in several ways, in this thesis a *receding horizon control* approach is followed which is briefly explained in the following.

Fig. 5.1 illustrates the control strategy used in MPC where $u(t)$, $y(t)$ and $r(t)$ represent the control, output and reference signals for a minimal working example system. The goal of the control system is to match output of the system $y(t)$ with the reference signal $r(t)$. In each time step t, a trajectory of control signals for the optimization horizon N is chosen by considering the past and current values of states and outputs of the system. The trajectory is then optimized through the minimization of a cost function, which in this case involves the errors between reference signal $r(t)$ and predicted output $y(t)$ for the entire horizon N. The cost function could also include bounds and penalties on the magnitude of control signal $u(t)$. Once a minimum cost solution is reached, the control signal for the present time step $u(t)$ is applied to the system, while the other calculated values are discarded.

At the next time step $(t+1)$, a problem of reduced size is solved while keeping the end of the optimization horizon fixed. The control signal for this time step $u(t+1)$ is thus obtained from the solution.

The above process is repeated until the end of horizon is reached. The result is a sequence of optimal control signals $u^*(t)$ for the entire horizon such that goal of the control system is achieved.

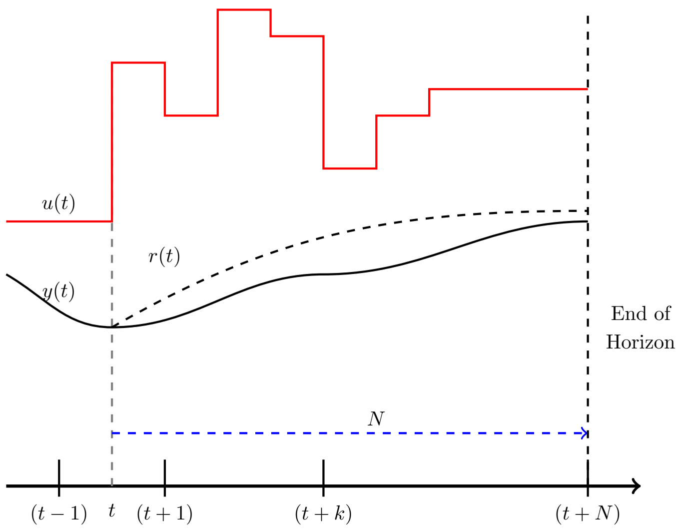


Figure 5.1: An illustration for Model Predictive Control (MPC) receding horizon operation strategy. At each time step t and optimization problem is solved to obtain the optimal control signals $u(t)$ for minimizing the errors between the expected output $y(t)$ and the reference signal $r(t)$ over the entire horizon N.

5.3 Control System in Intra-Day Operation

As discussed in Chapter 3, the intra-day operation of storage device is decoupled from the day-ahead scheduling. However, the day-ahead market supply contract and storage capacity reservations must be taken care of during the intra-day operation stage. The block diagram in Fig. 5.2 shows the open-loop control system architecture adopted in this stage. The commands for operation of the storage and bids for intra-day markets constitute the *control* signals which are manipulated in order to track the day-ahead market bids (*reference*) through the *receding horizon controller*. The improved wind forecasts as we move closer to the delivery period act as *disturbance* signals to which the controller must adapt its control strategy.

The control system consists of three blocks: *System Model*, *Future States and Outputs Predictor* and *Receding Horizon Controller*, whose functions are discussed in detail in the following.

5.3.1 System Model

The first step involved in control of storage device using MPC is the state space modeling of the system, which is illustrated in Fig. 5.3 and is described by Eqns. 5.1-5.4.

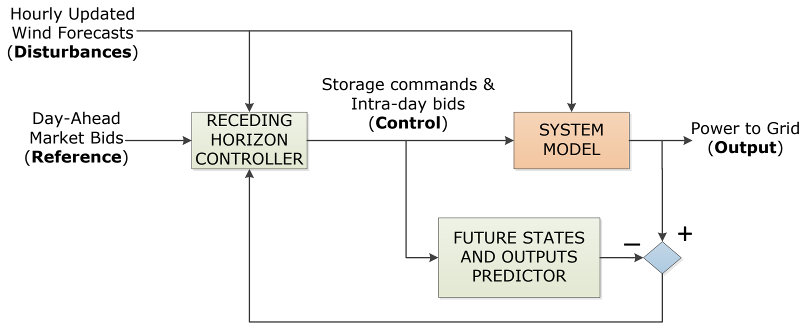


Figure 5.2: Block diagram for the Model Predictive Control (MPC) framework used in the intra-day operation stage. The receding horizon controller calculates control signals such that the output tracks the reference signal with minimum errors.

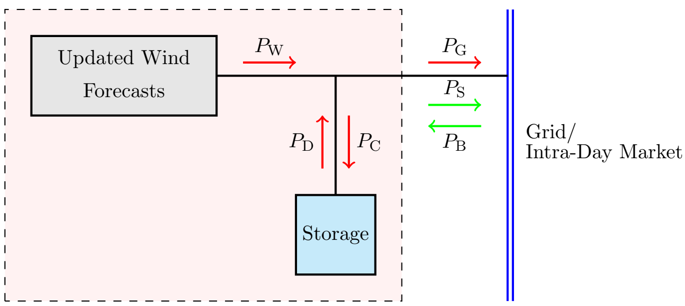


Figure 5.3: Modeling of the system for intra-day operation stage. The arrows illustrate the direction for positive power flow.

$$E_{\mathrm{S}}(h+1) = E_{\mathrm{S}}(h) + \tau \cdot [\eta_{\mathrm{C}}.P_{\mathrm{C}}(h) - \frac{P_{\mathrm{D}}(h)}{\eta_{\mathrm{D}}}] \tag{5.1}$$

$$P_{\mathrm{G}}(h) = \underbrace{[P_{\mathrm{D}}(h) - P_{\mathrm{C}}(h)]}_{\text{Storage Operation}} + \underbrace{P_{\mathrm{B}}(h) - P_{\mathrm{S}}(h)}_{\text{Intra-Day Market}} + \underbrace{P_{\mathrm{W}}(h)}_{\text{Wind Forecast}} \tag{5.2}$$

$$P_{\mathrm{D}}(h) \cdot P_{\mathrm{C}}(h) = 0,\ \forall h \tag{5.3}$$

$$P_{\mathrm{B}}(h).P_{\mathrm{S}}(h) = 0,\ \forall h \tag{5.4}$$

Variables

h	:	Hours of the day $(1,2,\cdots,24)$.
τ	:	Time of operation (1 hour).
$E_{\mathrm{S}}(h)$	:	Energy stored in storage device at the start of hour h.
$P_{\mathrm{D}}(h), P_{\mathrm{C}}(h)$	:	Discharging/Charging power from/into storage device in hour h.
$P_{\mathrm{B}}(h), P_{\mathrm{S}(h)}$	:	Buying/Selling bid made in intra-day market in hour h.
$P_{\mathrm{G}}(h)$	:	Power in-feed into the grid from wind and storage ensemble in hour h.
$P_{\mathrm{W}}(h)$	:	Best available forecast for wind power in hour h.
$\eta_{\mathrm{D}}, \eta_{\mathrm{C}}$	:	Discharging/Charging efficiency of the storage device.

