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Backtesting a Stochastic Coordinated Bidding Model for Sequential Electricity Markets

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Problem Description

A stochastic coordinated bidding model considering the day-ahead market and the balancing market is developed, and evaluated by backtesting. The model is based on a price-taking hydropower producer, located in the southern parts of Norway. Uncertainty in the market prices and balancing market demand is taken into account, and an artificial neural network is built to forecast the balancing market premium and volume.

Preface

This thesis is written for the degree of Master of Science at the Norwegian University of Science and Technology (NTNU), within the field of Managerial Economics and Operations Research at the Department of Industrial Economics and Technology Management. The work has taken place during the spring semester of 2018, and is a continuation of the studies carried out in the specialization project ”Coordinated Bidding in the Day-Ahead Market and the Balancing Market using Stochastic Programming”. The thesis is motivated by the curiosity of how a coordinated bidding model for sequential markets performs over a longer time period, and if the use of machine learning can provide forecasts for the balancing market.

We would especially like to thank our supervisors professor Stein-Erik Fleten and PhD candidate Ellen Krohn Aasgård, both from the Department of Industrial Economics and Technology Management at NTNU. Their guidance, and the discussions we have had, have been of great value during the work. We would also like to express our gratitude to our industrial partner. They have contributed with their expertise and experience within the field of hydropower scheduling, and have provided us with a great amount of data which was essential for the computational study.

Trondheim, June 8, 2018

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Summary

The volume in the markets for replacement reserves are expected to grow in the years to come, due to the increased share of renewable intermittent energy sources and a closer connected power system in Europe. The decision making process for providers of regulation services is thus increasing in complexity, as they have to consider taking subsequent markets into account in their bidding process. This work considers the coordinated bidding problem for a hydropower producer participating in the Nordic day-ahead market and the Norwegian balancing market. Uncertainty in the market prices and the balancing market demand is included. A forecast-based scenario generation method is used, for which the balancing market forecast is generated by designing and training an artificial neural network.

The gain of the coordinated bidding model is estimated by comparing the performance to a sequential bidding model, representing the sequential strategy used by most hydropower producers today. A comprehensive backtesting procedure is implemented to simulate the bidding and operation for both strategies over 200 consecutive days. The gain is estimated to be 0.07% for a hydropower producer using both hourly bids and block bids, and 0.11% when only hourly bids are used. It is thus still questionable whether a coordinated bidding strategy is worthwhile. Using the generated forecast provided a gain of 0.44% in the total value for the coordinated model, compared to using a forecast predicting zero imbalance. Making an effort in generating forecasts for the balancing market can thus increase the gain of coordinated bidding, and make it worthwhile.

Sammendrag

En økende andel av fornybare energikilder, og et stadig tettere koblet europeisk kraftmarked, gir en forventning om at volumet i reservemarkedene vil øke i årene som kommer. Ettersom flere markeder må tas hensyn til i budgivningen, blir beslutningsprosessen mer komplisert for tilbydere av reserver i kraftmarkedet. Denne oppgaven tar for seg det koordinerte budgivningsproblemet for en vannkraftprodusent som deltar i det nordiske dayaheadmarkedet, og det norske balansemarkedet. Usikkerhet er inkludert i markedsprisene og volumet i balansemarkedet. En scenariogenereringsmetode basert på prognoser er tatt i bruk, der prognoser for balansemarkedet er generert ved å designe og trene et nevralt nettverk.

Gevinsten av den koordinerte budgivningsmodellen er estimert ved å sammenligne resultatene med en sekvensiell budgivningsmodell, som representerer den sekvensielle strategien de fleste vannkraftprodusenter bruker i dag. En omfattende backtesting-prosedyre er implementert for å simulere budgivning og produksjonsplanlegging over en periode på 200 dager. En gevinst på 0.07% er estimert for en vannkraftprodusent som bruker både timesbud og blokkbud, og en gevinst på 0.11% når kun timesbud benyttes. Det er derfor fortsatt uklart om det vil lønne seg å ta i bruk en koordinert strategi for budgivning. Ved å bruke den genererte prognosen for balansemarkedet i den koordinerte modellen, i stedet for å prognosere ingen ubalanser i markedet, ble det observert en økning i total verdi på 0.44%. Gevinsten ved å bruke en koordinert modell ser dermed ut til å øke ved å legge en ekstra innsats i å generere prognoser for balansemarkedet.

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Chapter 1

Introduction

In the electrical power system, demand and supply have to be balanced at all times in order to maintain a stable grid frequency. Coordinating this balance is the responsibility of the transmission system operators. Market participants stand for most of the balancing in the system through trading in the day-ahead market, but imbalances may occur due to unforeseen events between the closure of the day-ahead market and the hour of delivery. To prevent the issue of frequency deviations, the system operators have introduced multiple markets with different closure times. The idea is for the markets further away from the operating hour to settle the majority of the demand, while markets closer to real time correct for smaller deviations (Jiang and Powell, 2015). With a more closely connected European system, and a larger share of intermittent renewable energy sources, the importance of real-time balancing and ancillary service markets increases (Statnett, a). An increase in less predictable renewable energy sources, and decommissioning of controllable production such as thermal and nuclear power plants, leads to a higher frequency of system imbalances. An increasing volume in real-time markets can give opportunities for providers of regulation services, as bidding into multiple markets may increase profits.

The literature regarding multimarket bidding is limited, as most research has focused on bidding in the day-ahead market only. The literature that do exist, is mainly within the field of optimization. Only a few of the studies considering multi-market bidding, investigate the added value of taking subsequent markets into account during the bidding process. The reported results from these studies indicate that the gains of such coordinated bidding are not significant in the current market situation. Several studies point out that the gains may increase if the future development of the reserve markets leads to an increase in volumes and prices. The most common approaches of modeling the uncertain electricity market prices in the bidding problem, is relying on econometric time series models. The few studies attempting to generate meaningful forecasts for the balancing market price and demand, come to the conclusion that it is hard to say anything about the balancing market before the closure of the day-ahead market.

In today's hydropower industry, the bidding process often rests on the skills of the operating engineers. A methodology for placing bids in the current multimarket structure is a highly relevant issue in the industry, which affects the scheduling and operation of the water systems. Due to the complexity of the problem at hand, it can be difficult for a producer to determine the bidding strategy to use. An optimal bidding strategy maximizes the profits, while taking all important aspects regarding the system operation into account. Experimenting with alternative bidding strategies can lead to loss of water, hence loss in profits. Most producers are therefore conservative in their bidding behavior, and consider the markets in a sequential order according to the time of the respective market clearing.

The purpose of this thesis is to further evaluate if it is worthwhile to take the balancing market into account when bidding in the day-ahead market, or if a simpler sequential bidding strategy should be used. In order to investigate this, a decision aid for a hydropower producer participating in the two sequential markets is developed. Using this decision aid, different bidding strategies can be tested over time through a simulated operation of the water system. A three-stage stochastic mixed-integer programming model (SMIP) is introduced to represent the coordinated bidding problem for a hydropower producer. The bidding decisions in the first- and second-stage are modeled as continuous variables, while the scheduling decisions in the third stage includes binary variables for assigning production to generation units. The uncertainty in the model lies in the market prices, and the balancing market demand. The model is formulated as its deterministic equivalent, based on previous work by Fleten and Kristoffersen (2007), Faria and Fleten (2011), and Boomsma et al. (2014). A node-variable formulation of the model is presented and implemented, in addition to a comprehensive setup for the backtesting procedure. A corresponding model representing the sequential bidding strategy is also implemented. In the backtest, the models are run daily for a large number of consecutive days to simulate the behavior of the bidding strategies. The strategies are evaluated using performance measures defined for the bidding models. To represent the inherent uncertainty in the market prices, and the balancing market demand, a scenario generation method based on forecasting errors is used. Forecasts for the day-ahead market can easily be obtained from a partner in the industry, while forecasts for the balancing market prices and volumes have to be generated. Extensive work is put into building an artificial neural network in order to generate forecasts for the balancing market. The added value of utilizing these forecasts in the bidding models is evaluated, and compared to forecasts predicting no imbalances in the system.

The main contribution of this work is the performance evaluation of a coordinated bidding strategy over time. To the knowledge of the authors, the gain of coordinated bidding has not previously been analyzed for several consecutive days. The option of block bids, fees related to delivering power to the grid, and the availability of the generators have been included in the models. Such factors have not been included in the evaluation of a coordinated strategy before, to the authors knowledge. Furthermore, a great amount of effort is put into generating forecasts using artificial neural networks, which has not previously been done for the balancing market.

The present work is structured into seven additional chapters. Chapter 2 gives a presentation of the electricity markets, and an introduction to the fundamentals of hydropower operation and scheduling. Related literature is presented in Chapter 3. Different bidding models for electricity markets, and how electricity market prices are predicted, is considered. The focus is the stochastic multi-market bidding problem for a hydropower producer without market power, and the use of artificial neural networks as a forecasting method. Chapter 4 gives a detailed description of the coordinated bidding problem. The mathematical formulation of the problem is presented in Chapter 5, in which the structure, notation and constraints are explained. To generate possible outcomes of the second-stage and third-stage nodes, forecasts of the markets are needed. Chapter 6 presents the development of a forecast of the balancing market by using an artificial neural network. Chapter 7 presents a computational study, in which the performance of the coordinated bidding model is evaluated. The revenues are compared to a sequential bidding model, and to an industrial partner. In addition, the value of utilizing a forecast for the balancing market in a coordinated bidding strategy is evaluated. Concluding remarks and potential future research are presented in Chapter 8.