The change in energy content of the storage device with time is quantified by Eq. 5.1, while the output from the system is defined by Eq. 5.2. Eqn. 5.3 ensures that the storage device is not charged and discharged in the same hour. Finally, Eq. 5.4 eliminates the situation when both buying and selling bids are made in the intra-day market for the same hour.

State Space Model

The resulting state-space model can be expressed in matrix form as follows:

$$\underbrace{\begin{bmatrix} E_{\mathrm{S}}(h+1) \end{bmatrix}}_{x(h+1)} = \underbrace{\begin{bmatrix} 1 \end{bmatrix}}_{A} \underbrace{\begin{bmatrix} E_{\mathrm{S}}(h) \end{bmatrix}}_{x(h)} + \underbrace{\begin{bmatrix} \frac{-\tau}{\eta_{\mathrm{D}}} & \tau \cdot \eta_{\mathrm{C}} & 0 & 0 \end{bmatrix}}_{B} \underbrace{\begin{bmatrix} P_{\mathrm{D}}(h) \\ P_{\mathrm{C}}(h) \\ P_{\mathrm{B}}(h) \\ P_{\mathrm{S}}(h) \end{bmatrix}}_{u(h)} \tag{5.5}$$

$$\underbrace{P_{\mathrm{G}}(h)}_{y(h)} = \underbrace{\begin{bmatrix} 1 & -1 & 1 & -1 \end{bmatrix}}_{D} \underbrace{\begin{bmatrix} P_{\mathrm{D}}(h) \\ P_{\mathrm{C}}(h) \\ P_{\mathrm{B}}(h) \\ P_{\mathrm{S}}(h) \end{bmatrix}}_{u(h)} + \underbrace{\begin{bmatrix} 1 \end{bmatrix}}_{E} \underbrace{P_{\mathrm{W}}(h)}_{v(h)} \tag{5.6}$$

Eqns. 5.5 and 5.6 can be written in short as:

$$x(h+1) = Ax(h) + Bu(h) \tag{5.7}$$

$$y(h) = Du(h) + Ev(h) \tag{5.8}$$

5.3.2 Prediction of State and Output Variables

The next step in the MPC system is the prediction of states and outputs for the entire horizon. The end of horizon is always kept fixed at the last hour of the day. This consideration follows from the energy neutrality criteria discussed in Section 4.1 wherein the storage device is operated such that its energy content at the end of the day is same as that at the start of the day.

In each hour h, the optimization is performed for a horizon N which is reduced every hour starting from 24 hours until the end of the day is reached. This means that in the first hour $N = 24$ and as we move towards the end of day, the final value of $N = 1$ is reached when optimization is performed only for the last hour of the day.

For the optimization horizon N at any given hour h, the future control trajectory can be expressed as:

$$U(h) = \begin{bmatrix} u(h) & u(h+1) & u(h+2) & \cdots & u(h+N-1) \end{bmatrix}^T \tag{5.9}$$

The updated wind power forecasts which are received in each hourly step are expressed in the vector V, such that it always contains the latest forecast information for each hour.

$$V(h) = \begin{bmatrix} v(h) & v(h+1) & v(h+2) & \cdots & v(h+N-1) \end{bmatrix}^T \tag{5.10}$$

The future state variables can be calculated as following:

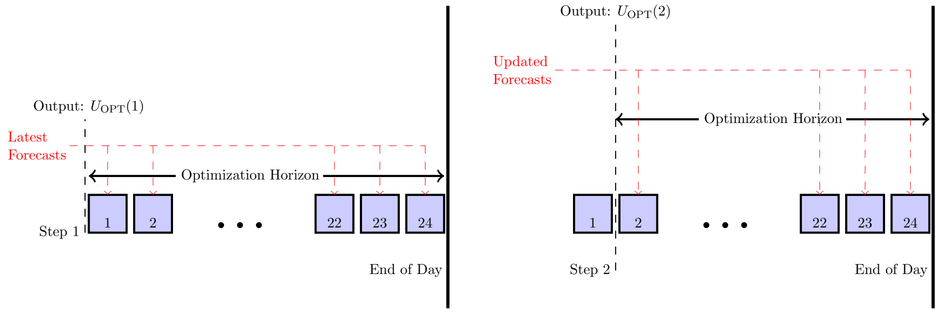
$$\begin{aligned}
x(h+1|h) \quad &= Ax(h) + Bu(h) \\
x(h+2|h) \quad &= Ax(h+1) + Bu(h+1) \\
&= A^2x(h) + ABu(h) + Bu(h+1) \\
x(h+3|h) \quad &= Ax(h+2) + Bu(h+2) \\
&= A^3x(h) + A^2Bu(h) + ABu(h+1) + Bu(h+3)
\end{aligned}$$

Finally the X vector which contains predicted state vectors in the hour h can be written as:

$$X = \begin{bmatrix} x(h+1|h) & x(h+2|h) & x(h+3|h) & \cdots & x(h+N|h) \end{bmatrix}^T \tag{5.11}$$

Similarly, the future outputs are calculated as in the following:

$$\begin{aligned}
y(h+1|h) &= Du(h+1) + Ev(h+1) \\
y(h+2|h) &= Du(h+2) + Ev(h+2)
\end{aligned}$$



(a) Step 1.

(b) Step 2.

Figure 5.4: Illustration for the first two steps of receding horizon controller. In each step, the best available forecasts for each hour of the remaining horizon are used and control signals (storage operation and intra-day market bids) for the immediate next hour are selected.

Collecting all the values, the predicted output vector Y in the hour h is expressed as:

$$Y(h) = \begin{bmatrix} y(h+1|h) & y(h+2|h) & y(h+3|h) & \cdots & y(h+N|h) \end{bmatrix}^T \tag{5.12}$$

The prediction of future values for states and outputs allows the optimization algorithm in the *receding horizon control* to iteratively choose the best control strategy for the entire horizon at the hour h, as described in the next section.