Chapter 2

Nordic Electricity Markets and Hydropower

An introduction to the electricity markets is given in Section 2.1, with a description of the current rules of the markets considered. The market rules are stated on the webpage of the operator for each of the markets, which is Nord Pool for the day-ahead market and Statnett for the balancing market. Section 2.2 presents an introduction to the fundamentals of hydropower operation, and the scheduling of production.

2.1 The Electricity Markets

In the early 1990s, power markets in the Nordic countries were deregulated and brought together to form a common Nordic market, Nord Pool. Deregulation means that free competition is introduced, which leads to a more efficient power market (Nord Pool, a). Today, Nord Pool covers large parts of Europe with transmission capacity, and provides coupling between the Nordic countries, the European continent, and the Baltics. The power in the grid comes from many different production technologies, with an increasing share of intermittent energy sources in the last years. The balance between supply and demand in the system is mostly secured in the day-ahead market, but other markets with later closing time have emerged to further secure this balance. Market participants are in that way able to trade the system into balance closer to the operating hour, as incidents causing an imbalance can occur between the closing of the day-ahead market and the hour of delivery.

2.1.1 The Day-Ahead Market

The day-ahead market is the main arena for power trading. Producers and consumers/wholesalers place orders, specifying the volume of power they want to deliver or buy. The orders are most commonly defined with several price steps, to be able to specify different volumes at different market prices. Nord Pool requires that the minimum order price is -500 EUR, and that the maximum order price is 3000 EUR. Orders have to be placed within 12:00 CET the day before delivery. The market prices for the delivery day are determined from the market equilibrium between supply and demand, and are typically announced to the market at 12:42 CET or later. Trades are settled when the market prices have been calculated, and delivery starts from 00:00 CET the day after clearing. The market is cleared within price areas, such that different area prices can affect the demand in areas with constrained transmission capacity. A price area may correspond to an entire country, or a country may be divided into several smaller price areas. Figure 2.1 illustrates the five different price areas in Norway today (Statnett, d).

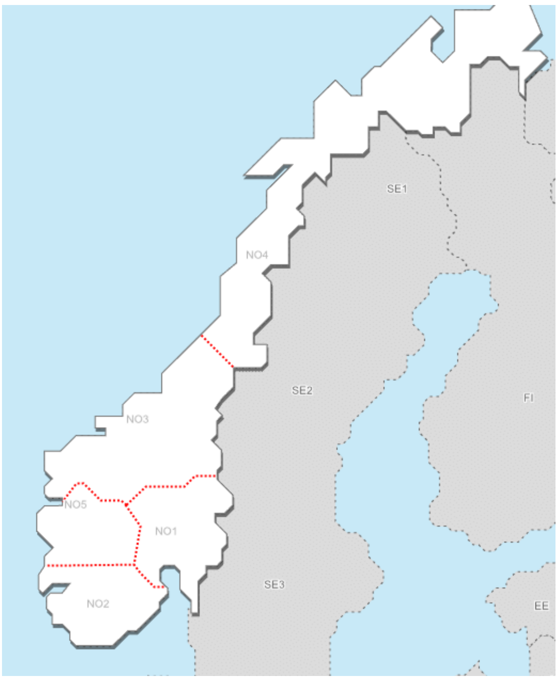


Figure 2.1: Price areas in Norway

Single hourly orders are the most common type of orders in the day-ahead market, for which the market participant specifies purchase and/or sales volume hour by hour for the delivery day. To calculate the commitment for a market participant, Nord Pool makes a linear interpolation of the orders and the market price. Another common order type in the day-ahead market is block orders. The market participant submits a specified volume and price for a number of consecutive hours, called a block. A sales/purchase block is fully accepted if the average day-ahead area price is below/above the order price, respectively.

2.1.2 The Balancing Market

Even if the settlements in the day-ahead market creates preliminary balance in the system, weather-related fluctuations in consumption, short-term changes in major industrial consumption, breakdowns in production facilities, power line outages, or other grid component breakdowns, can disturb this balance (Statnett, c). To handle such unforeseen events, there have to be sufficient reserves in the system. The transmission system operator (TSO) responsible for maintaining balance in Norway, is Statnett. The balancing market is a real-time market of replacement reserves for the Nordic power system, with an activation time of up to 15 minutes. These reserves are manually activated by Statnett, and replace the more flexible automatically activated reserves. The automatically activated reserves have to be ready to be used for new sudden momentary imbalances. Preliminary orders in the balancing market have to be placed within 21:30 CET the day before delivery, but can be changed up to 45 minutes before the hour of operation. The prices in the balancing market are based on activating the best bids first, which means to accept the cheapest resources first (Statnett, b). The balancing market price is thus determined from the last activated order in the price area. The price and volume are announced on Nord Pool's website one hour after the hour of operation has finished. The time line representing the clearing of both the day-ahead and balancing market is shown in Figure 2.2.

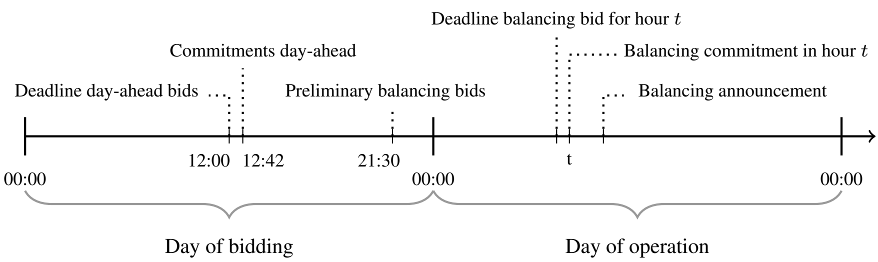


Figure 2.2: Clearing of the day-ahead market and the balancing market

The market participant can offer both production and consumption capacities in the same hour, but cannot be activated for both in the same period. If there is balance in the system, there is no need for regulation and the balancing market volume equals zero. If the demand in the system exceeds the available supply, the TSO starts to activate production orders.

Likewise, the TSO activates consumption orders if the supply in the system is larger than the demand. This is referred to as upward regulation and downward regulation, respectively. Need for both upward and downward regulation may occur in the same hour, but the TSO always defines a dominating direction.

The market rules ensure that the balancing market price for upward regulation is always higher than the day-ahead market price, and lower than the day-ahead market price for downward regulation. The difference between the day-ahead market price and the balancing market price is often referred to as the balancing premium. The size of the premium is required to be at least 5 NOK, and the order prices have to be divisible by 5. The size of the orders in the balancing market have to be at least 10 MW in either direction. If regulation is not needed the entire hour, the TSO can choose to use only parts of an order.

2.2 Hydropower

The basic principle behind the production of hydropower is using the energy of flowing or elevated water to produce electricity. Hydropower plants with storage schemes is the focus in this thesis. The possibility of storing water in one or several reservoirs until needed, in addition to small time delays of production, makes hydropower highly flexible compared to other renewable energy sources. This flexibility is what makes hydropower producers well suited as suppliers of regulation services, as other renewable energy sources cannot regulate production as easily. In the next section, an introduction to the operation and scheduling of hydropower is presented.

2.2.1 Operation

In a hydropower plant, the energy in elevated or flowing water is used to drive a turbine. The mechanical energy from the turbine is converted to electrical energy in a generator. The power output from the generator is given by equation (2.1), and is dependent on the overall efficiency of the power plant, η $[\%]$, the density of water, ρ $[kg/m^3]$, the gravitational constant, g $[m/s^2]$, the head level, H $[m]$, and the discharge of water, Q $[m^3/s]$. The efficiency, η, is dependent on the operating conditions of the power plant such as discharge and head level, which makes the relationship described by (2.1) non-linear.

$$P = \eta \rho g H Q \ \ [W] \tag{2.1}$$

Discharge and head levels may change due to variations in desired power production. The head is defined as the difference in elevation between the water surface in the upstream and downstream reservoir of the hydropower plant (Catalão et al., 2010). The turbine can not exploit the energy to the same degree for all operating conditions, as there exists a combination of discharge level, head level and rotational speed which gives the highest efficiency (Kjølle, 1980). The efficiency curve, with efficiency as a function of discharge, has a concave form for most generators. The highest efficiency is thus often achieved at a power output lower than the maximum power output. The conditions giving the highest efficiency are often referred to as the best efficiency point (Kjølle, 1980). However, it may sometimes be optimal to operate at a lower efficiency than best efficiency point in order to avoid frequent starts and stops, or to be able to provide replacement reserves (Klæboe, 2015).

Hydropower plants have a good regulation ability, as they quickly can adjust their supply according to the demand for power in the market. However, hydropower producers do not desire frequent starts and stops of the generators as it is associated with deterioration of the equipment. While most of the wear and tear is accumulated from many start-ups, the term start-up cost for a generator is an estimate of the cost associated with each start-up. The costs associated with a start-up are mainly caused by increased maintenance of windings and mechanical equipment, and malfunctions in the control equipment (Nilsson and Sjelvgren, 1997). Less important factors associated with start-ups, are loss of water during maintenance and start-up, and increase of unavailability during maintenance. In addition to the costs associated with start-ups, hydropower producers in Norway have to pay a fee when delivering power to the grid. This is referred to as the marginal loss cost. The marginal loss cost consists of a fixed term, and a variable term representing the marginal loss rate multiplied with the hourly day-ahead market price.

Water in the reservoirs comes for free, thus the direct variable cost of hydropower is very low (Doorman, 2009). The amount of water in the reservoirs may however be a scarce resource during periods with dry and cold weather combined with high consumption in the market. Inflow to the reservoirs is uncertain due to weather conditions, and is often badly aligned with demand (Doorman, 2009). In the winter months when demand is highest, inflow is at its lowest. Opposite, the demand is low in the summer when the inflow is high due to the melting of snow. This bad alignment gives considerable variations in market prices, and thus large fluctuations in the revenues for a hydropower producer. As hydropower has a strong position in the Nordic market, market prices and inflow are negatively correlated. It is thus important for hydropower producers to consider the associated alternative use of the water, as it either can be produced today or be stored for later use. This marginal opportunity cost is referred to as the water value, and indicates the marginal increase of income from a unit increase of water in the reservoir. The water value depends on the volume of water in the reservoir. When the water level is low and there is a shortage of resources, the water is highly valued. A hydropower producer is willing to produce at very low prices in order to avoid losing water as spill. The water value thus approaches zero as the water level increases towards the highest regulated level, and there is a risk of spillage. In some water systems, there is a possibility of sending water controlled from higher reservoirs to lower reservoirs, without sending discharge throug a power station for production. This is known as bypass, and can be used in cases with high reservoir volumes.

2.2.2 Scheduling

The principle behind hydropower scheduling is finding the optimal use of available generation resources, such that all relevant constraints are satisfied (Doorman, 2009). After the deregulation of the Nordic power markets in the 1990s, the formal objective of hydropower scheduling changed. The objective went from minimization of costs given an expected demand, to maximization of profits given an expected market price. In contrast to the bidding decisions which are determined the day-ahead, the scheduling problem is solved over a time horizon up to several years. The optimal decisions from the scheduling problem are important, as they are used as target points in the bidding process (Steeger et al., 2014).

Uncertainty in market prices, inflow, and demand, makes hydropower scheduling a non-trivial task. The scheduling problem is thus commonly decomposed into several smaller, but coupled optimization problems (Flatabø et al., 1998). The coupling between each problem is a challenge when a decomposition method is used. The best principle for coupling is using a resource price coupling (Fosso and Belsnes, 2004). The resource price is the water value, which often is described by marginal cost functions including an inter-reservoir dependency. The subproblems are often categorized according to their time horizon, as illustrated by Figure 2.3. The boundary conditions from models with long time horizon are used in the problems with shorter time horizon, to ensure proper coupling.

A long-term scheduling model calculates an optimal strategy for an aggregate-reservoir model using stochastic programming, and simulates the operation according to this strategy. A medium-term scheduling model also calculates and simulates an optimal strategy using stochastic programming, but with a more detailed description of the topology of the system. Medium-term models are often considered as a link between the long-term and short-term scheduling models, as they transfer the results from the long-term models to input which can be used in short-term models. The topology description for the medium-term model should thus be similar as for the short-term model, in order to give suitable

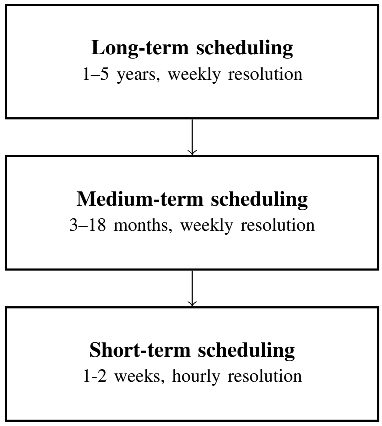


Figure 2.3: Scheduling problem decomposition

boundary conditions. The short-term scheduling models include a high level of system details, and the result is optimal generation schedules based on the longer-term strategies. Short-term models used in the industry are often deterministic and linear to make it possible to efficiently solve the problem. Detailed stochastic formulations have been considered to be computationally infeasible (Flatabø et al., 1998).

Decision support software is needed due to the size and complexity of the scheduling problem. Most of the largest participants in the Nordic system uses a long-term optimization and simulation model called EMPS (EFI's Multi-area Power-market Simulator). In deregulated markets, the main application of the models is the forecast of future day-ahead prices for all hydrological years. The price forecast is often used as input in another scheduling model that is widely used among producers, called the EOPS (EFI's One-area Power-market Simulator). This model performs medium-term scheduling, in which it calculates marginal water values that can be used in the short-term scheduling. A commonly used model for short-term scheduling is SHOP (Short-term Hydro Operation Planning), which maximizes profits by utilizing available resources and selling in the day-ahead market. All the aforementioned models are developed by SINTEF Energy Research (SINTEF).

Chapter 3

Related Literature

Several different approaches and solution methods for optimal bidding and electricity price forecasting are investigated in the literature. Section 3.1 presents some of the different variants of the bidding problem, and how they relate to this work. Different solution methods for the problem are also presented. Literature regarding multi-market bidding is presented in Section 3.2, with a special focus on the studies considering other markets while bidding in the day-ahead market. Section 3.3 presents literature on electricity market price forecasting, with a special focus on multi-market bidding and forecasting using computational intelligence methods.

3.1 Modeling the Bidding Problem

The behavior of participants in the power markets can be modeled in numerous ways. Ventosa et al. (2005) present three categories of models found in the literature: equilibrium models, simulation models and optimization models. Equilibrium models represent the overall market behavior, by including several producers and the competition between them. Models based on simulation can handle more complex assumptions than the equilibrium models, as they do not use exact mathematical modeling. Both equilibrium and simulation models are well suited for long-term scheduling. Optimization models are best suited for short-term scheduling problems, as they can handle more details and are more computationally tractable (Ventosa et al., 2005). A literature survey on the subject of optimal bidding strategies for hydropower producers can be found in Steeger et al. (2014), in which the time horizon varies between medium- and short-term. This work considers the short-term bidding problem from an individual producer's perspective. As equilibrium and simulation models consider the whole market, an optimization model is used. The bidding problem is often formulated as a unit commitment problem when using an optimization model, including which turbines to run and volumes to dispatch for all generators at each time step (Wallace and Fleten, 2003). Due to the inclusion of binary variables to indicate if generators are running or not, the problem is classified as a mixed-integer programming (MIP) model.

3.1.1 Market Assumptions

The optimization models considering the bidding problem can be classified depending on how the market prices are modeled: either as exogenous information, or as a function of the single producer's decisions (Ventosa et al., 2005). The first approach is the one used in this thesis, in which it is assumed that the producer does not affect the market prices through its bidding process. The second approach model a producer with market power, which often is referred to as strategic bidding. A literature survey on the subject can be found in David and Wen (2000). Fleten and Kristoffersen (2007) denote these two formulations as a price taker and a price maker producer, respectively. An example of a study considering optimal bidding for a price maker is found in Anderson and Philpott (2002). It presents a non-linear optimal control problem in which the uncertain demand and the behavior of competitors, are presented using a market distribution function. Further, optimality conditions for the bids are derived. According to Faria and Fleten (2011), optimal control approaches make it difficult to handle complex constraints and multiple state variables. Plazas et al. (2005) model a market participant without market power in the day-ahead market and the ancillary service market, but with market power in the balancing market. Klæboe et al. (2015) point out that modeling the same market participant with and without market power is hard to defend, as the product sold in both markets is energy.

The formulations of the bidding problem covered in the literature can also be distinguished by whether, or how, uncertainty in the input parameters is handled. As decision-making in electricity markets is subject to a lot of uncertainty, stochastic programming is often used due to its ability to characterize the uncertainty and to derive informed decisions (Conejo et al., 2010). Birge and Louveaux (2011) describe the basics of stochastic programming, while stochastic programming in energy models is presented by Wallace and Fleten (2003). Barroso and Conejo (2006) look at electricity markets specifically, and consider several stochastic programming models for decision-making under uncertainty in that context. While stochastic programs often are used to include the uncertainty in electricity market models, deterministic short-term models are often used in practice. The SHOP model is a deterministic optimization tool for short-term hydropower planning (Flatabø et al., 2002). Gross and Finlay (1996) use a deterministic approach, in which they introduce a globally optimal bidding strategy by bidding at cost and maximum capacity. Fleten and Kristoffersen (2007) and Belsnes et al. (2016) include uncertainty in their optimization models, and analyze the results compared to a deterministic strategy. Both conclude that a stochastic approach is beneficial. According to Wallace and Fleten (2003), a stochastic programming approach is meaningful due to the irreversible nature of investments and decisions in electricity markets. Uncertainty is included in the model presented in this thesis, thus the bidding problem is formulated as a stochastic mixed-integer programming (SMIP) model.