5.3.3 Receding Horizon Control

The receding horizon controller block of the system, as shown in Fig. 5.2, receives information in the form of updated wind forecasts and the day-ahead scheduled supply contract. At each hour h, a constrained optimization problem ($P2$) is solved to obtain the optimal control trajectory U_{OPT}.

The concept of *receding horizon control* is illustrated in Fig. 5.4. In Step 1 shown by Fig. 6.3(a), the optimization problem $P1$ uses 1-hour ahead wind power forecast for Hour 1, 2-hour ahead forecast for Hour 2, 3-hour ahead forecast for Hour 3 and so on. The result of the optimization is $U_{\text{OPT}}(1)$ which contains the optimal storage charge/discharge schedule and intra-day buy/sell bid for Hour 1. In the next step shown by Fig. 6.3(b), updated wind forecasts, that is, 1-hour ahead forecast for Hour 2, 2-hour ahead forecast for Hour 3 and so on are used to solve $P1$ again with a reduced problem size. The results are optimal control signals for Hour 2, $U_{\text{OPT}}(2)$. The process is repeated until Hour 24 is reached and the vector U_{OPT} containing the optimal control trajectory for the entire horizon is obtained.

Optimization Problem ($P2$)

$$\min_{u} \quad \sum_{N=24}^{1} \left(\sum_{h=(25-N)}^{24} \left[e(h)^T \Omega_{\text{imb}} e(h) + u(h)^T \Omega_{\text{con}} u(h) + w(h)^T \Omega_{\text{ex}} w(h) \right] \right)$$

$$\text{s. t.}, \forall h, \quad e(h) = (y(h) - P_{\text{sched}}(h)) \tag{5.13}$$
$$y(h) = Du(h) + Ev(h) \tag{5.14}$$
$$x(h+1) = Ax(h) + Bu(h) \tag{5.15}$$
$$u_{1,h} \cdot u_{2,h} = 0 \tag{5.16}$$
$$u_{3,h} \cdot u_{4,h} = 0 \tag{5.17}$$
$$0 \leq u_{1,h} \leq C_h^{\text{d}} \tag{5.18}$$
$$0 \leq u_{2,h} \leq C_h^{\text{u}} \tag{5.19}$$
$$0 \leq u_{3,h} \leq P_{\text{B}}^{\text{max}} \tag{5.20}$$
$$0 \leq u_{4,h} \leq P_{\text{S}}^{\text{max}} \tag{5.21}$$
$$(E_{min} - \omega(h)) < x(h) < (E_{max} + \omega(h)) \tag{5.22}$$
$$w(h) \geq 0 \tag{5.23}$$

Variables and Costs

$P_{\text{sched}}(h)$	:	Day-ahead scheduled power (MW) in hour h.
$C_h^{\text{d}}, C_h^{\text{u}}$	:	Discharging/Charging capacity reservations (MW) made in hour h.
$P_{\text{B}}^{\text{max}}, P_{\text{S}}^{\text{max}}$	:	Maximum buying and selling bids (MW) allowed in intra-day market.
E_{min}, E_{max}	:	Minimum and maximum operating limits allowed for energy content (MWh) in the storage device.
$y(h)$	:	Controller output, in-feed to the grid (MW) for hour h.
$e(h)$	:	Error (MW) in tracking the day-ahead scheduled power for hour h.
$x(h)$	:	Energy Content (MWh) of storage device at the start of hour h.
$u(h)$	:	Control vector in the hour h, ($\begin{bmatrix} P_D & P_C & P_B & P_S \end{bmatrix}$).
$v(h)$	:	Best available wind forecast for the hour h.
$w(h)$	:	Auxiliary variable (MWh) imposing soft constraints over energy storage limits.
Ω_{imb}	:	Cost for errors in meeting schedule.
Ω_{con}	:	Costs for control variables.
Ω_{ex}	:	Cost for exceeding storage operating limits.

The optimization problem $P2$ consists of three quadratic cost terms which are minimized. In addition to the penalty (Ω_{imb}) for errors in tracking the day-ahead scheduled bids, the objective function includes the cost for control vector (Ω_{con}) and the cost of exceeding storage operating limits (Ω_{ex}).

Ω_{con} is the cost for implementing control signals, which are storage scheduling and intra-day market bids. As discussed in Section 5.1, the risk associated with continuous trading mechanism of intra-day market is accounted for in the cost vector Ω_{con} through preference of storage operation, over intra-day market bidding. Furthermore, to maintain the energy-neutrality of the storage device suitable buying and selling bids are made in the intra-day markets such that net earnings from participation in hourly intra-day markets over the optimization horizon is maximized. This is accomplished through preference of buying bids in intra-day market in hours when market prices are expected to be low and vice-versa.

Ω_{ex} penalizes the violation of allowed storage operation range defined by $[E_{min}, E_{max}]$ through soft constraints, as expressed in Eq. (5.22). The soft constraints allow violation of operating limits of energy content (MWh) of storage if required, albeit at very high costs.

The constraint in Eq. (5.16) ensures that the storage device is not charged and discharged at the same hour. Similarly, constraint in Eq. (5.17) allows only buying or selling intra-day market bids in every hour.

The constraints in Eqns. (5.18)-(5.21) provide bounds on the control variables. The hourly storage capacity reservations received from the day-ahead scheduling stage are enforced as upper bounds for storage operation. The bounds on maximum intra-day selling and buying bids are pre-defined.

5.4 Controller Implementation

In each hour, the optimization problem ($P2$) is solved to obtain the charging/discharging schedule for the storage device for the next hour along with the intra-day buying/selling bids. The scheduled operation is undertaken irrespective of the actual wind realization in the next hour. This is because the storage device is decoupled from wind power producer and hence it doesn't provide real-time imbalance mitigation support. Instead, once the schedule for storage capacity operation to the wind power producer(s) has been made, the storage device owner may choose to further participate in price arbitrage for maximizing its profits.

The optimization problem ($P2$) is in the form of a quadratic program with mixed integer constraints (Eqns. 5.16-5.17). It is formulated in MATLAB using the YALMIP [26] toolbox and solved using IBM's ILOG CPLEX solver.

Chapter 6

Results and Discussion

This chapter defines various cases for validating the model proposed in this thesis. After the description of suitable simulation parameters and raw data, the simulation results for the various cases are compared and discussed.