3.1.2 Solution Methods

Different solution techniques have been used for decision-making under uncertainty in electricity markets. Hydropower producers have the alternative of storing water for later use, thus a time coupling is often introduced by the use of state variables and dynamic programming (Steeger et al., 2014). In the literature of hydropower scheduling, the stochastic dynamic programming (SDP) approach is widely used (Wallace and Fleten, 2003). When using SDP, the problem is solved by recursively maximizing profits in the current and future stages. King and Wallace (2012) emphasize that the SDP method is limited by the amount of stochastics it is able to handle, as the problem explodes in size when the number of scenarios increases. This problem is referred to as the curse of dimensionality. The method can neither handle complicated constraints, nor complex problem definitions. It is often necessary to aggregate or decompose the problem before solving, in order to use these methods (Wallace and Fleten, 2003). Stage-wise decomposition is proven to be difficult to use as a solution technique to the bidding problem (Klæboe, 2015). Kårstad et al. (2016) present an approach that exploits the structure of the SMIP, by using scenario-wise decomposition methods. However, their conclusion is that such methods are not valuable for obtaining optimal solutions to the problem.

Stochastic dual dynamic programming (SDDP) is a solution method that combines the solutions from SDP with multi-stage Benders decomposition (Pereira and Pinto, 1991). Using this method, one does not have to explore all future states. Gjelsvik et al. (1999) introduce a hybrid of SDP and SDDP. According to Steeger et al. (2014), there is a consensus in the research environment that the hybrid SDP/SDDP is the best solution approach for a price-taker hydropower producer. Löhndorf et al. (2013) introduce a solution method they refer to as approximate dual dynamic programming (ADDP), which is an integration of SDP and approximate dynamic programming (ADP). ADP is also used by Jiang and

Powell (2015), but they employ a convergent ADP algorithm which do not require any knowledge of the distribution function. Fleten and Kristoffersen (2007) and Boomsma et al. (2014) formulate the problem as its deterministic equivalent, and use a direct solution approach. In this thesis, we have chosen to solve the SMIP formulated as its deterministic equivalent in a similar matter. Solution approaches for MIP problems are thus applicable, and exact solutions are achievable (Zhu, 2006).

3.2 Multi-Market Bidding

The development in the European power market has led to most countries having a multi-market structure. As trading closes at different times for each market, the market prices are sequentially revealed. Klæboe and Fosso (2013) and Aasgård et al. (2018) present literature reviews of methods and models for optimal multi-market bidding.

3.2.1 Approaches

Many of the earliest contributions in the literature regarding multi-market bidding, study bidding strategies for the Spanish market, such as Plazas et al. (2005), Ugedo et al. (2006), and Corchero and Heredia (2010). Plazas et al. (2005) is one of the first studies that defines a stochastic program for optimal bidding into several sequential markets. While Plazas et al. (2005) and Corchero et al. (2011) present the bids for the day-ahead market only, Ugedo et al. (2006) present bids for each of the sequential markets considered. Triki et al. (2005) and Deng et al. (2006) consider optimal capacity allocation strategies for multiple markets, instead of looking at bidding strategies. How the existence of market power and arbitrage can prevent price convergence in sequential markets, is studied by Ito and Reguant (2016). Most of the literature considers a conventional thermal or hydropower producer, while de la Nieta et al. (2016) expand the field by considering multi-market bidding for a wind power farm which is linked with a hydro-pump power unit. A recent study by Ottesen et al. (2018), consider multi-market bidding for a flexible aggregator on the demand side, instead of a power producer.

Klæboe and Fosso (2013) point out that most of the literature is case-oriented, focusing on the formulation of the problem and how different formulations can affect the results. None of the aforementioned studies explore whether an inclusion of subsequent markets in the bidding strategy, increase profits. Fodstad et al. (2015), Braun (2016), and Schillinger et al. (2017), consider the benefit of multi-market trading, compared to trading in the day-ahead market only. Fodstad et al. (2015) present gains up to 1.1% by participating in the balancing market, and find that the gain increases with production flexibility. Braun (2016) and Schillinger et al. (2017) use deterministic models, both proposing that a substantial increase in profits can be achieved by allowing trades in other markets. While Braun (2016) looks at trading in subsequent markets on top of the day-ahead position, Fodstad et al. (2015) and Schillinger et al. (2017) consider subsequent markets while bidding in the day-ahead market. These two different processes are referred to as sequential and coordinated bidding, respectively (Klæboe and Fosso, 2013).

3.2.2 Gains of Coordinated Bidding

In the early case study by Faria and Fleten (2011), no significant gains were found by coordinated bidding. They evaluated the effect of considering the intraday market when bidding in the day-ahead market, for a hydropower producer without market power. Whereas Faria and Fleten (2011) approximate the problem using only two stages, Boomsma et al. (2014) formulate the problem as a multi-stage model. This capture the dynamics of the markets, by making the day-ahead market decisions day-ahead, and the decisions regarding the balancing market hour-ahead. Boomsma et al. (2014) present an analytic approach, deriving bounds on the possible gains from coordinated bidding between the day-ahead market and the balancing market. The results of their case study based on the Nordic market, showed gains up to 2% for a producer with no market power, and up to 1% when allowing for price response in the balancing market. However, they do not ensure the market rules that requires most of the power to be traded in the day-ahead market. Imposing a bound on the volume that can be traded in the balancing market to 50% of production capacity, gave substantially lower gains. Faria and Fleten (2011) used a fixed limit to ensure that the intraday market is used for unexpected situations only, while Fodstad et al. (2017) limit the trading in the balancing market to the historically traded quantities.

According to Klæboe et al. (2018), one of the most problematic issues in these types of studies, is ensuring realistic distribution of volumes between the markets. Having no implicit or explicit limits (Boomsma et al., 2014), or a fixed limit (Faria and Fleten, 2011; Fodstad et al., 2017), are two simple approaches used in current literature. Both Klæboe et al. (2018) and Kongelf et al. (2018) choose to model the limit of the volume traded in the balancing market by a stochastic variable representing the total balancing market volume. In addition, Kongelf et al. (2018) multiply the total balancing market volume by a market share of the hydropower producer. This is also the formulation chosen in this thesis. Klæboe et al. (2018) point out that modeling price response is another way of ensuring that the distribution of volumes between markets is realistic. Kongelf et al. (2018) and Klæboe et al. (2018) found the gains of coordinated bidding to be 0.7% and 0.1%

respectively. Klæboe et al. (2018) conclude that market participants offering regulation should monitor the balancing market closely, as the gain increases with an increase in demand in the market. In the current market situation however, coordinated bidding may not be worth the extra calculation time. Kongelf et al. (2018) point out that in addition to a modest increase in total profits, there is a shift towards utilizing the reserve markets. However, they also underline that the potential is limited due to the size of the balancing market.

3.3 Forecasting the Electricity Markets

When optimizing the profits from trading in electricity markets, support tools are needed in order to make informed decisions. As most of the power is traded in the day-ahead market, this is also the market which is most investigated in the literature. Forecasting the outcomes of the day-ahead market before market clearing has been an important tool in the industry since deregulation. Weron (2014) reviews the various techniques investigated in the literature, and categorizes them into; multi-agent models, fundamental models, reduced-form models, statistical models, and computational intelligence models. In the field of multi-market bidding, statistical models are widely used. In addition, fundamental factors are frequently used as input, in which hybrid solutions with time series, regression, and neural network models are considered (Weron, 2014). Some of the parameters that often have been included are Nordic demand, Danish wind power, air temperature, and weekday indicators (Weron and Misiorek, 2008; Kristiansen, 2012; Gonzalez et al., 2012; Conejo et al., 2005). Vehviläinen and Pyykkönen (2005) build a model to forecast the day-ahead market price, which include almost 30 exogenous parameters. Aggarwal et al. (2009) conclude that there is no systematic evidence of one model outperforming others. However, Conejo et al. (2005) find dynamic regression and transfer function algorithms to be more efficient than ARIMA models in predicting the day-ahead market price. In some cases, even more efficient than non-linear models. The day-ahead market is well explored in the literature, and accurate forecasts are well established. However, forecasting of balancing and ancillary service markets are rather rare in the literature, especially models including multiple exogenous factors.

3.3.1 Artificial Neural Networks

In the later years, the use of artificial neural networks (ANNs) have been investigated in the field of electricity price forecasting. In some fields, simple neural networks have proven to outperform more complex methods, in addition to being able to represent non-linear relations between variables (Kaastra and Boyd, 1996). Aggarwal et al. (2009) show that a large part of the literature concerning prediction of electricity prices with ANNs, use the same type of network and learning algorithm. This is the so-called multilayer feed-forward neural network, with a backpropagation algorithm (Conejo et al., 2005; Szkuta et al., 1999). Conejo et al. (2005) implement a three-layer architecture, but finds time series techniques as more efficient. The same architecture is used by Singhal and Swarup (2011), which find the model to be efficient for days with normal trends. However, in days where price spikes occurred, the performance was observed to decrease.

Both Pao (2007) and Wang and Ramsay (1998) use a sigmoid transfer function in the multilayer feed forward neural network. Conejo et al. (2005) state that feedforward back-propagation neural networks are especially suited for electricity price forecasting, as they can process non-linearity by using sigmoid functions for the input and linear functions for the output. Wang and Ramsay (1998) take weekends and public holidays into consideration, and report reasonable correlations with observed values. Pao (2007) reports a quite accurate prediction, and evaluates the effects of different lengths of forecasting horizon. The results are proven not to be very sensitive to the forecasting horizon being relatively short or long, such as autoregressive error models are. ANN are proposed as more robust multi-step ahead forecasting method than autoregressive error models. Despite the promising results for the day-ahead market, no studies for other electricity markets have been carried out, as the authors are aware of.

3.3.2 The Balancing Market

Due to the increase of multi-market trading and the concept of coordinated bidding, studies forecasting prices in other energy markets have increased. However, most of the existing literature focus on time series models. Klæboe et al. (2015) compare and benchmark multiple methods used to predict the balancing market in the literature, and conclude that it is difficult to forecast the balancing market before the closure of the day-ahead market. However, it is found that models including the balancing state information performs better.

Kongelf et al. (2018), Olsson and Söder (2008), and Jaehnert et al. (2009) explicitly forecast the state of the balancing market, and use this information to forecast the prices. On the other side, Boomsma et al. (2014) and Brolin and Söder (2010) use models which implicit forecast the balancing state. Boomsma et al. (2014) determine the state implicit by the size of the balancing market price. In this thesis, the state is determined implicit by the size of the estimated balancing volume. The literature distinguish between modelling the price (Boomsma et al., 2014), or the difference between the day-ahead market price and the balancing market price, known as the balancing premium (Jaehnert et al., 2009; Skytte, 1999; Kongelf et al., 2018).

Forecasting the balancing market implies collecting information about the state, demand, and premium for a given hour. Olsson and Söder (2008) use a combination of SARIMA and discrete Markov processes, and report appropriate results of the balancing market prices, suitable for generating price scenarios for a stochastic model. Jaehnert et al. (2009) also present a SARIMA model to predict the premium, in addition to including the estimated balancing volume as an exogenous factor. Skytte (1999) includes in the same manner the influence of the balancing volume, and a high correlation between the day-ahead market price and the balancing market price is detected. Conversely, Jaehnert et al. (2009) do not find any relations between the two market prices. In the benchmarking study of Klæboe et al. (2015), high performance was detected among models which included exogenous variables, such as the day-ahead market price, balancing market volume, and/or power production.

3.4 Contribution to the Literature

The existing literature focusing on the possible gains of coordinated bidding compared to a sequential bidding strategy, is summarized in Table 3.1. The literature considers different approaches of the coordinated bidding problem, by accounting for different combinations of the day-ahead market (DA), intraday market (ID), primary reserve market (PR), and the balancing market (BM). The main contribution of this thesis, is the focus of measuring the gains of a coordinated bidding strategy over time. In addition, block bids are available in the day-ahead market. Whereas most of the relevant literature only focus on the size of the commitments in the real-time markets, this thesis construct bid curves for both markets. The stochastic balancing market outcomes are generated based on forecasts developed by an artificial neural network. In addition, the opportunities in the balancing market are restricted by a stochastic demand parameter and a market share parameter.

Table 3.1: Studies focusing on gains of coordinated bidding

Study	Markets	Block	Volume bound	Bid curves	Price modelling
This work	DA+BM	Yes	Stochastic parameter + Market share	DA+BM	Artificial neural networks
Faria and Fleten (2011)	DA+ID	Yes	Fixed	DA	Statistical models
Boomsma et al. (2014)	DA+BM	No	None	DA+BM	Statistical models
Kongelf et al. (2018)	DA+PR+BM	No	Stochastic parameter + Market share	DA	Statistical models
Fodstad et al. (2017)	DA+ID+BM	No	Fixed	None	Perfect foresight
Klæboe et al. (2018)	DA+BM	No	Stochastic parameter	DA	Statistical models

Chapter 4

The Coordinated Bidding Problem

The bidding problem for a hydropower producer implies deciding how to utilize available resources, in order to maximize profits. The main part of the problem consists of deciding the optimal sets of bids for each of the markets considered. In this thesis, a coordinated bidding strategy is analyzed. Thus, the problem is hereby referred to as the coordinated bidding problem. The markets included are physical markets based on the market rules corresponding to the Nordic day-ahead market, and the Norwegian balancing market. Hedging in financial markets is not included in the short-term scheduling problem, neither is bilateral exchange. The optimal allocation of production resources based on the market commitments, is an important part of the problem. Section 4.1 describes the revenues and operational costs for a hydropower producer participating in the day-ahead market and the balancing market. Due to the complexity of the bidding problem, it is difficult to account for all relevant aspects while still being able to find a feasible solution within a reasonable amount of time (Doorman, 2009). The considerations that have to be included due to market rules and water system restrictions are presented in Section 4.2.

4.1 Maximizing Profits

The goal for hydropower producers is to maximize profits, given an expected market price. The producer has to place bids in the different markets such that expected revenues are as high as possible, while keeping the costs of operation low.

4.1.1 Market Revenues

The hydropower producer's income from trading in electricity markets, is determined by the market prices and the amount of power sold in each market. The commitments are a result of bids placed before market clearing, which are accepted depending on the bid price and the resulting market prices. In the day-ahead market and the upward balancing market the hydropower producer sell power, which gives a positive contribution to the income. In the downward balancing market, the producer commits to a repurchase agreement of buying back power which is already sold, thus inducing a cost. However, downward regulation is profitable for the producer if the downward balancing market price is lower than the producer's valuation of the water. The optimal bids for the day-ahead market and the balancing market are determined using a coordinated bidding strategy, which means that the hydropower producer plans for both markets simultaneously. It can be profitable to hold back capacity in the day-ahead market, if the producer can get a higher price in the upward balancing market. Conversely, it can be wise to produce at unprofitable prices in the day-ahead market, if water can be bought back at low prices.

The hydropower producer is assumed to have no market power, which implies that the market prices are not affected by the bidding behavior of the producer. Market prices and demand are unknown at the time of bidding. Thus, bidding decisions have to be based on an expected distribution of the market prices. The optimal bids based on this expectation, are not necessarily optimal with respect to the realized market prices. Given the price uncertainty, the predetermined bids may not be optimal in hindsight, which can lead to unprofitable commitments for the hydropower producer. In addition, there is a risk of not obtaining any commitments, which is especially prominent in the balancing market. The commitments in the balancing market are restricted by an uncertain demand, hence there may be no or very small opportunities in the balancing market when entering the operating hour.

4.1.2 Operational Costs

Optimal bidding and operation of the system also implies minimizing the operational costs. Commitments leading to frequent starting and stopping of the generators is undesired. Thus, the process of determining the optimal bids considers the induced start-up costs. In addition, the marginal loss cost should be taken into account when bidding, as this is a direct marginal cost of production. The fixed part of the cost does not affect the bidding, as it remains the same for all realizations. However, the variable part is considered, as it differs with the market prices and commitments.

Water stored in the reservoirs can either be sold in the market tomorrow, or saved for production in the near or distant future. The expected market prices for the upcoming days are thus considered in the bidding process, to make sure that the production capacity is allocated to the hours with the highest expected market prices. The value of the water remaining in the reservoirs at the end of the scheduling horizon, is also accounted for in the bidding process for the same reasons.

4.2 Considerations

While maximizing the profits for a hydropower producer, there are many aspects that have to be taken into consideration. The bids have to be in accordance with the required market rules, and restrictions related to the water system have to be taken into account.

4.2.1 Market Rules

Bids are submitted as hourly volume-price points, which indicate how much power a producer is willing to supply at a certain market price in a given hour. The set of volume-price points make up a bid curve. The market rules define the form of the bid curves, either as piece-wise linear or step-wise constant functions, depending on how the commitments are determined. The committed volumes from hourly bids in the day-ahead market are determined by interpolation between the volume-price points in the accepted bid. For block bids, the commitments are determined directly from the accepted bid volume. In the same manner as for block bids, commitments in the balancing market are determined directly from the accepted bid volume. It is assumed that the demand for replacement reserves is constant within the entire hour. A market rule that applies to bid curves in all markets, is the requirement of either monotonic increasing or decreasing bid curves. This rule makes it mandatory for the hydropower producer to produce either at the same, or at a higher level, when the market prices move in an improving direction.

The sequential nature of the markets leads to a certain dependency between the decisions in the problem. Bids in the day-ahead market are determined before any information regarding the market prices or demand is revealed. The highest bid in the day-ahead market cannot exceed the total production capacity for the hydropower producer. The day-ahead commitments differ depending on the resulting day-ahead market prices, which are revealed before the balancing market close. The bids in the balancing market are thus adjusted according to the commitments in the day-ahead market. The highest upward balancing bid cannot exceed the remaining production capacity for the producer, subtracting the commitments in the day-ahead market from the total production capacity. The highest downward balancing bid can maximum equal the commitment in the day-ahead market. Bids in the balancing market have to be at least 10 MW to be accepted. The maximum and minimum bid prices depicted by the market rules are included for both markets. Other restrictions for bid volumes and bid prices are not included in the problem. Commitments for the balancing market are calculated based on the resulting balancing market prices and demand in the market.