6.1 Cases Definition

To validate performance of the model developed in this thesis, we consider a wind power producer which participates in an auction-based day-ahead market. Four cases are defined with regards to the actions taken by wind power producer to minimize the occurrence of imbalances thereafter. Table 6.1 summarizes the characteristics of the various cases defined.

Case	**Description**
Perfect Forecast	Perfect Wind Forecasts, No storage requirement, No intra-day market participation
Only Intra-day	Uncertain wind, No storage access, With intra-day market participation
Only Storage	Uncertain wind, With storage, No intra-day market participation
Storage+Intra-day	Uncertain wind, With storage access, With intra-day market participation

Table 6.1: Summary of the various cases.

In the *Perfect Forecast* case, the wind power producer faces a hypothetical scenario of having perfect information of future wind realization before making day-ahead market bids. Thus, the requirements of storage operation or intra-day market participation are alleviated.

Wind uncertainty is taken into account in all other cases. Since wind power forecasts move closer to the actual value as the power delivery period is approached, the case of *Only Intra-day* involves bidding in the intra-day markets with better forecasts. This strategy of participating in intra-day markets, which is recently becoming of interest for wind power plants, has been described in detail in [28]. Due to the growing interest of wind power plants to participate in intra-day markets, it is apt to compare the performance of this strategy with the model developed in this thesis.

Cases *Only Storage* and *Storage+Intra-day* involve a second-party owned storage device for mitigation of wind power imbalances. In the *Only Storage* case, no bids in the intra-day markets are allowed during the intra-day operation stage.

6.2 Simulation Parameters

Simulations for a time period of 10 days are performed for each of the cases defined in the previous section. The various model parameters used in the simulations are described in the following.

6.2.1 Wind Power Plant Data

In all cases, a medium-size onshore wind power farm is considered with an assumed installed capacity of 50 MW.

6.2.2 Storage Device Parameters

Table 6.2 shows parameters of the storage device considered in cases which include the use of storage. The size of storage device at 20 MWh could be deemed minimally sized for a 50 MW wind farm. However, such a choice of sizing demonstrates the idea that imbalances of a wind power plant could be managed by a relatively smaller sized storage device.

Parameter	**Units**	**Value**
Net Energy Capacity	MWh	20
Maximum Operating Energy Limit (SOC=0.8)	MWh	16
Minimum Operating Energy Limit (SOC=0.2)	MWh	4
Initial Energy Stored (SOC=0.5)	MWh	10
Rated Power Capacity	MW	10
Discharging (Turbining) Efficiency		0.9
Charging (Pumping) Efficiency		0.9

Table 6.2: Characteristics of the storage device considered for simulation.

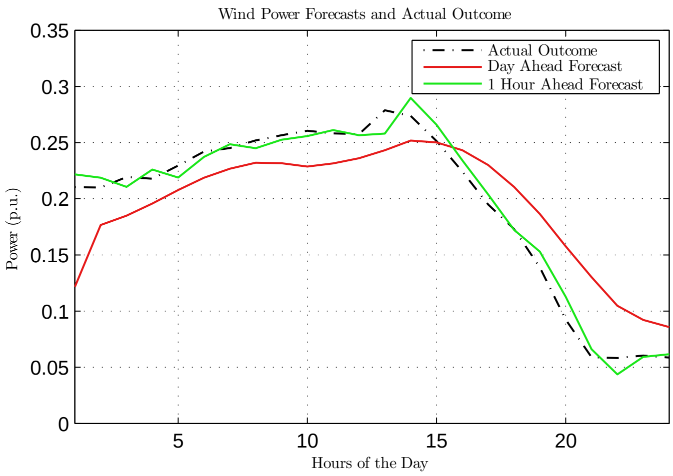


Figure 6.1: Gain in accuracy of forecasts from previous day to 1-hour ahead.

6.2.3 Wind Power Data

The robustness of the model developed is tested with respect to the uncertainty in wind power. It is assumed that wind power at every time step is the sum of available wind power forecast and a stochastic component.

Wind Power Forecasts For the optimization problem in day-ahead scheduling stage, hourly wind power forecasts (W) generated one day in advance have been used. For the same days, optimal storage operation is performed by the Model Predictive Control (MPC) system using forecasts with smaller look-ahead periods.

The hourly forecast data used is obtained by aggregating the data from several wind farms across Germany for the months January-March 2008, normalized by the total installed capacity in those months. Forecasts with smaller look-ahead times which are used in the intra-day operation are approximations to real data and are generated via statistical methods.

It is expected that using real forecasts for the intra-day stage instead of statistically generated data would be more accurate. For the sake of validating the proposed model, statistically generated data works fine as long as the inter-temporal trends in the forecasts are preserved. This implies that the forecasts should move closer to the actual value as its look-ahead time is reduced. Fig. 6.1 shows the wind power forecast for a sample day considering different look-ahead times. It can be noticed that errors in wind power forecasts are considerably reduced in closer look-ahead time, as expected.

Stochastic Component The stochastic component in wind power is modeled using a Markov chain mechanism. The method followed in generat-

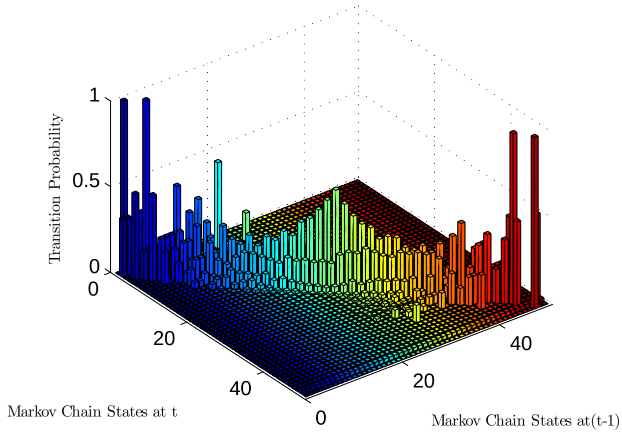


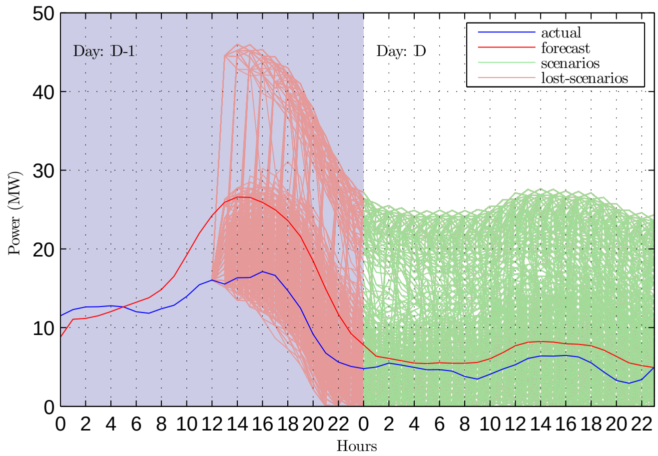
Figure 6.2: Transition probability matrix for the wind power error, using a Markov chain with 50 states.

ing wind power realizations is called Markov Chain Monte Carlo (MCMC) method and is motivated by [29], where it is described in detail.