When entering the operating hour, the hydropower producer has to release water in order to produce the volume corresponding to the sum of the market commitments. The total production volume has to be within the capacity range of the producer. As the bids are determined based on expectations, the resulting market prices can lead to production plans quite different from the plans prepared in the bidding phase. This may in worst-case lead to production volumes which in some hours may be infeasible for the hydropower producer. When the hydropower producer is not able to match the power generation with the commitments, the deviations can be handled by including the possibility for imbalances or by rejecting bids leading to infeasible commitments. In this thesis, the hydropower cannot trade back into balance, and bids leading to such commitments are thus rejected.

4.2.2 Water System

Hourly production and discharge levels for the scheduling period have to be determined based on the commitments in the markets. As balancing market bids are specific for each water system the hydropower producer possesses, the coordinated bidding problem considers the operation of one water system only. The topology of a water system may however be quite complex, with many reservoirs and power stations, including complicated connections and transfers from other systems. Water mainly come into the reservoirs as inflow, but also from connected reservoirs at a higher level. The waterways in the system define where production discharge, bypass and spill from a reservoir ends up. The water can go to a reservoir downstream, or be lost from the system. Time delays between reservoirs are not considered when sending water through the waterways. Neither are pumps, as pumps often can be modeled as extra intake reservoirs.

An important aspect of the system operation, is balancing the water levels as to prevent spill. Even if time delays are neglected, there is still a limit on the bypass and discharge capacity. Thus, unlimited amounts of water cannot be moved instantly. The hydropower producer also has to account for the different water values of the reservoirs when planning how to operate the system. Each power station in the system can hold one or more production units, with different properties such as maximum production capacity, efficiency, and start-up costs. There are thus multiple optional production schedules, using different combinations of reservoirs, generators, and production levels. A production unit can have periods in which it is partly or fully unavailable for production.

Chapter 5

Mathematical Model

The stochastic mixed-integer programming model (SMIP) representing the coordinated bidding problem, is in this chapter formulated as its deterministic equivalent. Section 5.1 explains the three-stage structure of the model. In Section 5.2, the notation with all sets, indices, parameters, and variables in the model is presented. The formulation of the bidding process in the day-ahead market and balancing market is described in Section 5.3, while the formulation of the hydropower operation is presented in Section 5.4. The final objective function and domain constraints are presented in Section 5.5. Modeling assumptions are discussed as the formulation is presented. The entire model presentation can be found in Appendix A.

5.1 Stages

The coordinated bidding problem is modeled with three stages. The first-stage decisions are the bid curves for the day-ahead market, which represent the here-and-now decisions. The uncertain day-ahead market price is revealed in the second stage, and the commitments in the day-ahead market are calculated based on the realization. The second-stage decisions are the bid curves for the balancing market. Bidding decisions in both markets are modeled day-ahead, assuming that the hydropower producer does not change the balancing market bids after submitting the preliminary bids the day before delivery. Entering the third stage, the uncertain balancing market price and demand are revealed. Again, the realization determines the commitments in the balancing market. The third-stage decisions are the optimal production schedule for the water system, based on the market commitments. The decision tree is illustrated in Figure 5.1. Decision nodes are represented by squares, while circles represent chance nodes and the arrival of new information.

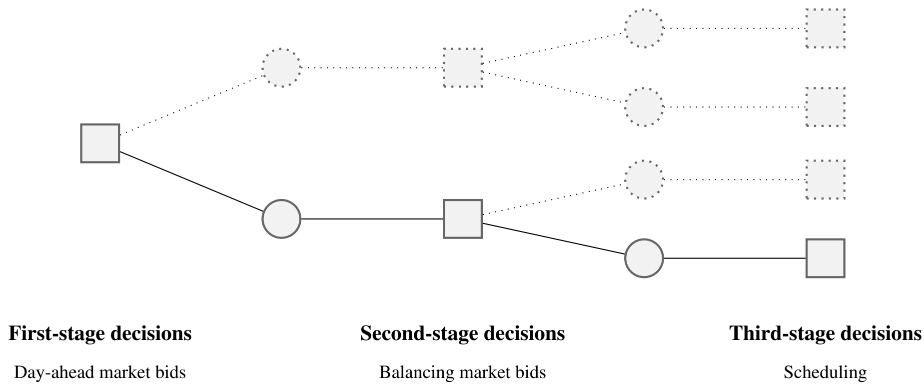


Figure 5.1: Three-stage decision tree for the coordinated bidding problem

5.2 Notation

The notation for the sets, indices, parameters, and variables used in the model is presented in this section. Capital calligraphic letters are used for sets, and lower-case letters for indices. Stochastic parameters are represented by the Greek letters π, ρ, μ, and ν, while upper-case Roman letters are used for deterministic parameters. Lower-case letters, with the indices as subscript, represent decision variables. Binary decision variables are represented by the Greek letter δ. Superscript D and B, represents the day-ahead market and balancing market, respectively.

Sets & Indices

$\mathcal{G}$	Set of generators, indexed by g
$\mathcal{G}_r$	Set of generators, $\mathcal{G}_r \subset \mathcal{G}$, connected to a given reservoir r, indexed by g
$\mathcal{T}$	Set of time intervals, indexed by t
$\mathcal{T}^P$	Set of time intervals, $\mathcal{T}^P \subset \mathcal{T}$, with pre-determined production, indexed by t
$\mathcal{T}^O$	Set of time intervals, $\mathcal{T}^O \subset \mathcal{T}$, of operation, indexed by t
$\mathcal{T}^H$	Set of time intervals, $\mathcal{T}^H \subset \mathcal{T}$, in the long horizon without bidding, indexed by t
$\mathcal{E}$	Set of discharge segments, indexed by e
$\mathcal{B}$	Set of blocks, indexed by b
$\mathcal{B}_t$	Set of blocks, $\mathcal{B}_t \subset \mathcal{B}$, connected to a given time t, indexed by b
$\mathcal{I}$	Set of bid points, indexed by i
$\mathcal{R}$	Set of reservoirs, indexed by r
$\mathcal{S}$	Set of second-stage outcomes of the day-ahead market price, indexed by s
$\mathcal{C}$	Set of third-stage outcomes of the balancing market price, indexed by c
$\mathcal{C}_s$	Set of third-stage outcomes, $\mathcal{C}_s \subset \mathcal{C}$, given the second-stage outcome s, indexed by c
$\mathcal{M}$	Set of balancing market states, indexed by m

Stochastic Parameters

π_s^D	Probability of the second-stage outcome s
π_{sc}^B	Probability of the third-stage outcome c, given second-stage outcome s
ρ_{ts}^D	Day-ahead market price in time t and outcome s
$\overline{\rho}_{bs}^D$	Day-ahead market price in block b and outcome s
ρ_{tsc}^B	Balancing market price in time t in outcomes s and c
μ_{tsc}^B	Balancing market premium in time t in outcomes s and c
ν_{tsc}^B	Balancing market demand in time t in outcomes s and c

Deterministic Parameters

P_i^D	Price in bid point i for the day-ahead market
P_{im}^B	Price in bid point i for balancing market state m
$\underline{M}$	Minimum bid volume for the balancing market
S_m	Market share for balancing market state m
U_m	Market state indicator, $= 1$ for market state $m = 1$, -1 for market state $m = 2$
C_g^S	Unit start cost of generator g
C_{ts}^L	Marginal loss cost in time t and outcome s
L_t	Loss rate in time t
R_{ge}	Resource usage of generator g in segment e
P_{gt}	Production plan for generator g in time t
$\overline{V}_r$	Maximum volume of reservoir r
$\underline{V}_r$	Minimum volume of reservoir r
V_r^0	Initial volume for reservoir r
$\overline{Q}_g$	Maximum capacity of generator g
$\underline{Q}_g$	Minimum capacity of generator g
A_{gt}	Available capacity share of generator g in time t
$\overline{Q}_{gt}$	Maximum available capacity of generator g in time t
$\overline{D}_{ge}$	Maximum discharge for generator g and discharge segment e
$\underline{D}_g$	Minimum discharge for generator g
$\overline{B}_r$	Maximum bypass of reservoir r
$\underline{B}_r$	Minimum bypass of reservoir r
I_{tr}	Inflow in time t to reservoir r
W_r	Water value in reservoir r at the end of the scheduling period
$M_{r'r}^D$	Discharge matrix from reservoir r' to reservoir r
$M_{r'r}^S$	Spill matrix from reservoir r' to reservoir r
$M_{r'r}^B$	Bypass matrix from reservoir r' to reservoir r
E	Energy equivalent
Z	Unit spill penalty

Variables

u^D_{ti}	Hourly bid volume for the day-ahead market in time t and bid point i
u^D_{bi}	Block bid volume for the day-ahead market in block b and bid point i
u^B_{tsim}	Hourly bid volume for the balancing market in time t, bid point i, outcome s and market state m
w^D_{ts}	Committed hourly volume in the day-ahead market in time t and outcome s
w^D_{bs}	Committed block volume in the day-ahead market in block b and outcome s
w^B_{tscm}	Committed hourly volume in the balancing market in time t, outcomes s and c, and market state m
x_{gtsc}	Produced power from generator g in time t, for outcomes s and c
d_{gtsc}	Discharge from generator g in time t, for outcomes s and c
d^E_{gtesc}	Segment discharge in segment e from generator g in time t, for outcomes s and c
v_{trsc}	Volume in time t in reservoir r and outcomes s and c
s_{trsc}	Spill in time t from reservoir r and outcomes s and c
b_{trsc}	Bypass in time t from reservoir r and outcomes s and c
o_{trsc}	Inflow from other reservoirs into reservoir r, in time t and outcomes s and c
y_{gtsc}	Start cost from generator g, in time t and outcomes s and c

Binary variables

$$\delta^B_{tscm} = \begin{cases} 1 & \text{if there is committed volume in time } t\text{, outcomes } s \text{ and } c\text{, and market state } m \\ 0 & \text{otherwise} \end{cases}$$

$$\delta^G_{gtsc} = \begin{cases} 1 & \text{if generator } g \text{ is running in time } t\text{, in outcomes } s \text{ and } c \\ 0 & \text{otherwise} \end{cases}$$

5.3 Market Modeling

The planning horizon for the hydropower producer is divided into hourly time intervals, denoted by $\mathcal{T} = \{1, \ldots, T\}$. The hourly time intervals coincide with the granularity of the markets. The subset $\mathcal{T}^P = \{1, \ldots, 24\} \subset \mathcal{T}$ represents the day of bidding, which is deterministic with a pre-determined production schedule. The hours of operation make up the second day of the planning horizon, and are thus denoted by the subset $\mathcal{T}^O = \{25, \ldots, 48\} \subset \mathcal{T}$. Bids are only placed for the day of operation, as bidding for the rest of the horizon is relaxed. After hour 48, the producer adjusts the production according to the market prices, without going through the process of bidding. This period is denoted by the subset $\mathcal{T}^H = \{49, \ldots, T\} \subset \mathcal{T}$.

The prices in hour t for the day-ahead market and the balancing market, are denoted by the parameters ρ_t^D and ρ_t^B, respectively. The balancing market price is defined as the sum of the day-ahead market price and a balancing market premium, μ_t^B, and is described in (5.1). The premium can be positive or negative, leading to a balancing market price above or below the day-ahead market price. The demand in the balancing market is denoted by ν_t^B. The set of random variables, $\boldsymbol{\gamma} = \{\rho_t^D, \mu_t^B, \nu_t^B, t \in \mathcal{T}\}$, describing the market prices and demand throughout the planning horizon, is a continuous stochastic process. $\boldsymbol{\gamma}$ is approximated by the discrete stochastic process $\boldsymbol{\lambda}$, so that $\boldsymbol{\gamma} \approx \boldsymbol{\lambda} = \{\rho_{ts}^D, \mu_{ts}^B, \nu_{ts}^B, t \in \mathcal{T}, s \in \mathcal{S}\}$. Each scenario $\boldsymbol{\lambda}(s)$ has an associated probability of occurrence, which equals $\pi(s)$.

$$\rho_t^B = \rho_t^D + \mu_t^B \qquad t \in \mathcal{T}^O \tag{5.1}$$

When developing a mathematical formulation of a stochastic programming model, one distinguishes between two different types of formulations depending on how the variables are defined. A node-variable formulation of the bidding problem is presented and implemented, in which the variables are associated with decision points. The other option would be a scenario-variable formulation, in which the variables are associated with scenarios. While a scenario-variable formulation presents an exploitable structure which is well suited for decomposition, a node-variable formulation gives a more compact formulation which is well suited for a direct solution approach (Conejo et al., 2010). Non-anticipativity constraints, ensuring that all decision variables with the same realizations up to a certain node are identical, are implicitly taken into account through the node-variable formulation (Conejo et al., 2010). Figure 5.2 illustrates the scenario tree. The set of possible outcomes for the second-stage nodes is denoted $\mathcal{S}$, while the set of possible outcomes for the third-stage nodes is denoted $\mathcal{C}$. The third-stage nodes represent the leaves of the scenario tree, and define the number of scenarios. A subset $\mathcal{C}_s \subset \mathcal{C}$ is introduced, which represents the possible outcomes for the third-stage nodes given an outcome s in the second stage. A scenario is defined as a combination of two nodes, given an outcome $s \in \mathcal{S}$ and $c \in \mathcal{C}_s$. The uncertain market parameters is thus denoted as ρ^D_{ts}, ρ^B_{tsc}, and ν^B_{tsc}. The probability for an outcome s in the day-ahead market is given by π^D_s, while the probability for an outcome c in the balancing market is given by π^B_{sc}. The probability for a scenario is thus defined as $\pi^D_s \cdot \pi^B_{sc}$.

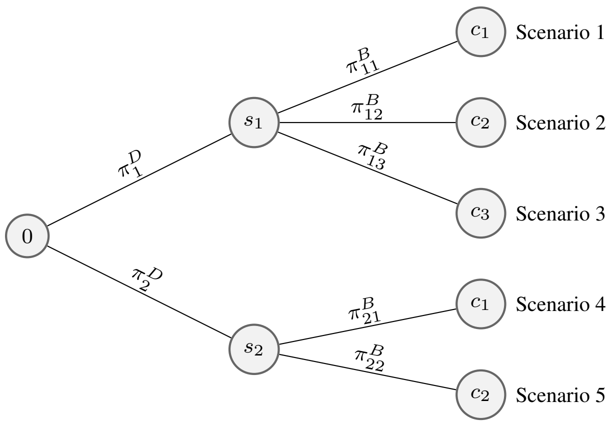


Figure 5.2: Scenario tree for the coordinated bidding problem

5.3.1 The Day-Ahead Market

For the day-ahead market, both hourly bids and block bids are included as an option in the model formulation. A set of blocks $\mathcal{B} = \{b_1, \ldots, b_B\}$ is introduced, for which each block b consists of a number of $|b|$ consecutive hours throughout the day of delivery. One specific hour can be included in several blocks, which is often referred to as crossing blocks. The number of possible blocks within a day is $B = 276$ due to all possible combinations of two or more consecutive hours. The block price, $\overline{\rho}^D_{bs}$, is defined as the average of the day-ahead market price over all hours included in the block, as described by (5.2).

$$\overline{\rho}^D_{bs} = \frac{1}{|b|} \sum_{t \in b} \rho^D_{ts} \qquad b \in \mathcal{B}, s \in \mathcal{S} \tag{5.2}$$

Bids are given as price-volume pairs, which make up a set of bid points $\mathcal{I} = \{1, \ldots, I\}$. The number of bid points, I, is freely chosen by the market participant, but an upper limit is given by $I = 64$ according to the market rules (Nord Pool, b). The process of placing bids gives a non-linear problem when determining both the bid price and the bid volume. To preserve the linearity of the model, the bid prices for the day-ahead market, P_i^D, are modeled as fixed parameters, while the bid volumes are modeled as decision variables (Fleten and Pettersen, 2005). The bid volumes for hourly bids and block bids are denoted u_{ti}^D and u_{bi}^D, respectively. Accumulated volumes are used, and not the marginal increase for each bid point. The values of the bid prices can be determined by fixing equidistant price points, or by fixing the price points in such a way that they reflect the distribution of market prices (Fleten and Kristoffersen, 2007). In accordance with the market rules, the bid prices for the day-ahead market are required to be strictly increasing. For hourly bids, the decision variables representing commitments, w_{ts}^D, are determined by linear interpolation between the volume-price pairs $(u_{t(i-1)}^D, P_{i-1}^D)$ and (u_{ti}^D, P_i^D), as expressed by (5.3). An example of an hourly bid curve in hour t, with three bid points, is given in Figure 5.3a. The market rules require that the bid curves are monotonically non-decreasing, meaning that the bid volumes have to increase with an increase in bid point, i. This requirement is enforced by (5.4).