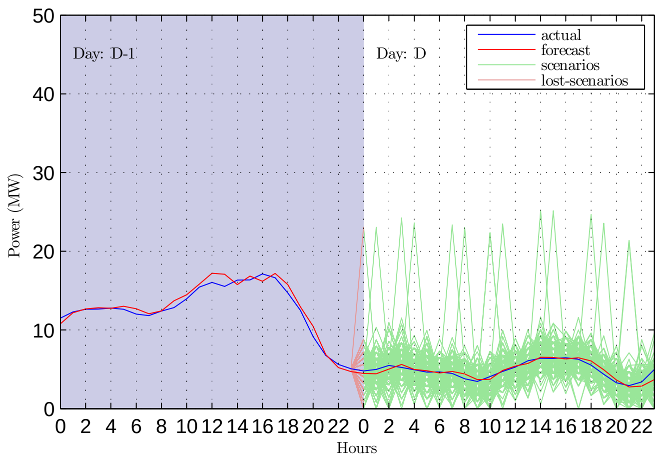
In this method, first the stochastic process (in this case, wind power forecast error) is discretized into a pre-defined number of states. Further, it is assumed that the forecast errors at the present time step t depends only on the errors at the last time step $(t-1)$ and not on the errors that have occurred further back in the past. With such a first-order Markov chain modeling and using measured historical values of the forecast errors, a transition probability matrix containing the probabilities for transitions between the states is constructed. Finally, using the knowledge of the state of forecast error at the initial time step $(t-1)$, a large number of scenarios for the future forecast error realizations can be extracted.

For the simulation in this thesis, normalized hourly values of wind power forecasts and actual wind in-feed in the whole of Germany over the years 2007-2011 are used. The hourly forecast errors are then used to "train" the transition probability matrix. Fig. 6.2 shows the resulting transition probability matrix when a 50-state first-order Markov chain is constructed using the forecast error data. The block-triangular structure of the matrix suggests that the wind forecast errors are strongly correlated in time.

Fig. 6.3(a) shows an example of the wind power scenarios drawn for day-ahead market participation of the 50 MW wind power plant considered in the *Only Intra-day* case. Since the bids for the day (D) in the EPEX Spot day-ahead markets have to be decided before Hour 12 in the previous day $(D-1)$, the wind power scenarios drawn for the Hours 13-24 of the day $(D-1)$ are termed as "lost scenarios".



(a) Wind power outcome scenarios generated before the day-ahead market clearing.



(b) Wind power outcome scenarios generated before each hourly intra-day market clearing.

Figure 6.3: Hourly wind power production scenarios for the day D generated using MCMC. The area shaded in "blue" represents the hours of the day $(D-1)$.

Fig. 6.3(b) shows the scenarios drawn for participation in hourly intra-day markets in the day (D) in the *Only Intra-day* case. The forecast values in this case contain the wind power forecasts for each hour of day D made with a look-ahead time of 1 hour.

6.2.4 Electricity Market Price Data

For simplification in modeling, it is assumed that the prices of electricity in day-ahead and intra-day markets are deterministic and are known prior to beginning of the simulation. In the simulation, these prices are sourced from historical market prices for Germany published in European Power Exchange (EPEX) Spot [30], the online public portal for The European Energy Exchange (EEX) spot markets. The values of market prices in day-ahead and intra-day markets used are presented in Appendix A.

6.2.5 Intra-day Market Clearing

While bidding in intra-day markets, best forecasts available at the time of closing (assumed 45 minutes prior to real-time delivery) of the hourly markets are used. However, it has been assumed that all such bids have found a suitable counter-party and hence have been accepted. It is important to note that this assumption is optimistic because as more and more wind power producers participate in the intra-day markets, the chances of finding a suitable counter-party is reduced. This situation arises because wind power plants in one geographic region, relying on single meteorological forecast source, are likely to bid in the same direction (buying or selling). Therefore, a skewness in selling bids (supply) and buying bids (demand) in the intra-day market can be expected which would result in lower chances of acceptance of the bids.

6.2.6 Modeling of Imbalances

The procedure followed for modeling the occurrence of imbalances during real-time delivery of power in each case is discussed in the following.

- *Perfect Forecast* case involves zero imbalance penalties.
- *Only Intra-day* case allows intra-day bids to be placed one hour ahead of physical delivery taking the best available forecasts into account. However, the actual wind realization is manifested in the form of 5000 scenarios drawn using the MCMC method discussed in the previous section. The scenarios are drawn one hour ahead of the actual value, as shown in Fig. 6.3. The imbalance for hour h is calculated using the Eq. 6.1 where P^h_{ACT}, P^h_{DA} and P^h_{ID} represent the actual wind realization, bid made in day-ahead market and the buying(+)/selling(−) bid made in the intra-day market.

$$P^h_{\mathrm{IMB}} = |P^h_{\mathrm{ACT}} - (\underbrace{P^h_{\mathrm{DA}} + P^h_{\mathrm{ID}}}_{\text{Adjusted Bid}})| \tag{6.1}$$

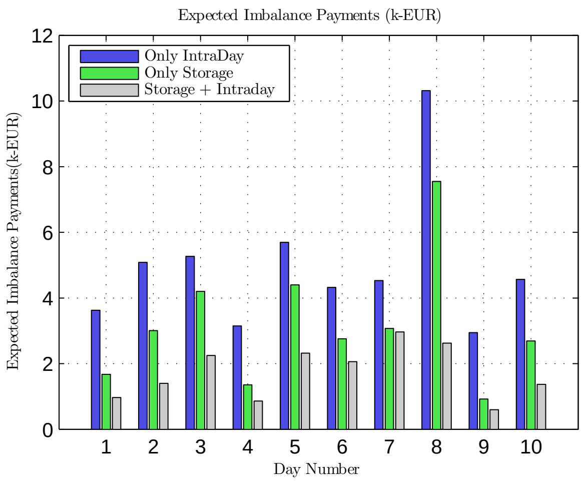


Figure 6.4: Expected imbalance payments at the end of the day for different cases.

- *Only Storage* and *Storage+Intra-day* cases allow scheduling of storage operation using hour-ahead wind forecasts. Thus, imbalances occur if the scheduled operation of storage and cleared intra-day bids are not sufficient in mitigating the difference between actual wind realization and the day ahead market bid, as shown in Eq. 6.2. P^h_{SO} is the scheduled discharging(+)/charging(−) storage operation for the hour h.

$$P^h_{\text{IMB}} = |P^h_{\text{ACT}} - (\underbrace{P^h_{\text{DA}} + P^h_{\text{ID}}}_{\text{Adjusted Bid}} + P^h_{\text{SO}})| \tag{6.2}$$

6.3 Simulation Results

Since goal of the model developed in this thesis is to maximize the profits of a wind power farm, we evaluate the net imbalance paid and the net profits earned at the end of each day for the various cases discussed before. Appendix A presents a table with the prices for imbalances and storage used for calculating the imbalance payments and end-of-day profits.

6.3.1 Imbalance Payments

For the 10 days considered in the simulation, Fig. 6.4 shows the expected imbalance payments made at the end of each day for different cases. Since the *Perfect Forecast* case has no imbalances, it is excluded from the figure. As can be observed from the figure, daily expected imbalance payments are reduced for the *Storage+Intra-day* case on all days as compared with the

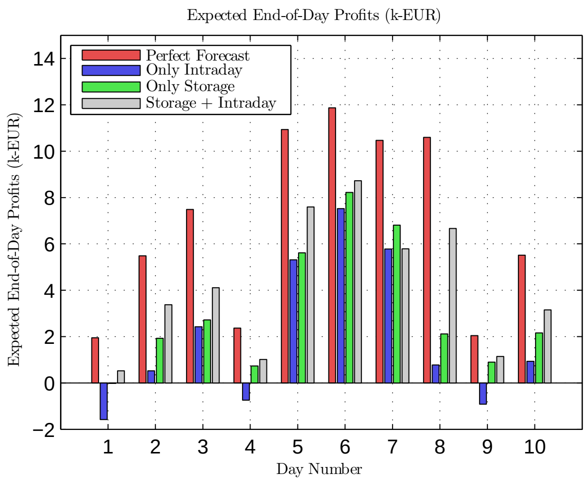


Figure 6.5: Expected profits earned at the end of the day for different cases.

Only Intra-day case.

However in the *Only Storage* case, the lack of intra-day market participation leads to loss of the certainty that sufficient storage energy (MWh) is available for imbalance mitigation at all hours of the day. For example, in a given day, several consecutive hours of deficits in wind outcome as compared to day-ahead bids could lead to the emptying of storage device. This results in the unavailability of sufficient stored energy for discharging requirements in the subsequent hours. Conversely, the storage device could be full after a number of consecutive hours of charging operation. Since in the modeling, curtailment of wind power plants is not considered, imbalances are incurred for subsequent hours of excess wind.

6.3.2 End-of-day Profits

Eq. 6.3 shows the method of calculating profits at the end of each day d:

$$\text{Profits}^d = \text{Revenues}^d_{\text{DA}} + \text{Revenues}^d_{\text{ID}} - \underbrace{\text{Imbalances}^d - \text{Storage}^d}_{\text{Costs}} \qquad (6.3)$$

The end-of-day revenues from intra-day (ID) market settlements could be positive or negative depending upon the sum of all buying and selling cash flows during the day. The expected profit is calculated as the average of profits in all the scenarios. In cases involving the use of a storage, profits are calculated after the cost of storage operation and reservation have been accounted for.

As can be observed from Fig. 6.5, since the *Perfect Forecast* case is not associated with either of the two costs mentioned in Eq. 6.3, the profits in

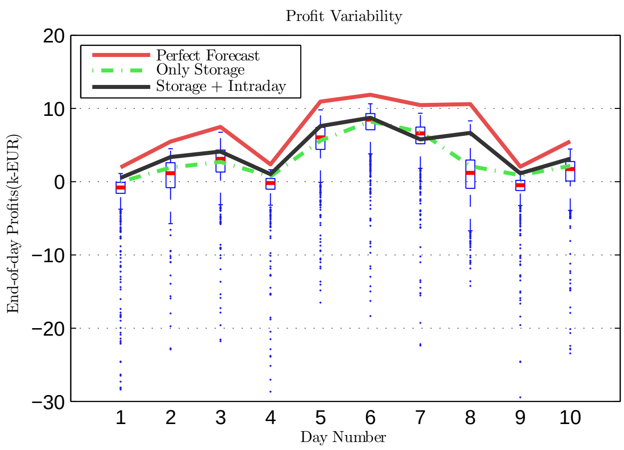


Figure 6.6: Variability of the profits earned at the end of the day for various cases. The boxplot shows the statistical distribution of profits for the *Only Intra-day* case.

this case act as an upper bound for possible profits which can be made in the day. In the *Only Intra-day* case, there are instances when expected profits are negative. On a closer look, it is realized that this occurs for days with low profits even for the *Perfect Forecast* case. This indicates that relatively lower total energy is bid into the day-ahead market on those days and that attempts at managing imbalances only using intra-day bids can be risky for such days. On the other hand, using a storage device as in the other two cases, leads to higher profits even after the costs of operating storage have been taken into consideration.

The benefits of using a storage device becomes clearer if variability in the end-of-day profits is evaluated, as shown in Fig. 6.6. The box-plot shows the descriptive statistics for the end-of-day profits in the *Only Intra-day* case, such that edges of the box represent the 25th and 75th percentiles and red-colored ticks inside the boxes represent the median value. The variability of profits indicated by whiskers around the box represents 99% of occurrences. It can be observed that in the *Only Intra-day* case, the chances of making less profits and even negative profits is quite high.

Hence, it can be concluded that even after including the costs of storage operation, cases *Only Storage* and *Storage+Intra-day* lead to firm profits in each day, without the downside risk of profit variability.

6.3.3 Cost of Storage for Imbalance Mitigation

For the *Only Intra-day* and *Storage+Intra-day* cases, Fig. 6.7 shows the average cost of storage operation for incremental values of % imbalances mitigated for the 10 days of simulation. Percentage of imbalances mitigated is defined as:

$$\% \text{ Imbalances mitigated} = 100 \times \left(\frac{\sum_{h=1}^{24} \text{Deviations from schedule [MW]}}{\sum_{h=1}^{24} \text{ Scheduled power [MW]}} \right) \tag{6.4}$$

These curves are obtained by changing the energy rating of storage device (MWh) such that a saturation in % imbalances mitigated could be reached. The figure clearly shows that the *Storage+Intra-day* case is preferable over the *Only Storage* because for the same cost of storage, the percentage of imbalances mitigated in the former is higher. As reasoned before, the absence of the option to participate in intra-day markets leads to higher imbalances in the *Only Storage* case.

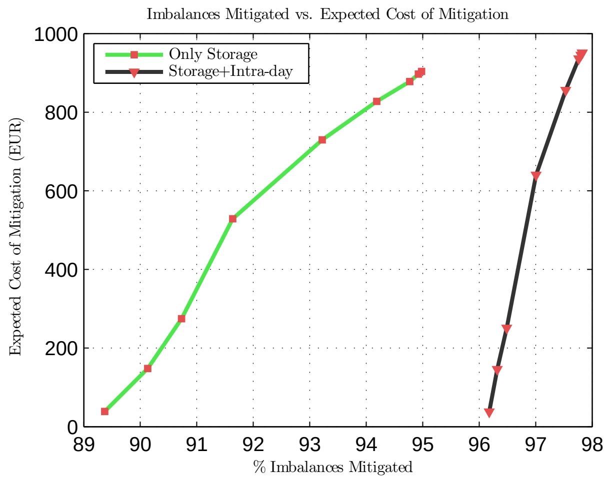


Figure 6.7: Expected costs of using storage for imbalance mitigation for *Only Storage* and *Storage+Intra-day* cases.

Chapter 7

Conclusions and Outlook

This chapter summarizes the most important points discussed in the thesis and provides an outlook which connects the concepts discussed in this thesis with reality. The chapter ends with a list of some of the possible extensions to this thesis.

7.1 Conclusion

In this thesis, a model for enabling profitable market participation of wind power plants using energy storage devices is proposed. The idea that wind power producers need not own storage devices is explored. The concept of storage reservation contract is presented wherein wind power producers pay a certain premium (reservation costs) for hedging against unfavourable wind outcomes with respect to the day-ahead market bids. The energy neutrality criteria for day-ahead bids strengthens the decoupling of operation of storage device from the wind power producer. In the intra-day operation stage, the storage device owner assists the wind power producer in tracking its day-ahead market bids through suitable storage scheduling. The bids in intra-day market allow the storage device owner to make buy/sell bids to maintain the energy level in the storage device.

The model is validated by comparing it with the situation when wind power plants participate in electricity markets on their own. The case study in Chapter 6 shows the following:

1. Even after considering the costs of storage reservations and storage operation, the proposed model leads to higher profits for the wind power plants.

2. The profit variability associated with participation of wind power plants in intra-day markets can be eliminated through the use of storage devices.

3. Combining the benefits of updated wind forecasts and suitable intra-day market participation, a storage device of smaller energy capacity (MWh) and power rating (MW) can mitigate the imbalances of a large wind power plant to a great extent (Figure 6.7), while maintaining its daily energy-neutrality.

Finally, it can be concluded that this thesis demonstrates that lost opportunity costs of having a joint wind-storage power plant can be avoided. Mitigation of imbalance penalties for the wind power producer can be seen as a secondary function the storage device while it can still participate in electricity markets on its own.

7.2 Outlook

The basic concepts introduced in this thesis can be extended in different directions.

7.2.1 Imbalance Costs as an Externality

In economic terms, imbalances in supply can be seen as an economic externality. In that context, additional costs of running operational reserves and expensive power plants can be considered as *social costs* caused by the externality. With such modeling, it would be possible to reach an optimal level of mitigation of the externality such that net social benefits after mitigation are maximized.

Figure 6.7 introduces the concept of determining the cost of storage required for mitigating a certain percentage of imbalances. Similarly, the benefits of mitigating imbalances need to be quantified and an economic optimal point could be reached at which the marginal cost of mitigating imbalances would equal the marginal benefits of having a firm supply.

7.2.2 Marginal Cost Bidding for Wind Power Plants

The cost of mitigating imbalances through storage operation could be viewed as the cost of generation associated with wind power plants. The wind power plants could then bid their “reliable” generation into the market, at the cost of these imbalance mitigating storage contracts.
As of today, wind power plants bid in electricity markets at zero prices so that most of their generation bids are accepted. However, as discussed in Chapter 1, rising share of wind energy in net generation mix leads to higher operation costs for power systems.
A market mechanism where wind power plants pay for their imbalances themselves minimizes the requirements for running operational reserves by

the Transmission System Operator (TSO) and the costs associated with them, thereby maximizing overall social welfare.

7.3 Future Work

In the following, a list of some of the possible extensions for the work done in this thesis is presented.

- The modelling of wind farm as a "price-taker" in this thesis should be extended to include the situations when wind producers act as "price-makers" in the market.

- While the errors in wind forecasts have been considered as being normally distributed around the available point forecasts, follow-up research should identify the inter-hour correlations of the errors within the day. The modeling should be extended to other continuous probability distributions as well.

- In the case study presented in Chapter 6, profits have been discussed only from a wind power producer's point of view. In further work, the opportunity for the storage device owners to earn profits from opportunities of price arbitrage in markets should be considered along with the function of imbalance mitigation. Such an analysis could evaluate the net social welfare when the storage is decoupled from wind power plants as compared to a joint operation.

- In this thesis, the imbalances have been modelled such that any deviation from the day-ahead schedule is penalized. Further study should include the signals from the TSO regarding the state of the overall system. If included in the intra-day operation stage of this model, such signals could lead to even better decision making from a system's perspective.

Appendix A

Optimization Parameters

Day-Ahead Scheduling

The values of various cost and reward parameters used in the solving the optimization problem $P1$ in the day-ahead scheduling stage are shown in Table A.1.

Parameters	**Values**
Reward for Day-Ahead Bids	λ^{DA} (Day-ahead market price)
Cost for Imbalance Penalty (λ^{I})	1.5 x λ^{DA}
Cost for Storage Reservations ($\lambda^{\mathrm{C}_u}, \lambda^{\mathrm{C}_d}$)	0.1 x λ^{DA}
Cost for Storage Use (λ^{I})	1 x λ^{DA}
Cost for Ramping Penalty (λ^{R})	0.2 x λ^{DA}
Criticality of Energy-neutrality (ρ)	0.5 (equal weight for both terms in $P1$)

Table A.1: Description of the parameters used in the day-ahead scheduling stage.

Intra-Day Operation

In the intra-day storage operation stage, the costs used in the optimization problem $P2$ which is solved in the receding horizon controller are shown in Table A.2.

Parameters	**Values**
Cost for errors in meeting schedule (Ω_{imb})	10^{3}
Cost for control variables (Ω_{con})	λ_{ID} (Intra-day market price)
Cost for exceeding storage operating limits (Ω_{ex})	10^{4}

Table A.2: Description of the parameters used in the intra-day storage operation stage.

Electricity Market Prices

Figure A.1 shows the day-ahead and intra-day market prices from 01.10.2013 to 10.10.2013 (10 days) which are used in the simulation.

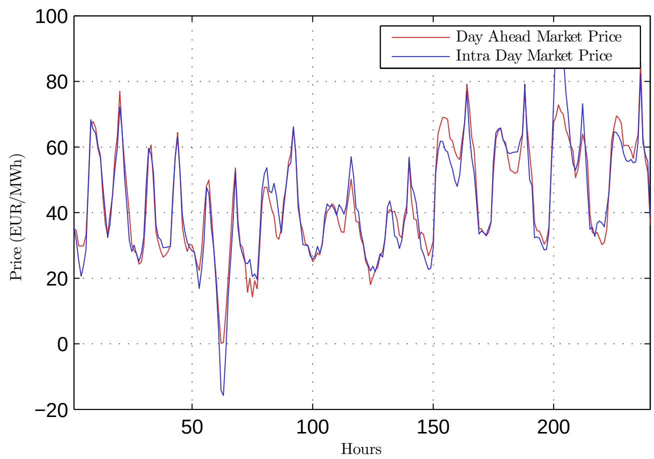


Figure A.1: Market price of electricity in EPEX Spot for 10 days (01.10.2013-10.10.2013) [30].

Appendix B

List of Symbols

A list of symbols used, arranged by the chapters in which they appear, is presented in the following.

Day-Ahead Scheduling

h	Hours of the day (1,2,$\cdots$,24).
X_h	Random variable for wind power (MW) realization in hour h.
W_h	Available point forecast for wind power (MW) in hour h.
B_h	Bid (MW) in day ahead market in hour h.
α_h	Dynamically selected risk tolerance factor to decide position of bounds in hour h.
b_h^u, b_h^d	Upper and lower bounds (MW) for day-ahead market bid B_h in hour h.
C_h^u, C_h^d	Up (charge) and down (discharge) storage capacity reservation (MW) in hour h.
R_h	Ramping energy (MWh) spent between hours $(h-1)$ and h.
I_h^u, I_h^d	Expected imbalances (MW) occurring in hour h.
S_h	Expected use of storage (MW) in hour h.
ρ	Fixed parameter to control strictness of energy-neutrality requirement in day-ahead bids.
δ	Maximum change in bids allowed in bids between subsequent hours (MW/hour).
λ_h^{DA}	Day-ahead market price (€/MW) forecast in hour h.
$\lambda_h^{\mathrm{C}_u}, \lambda_h^{\mathrm{C}_d}$	Storage reservation costs (€/MW) in the up (charging) and down (discharging) directions in hour h.
λ_h^R	Penalty for ramping energy (€/MWh) in hour h.
λ_h^{I}	Penalty for imbalances (€/MW) in hour h.
Λ_h	Cost vector in hour h.
λ_h^{S}	Cost for storage operation (€/MW) in hour h.

Intra-Day Operation

h	Hours of the day (1,2,$\cdots$,24).
τ	Time of operation (1 hour).
$E_{\mathrm{S}}(h)$	Energy stored in storage device at the start of hour h.
$P_{\mathrm{D}}(h), P_{\mathrm{C}}(h)$	Discharging/Charging power from/into storage device in hour h.
$P_{\mathrm{B}}(h), P_{\mathrm{S}(h)}$	Buying/Selling bid made in intra-day market in hour h.
$P_{\mathrm{G}}(h)$	Power in-feed into the grid from wind and storage ensemble in hour h.
$P_{\mathrm{W}}(h)$	Best available forecast for wind power in hour h.
$\eta_{\mathrm{D}}, \eta_{\mathrm{C}}$	Discharging/Charging efficiency of the storage device.
$P_{\mathrm{sched}}(h)$	Day-ahead scheduled power (MW) in hour h.
$C_h^{\mathrm{d}}, C_h^{\mathrm{u}}$	Discharging/Charging capacity reservations (MW) made in hour h.
$P_{\mathrm{B}}^{\max}, P_{\mathrm{S}}^{\max}$	Maximum buying and selling bids (MW) allowed in intra-day market.
$y(h)$	Controller output, in-feed to the grid (MW) for hour h.
$x(h)$	Energy Content (MWh) of storage device at the start of hour h.
$u(h)$	Control vector in the hour h.
$v(h)$	Best available wind forecast for the hour h.
$w(h)$	Auxiliary variable for (MWh) soft constraints over energy storage limits.
Ω_{imb}	Cost for errors in meeting schedule.
Ω_{con}	Costs for control variables:$P_{\mathrm{D}}, P_{\mathrm{C}}, P_{\mathrm{B}}, P_{\mathrm{S}}$.
Ω_{ex}	Cost for exceeding storage operating limits.

Results and Discussion

P_{IMB}^h	Power imbalance (MW) incurred in hour h.
P_{ACT}^h	Actual wind realization (MW) in hour h.
P_{DA}^h	Scheduled bid (MW) in day-ahead market in hour h.
P_{ID}^h	Buying(+)/Selling(−) bid (MW) in intra-day market in hour h.
P_{SO}^h	Discharging(+)/Charging(−) storage operation(MW) in hour h.
$\mathrm{Profits}^d$	End-of-day profits (€) in day d.
$\mathrm{Revenues}_{\mathrm{DA}}^d$	End-of-day revenues (€) from day-ahead market in day d.
$\mathrm{Revenues}_{\mathrm{ID}}^d$	End-of-day revenues (€) from intra-day markets in day d.
$\mathrm{Imbalances}^d$	End-of-day imbalance payments (€) from intra-day markets in day d.
$\mathrm{Storage}^d$	End-of-day costs of storage (€) in day d.

Appendix C

CD-ROM Contents

The CD-ROM accompanying this report contains:

Literature PDFs of some of the literature used in this thesis.

Presentations The presentation slides.

Report Digital form and LaTex source code of this report.

Software The most important codes and programs developed during the course of this thesis.

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