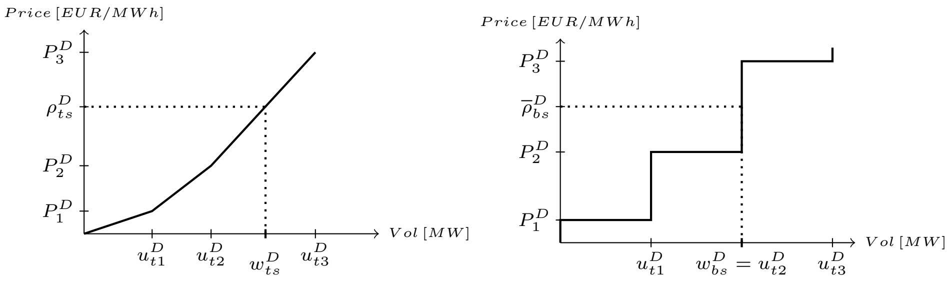
$$w_{ts}^D = u_{t(i-1)}^D + (u_{ti}^D - u_{t(i-1)}^D)\frac{\rho_{ts}^D - P_{i-1}^D}{P_i^D - P_{i-1}^D} \quad \text{if } P_{i-1}^D \leq \rho_{ts}^D < P_i^D, t \in \mathcal{T}^O, s \in \mathcal{S}, i \in \mathcal{I} \setminus \{1\} \tag{5.3}$$

$$u_{ti}^D \geq u_{t(i-1)}^D \qquad t \in \mathcal{T}^O, i \in \mathcal{I} \setminus \{1\} \tag{5.4}$$

Unlike hourly bids, the block commitments, w_{bs}^D, are not determined by interpolation. If the block price, $\overline{\rho}_{bs}^D$, is greater than or equal to bid price P_{i-1}^D, but lower than bid price P_i^D, the commitment in that block equals the bid volume $u_{b(i-1)}^D$. The bid volume, u_{bi}^D, is the same for all hours in block b. The requirement of monotonically non-decreasing curves is ensured by (5.6). An example of a bid curve for a block bid in a given hour t, is illustrated in Figure 5.3b.

$$w_{bs}^D = u_{b(i-1)}^D \qquad \text{if } P_{i-1}^D \leq \overline{\rho}_{bs}^D < P_i^D, \quad b \in \mathcal{B}, i \in \mathcal{I} \setminus \{1\}, s \in \mathcal{S} \tag{5.5}$$

$$u_{bi}^D \geq u_{b(i-1)}^D \qquad b \in \mathcal{B}, i \in \mathcal{I} \setminus \{1\} \tag{5.6}$$



(a) Hourly bid curve

(b) Block bid curve

Figure 5.3: Examples of bid curves in the day-ahead market

A set of production units, $\mathcal{G} = \{1 \dots G\}$, is introduced. The accumulated bid volumes for hour t in the day-ahead market, cannot exceed the available production capacity of the system. The hourly available production capacity, $\overline{Q}_{gt}$, is defined in (5.7). A_{gt} represents the hourly percentage of availability for the generator, while $\overline{Q}_g$ denotes the upper production limit of the generator. The total production capacity of the system is found by summarizing over all production units, as expressed by (5.8).

$$\overline{Q}_{gt} = A_{gt}\overline{Q}_g \qquad g \in \mathcal{G}, t \in \mathcal{T} \tag{5.7}$$

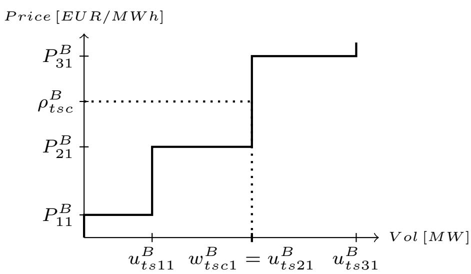
$$\sum_{b \in \mathcal{B}_t} u_{b|I|}^D + u_{t|I|}^D \leq \sum_{g \in \mathcal{G}} \overline{Q}_{gt} \qquad t \in \mathcal{T}^O \tag{5.8}$$

5.3.2 The Balancing Market

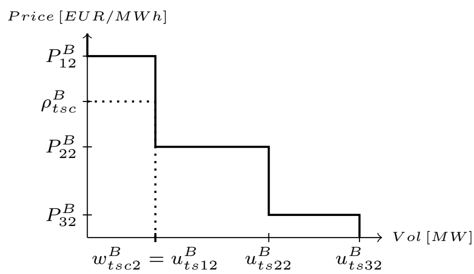
The market participant can both sell to and buy from the balancing market. One supply curve and one demand curve are thus submitted for each hour of operation. However, in each hour, the market participant can only be dispatched in the dominating direction of the system. The stochastic demand parameter, ν_{tsc}^B, defines the direction and quantity demanded in hour t, for the price area the market participant belongs to. The market rules are somewhat different depending on the state of the system, thus a set of balancing market states, $\mathcal{M}$, is defined to distinguish between upward and downward regulation.

$$\mathcal{M} = \begin{cases} 1 & \text{upward balancing market} \\ 2 & \text{downward balancing market} \end{cases}$$

As for the day-ahead market, bids are given as price-volume pairs with bid prices, P_{im}^B, as parameters, and bid volumes, u^B_{tsim}, as decision variables. The set of bid points, $\mathcal{I} = \{1, \dots, I\}$, is the same as for the day-ahead market, but the corresponding bid prices are different for each of the balancing market states. The bid prices for upward regulation are strictly increasing, while they are strictly decreasing for downward regulation. Examples of bid curves in the balancing market in hour t, are given in Figure 5.4. The commitments in the upward balancing market are determined in the same manner as for block bids, as ensured by (5.9). In addition, the system has to be in an upward regulated state ($\nu^B_{tsc} > 0$). The opposite applies to bids for the downward balancing market. The bid is accepted if the balancing market price, ρ^B_{tsc}, is less than or equal to bid price $P^B_{(i-1)2}$, but greater than bid price P^B_{i2}. The system also have to be in a downward regulated state ($\nu^B_{tsc} < 0$), as expressed by (5.10). It can be numerically difficult to separate between the case of a number being positive or non-positive, or negative or non-negative, such as described by (5.9) and (5.10). However, the market rules require a minimum bid volume for the balancing market, denoted $\underline{M}$. As it is assumed that the replacement reserves are needed the entire hour, ν^B_{tsc} is either exactly equal to zero, or in the intervals $\big(-\infty, -\underline{M}\big]$ or $\big[\underline{M}, +\infty\big)$. Hence, the problem of separating between such cases is not a problem in the model.



(a) Upward balancing (m=1)



(b) Downward balancing (m=2)

Figure 5.4: Examples of bid curves in the balancing market

$$w^B_{tsc1} = \begin{cases} u^B_{ts(i-1)1} & \text{if } P^B_{(i-1)1} \leq \rho^B_{tsc} < P^B_{i1} \text{ and } \nu^B_{tsc} > 0 \\ 0 & \text{if } \nu^B_{tsc} \leq 0 \end{cases} \tag{5.9}$$

$$t \in \mathcal{T}^O, s \in \mathcal{S}, c \in \mathcal{C}_s, i \in \mathcal{I} \setminus \{1\}$$

$$w^B_{tsc2} = \begin{cases} u^B_{ts(i-1)2} & \text{if } P^B_{(i-1)2} \geq \rho^B_{tsc} > P^B_{i2} \text{ and } \nu^B_{tsc} < 0 \\ 0 & \text{if } \nu^B_{tsc} \geq 0 \end{cases} \tag{5.10}$$

$$t \in \mathcal{T}^O, s \in \mathcal{S}, c \in \mathcal{C}_s, i \in \mathcal{I} \setminus \{1\}$$

The market rules require monotonically increasing bid curves for upward regulation, and monotonically decreasing bid curves for downward regulation. The bid volumes are always positive, so the requirement for both states is enforced by (5.11). As the balancing market clears after the day-ahead market, the available capacity for regulation is dependent on the day-ahead market commitments. For upward regulation, the quantity available for regulation is defined as the total available production capacity in hour t, less the committed volumes in the day-ahead market in the same hour (5.12). The quantity available for downward regulation is equal to the commitment in the day-ahead market (5.13).

$$u^B_{tsim} \geq u^B_{ts(i-1)m} \qquad t \in \mathcal{T}^O, s \in \mathcal{S}, i \in \mathcal{I} \setminus \{1\}, m \in \mathcal{M} \qquad (5.11)$$

$$u^B_{ts|I|1} \leq \sum_{g \in \mathcal{G}} \overline{Q}_{gt} - (w^D_{ts} + \sum_{b \in \mathcal{B}_t} w^D_{bs}) \qquad t \in \mathcal{T}^O, s \in \mathcal{S} \qquad (5.12)$$

$$u^B_{ts|I|2} \leq w^D_{ts} + \sum_{b \in \mathcal{B}_t} w^D_{bs} \qquad t \in \mathcal{T}^O, s \in \mathcal{S} \qquad (5.13)$$

The commitments in the balancing market are limited by the demand, ν^B_{tsc}, for replacement reserves in the given price area. The demand in the balancing market is very low compared to the demand in the day-ahead market, and often so low that a single market participant is able to produce the entire volume demanded. As the balancing market price is set from the last activated bid, a producer can in theory set the market price in cases when there are no other producers placing lower bids. However, lower volumes in the balancing market are in itself not an argument for market power (Klæboe et al., 2015). The price taker assumption can thus be considered valid, also in the balancing market. A market share parameter, S_m, is introduced to restrict the hydropower producer's share of the available volume in the balancing market. The product of the balancing market demand and the market share, is used as an upper limit for the commitments in the balancing market. The commitments are positive disregarding the balancing market state, while the demand is negative when the system is in the downward balancing market state. A market indicator, U_m, which equals $+1$ for $m = 1$ and -1 for $m = 2$, is introduced. Multiplying the market indicator with the demand gives a positive upper limit for both regulating states. The upper and lower limits for the commitments in the balancing market are expressed by (5.14). The binary variable, δ^B_{tscm}, forces the commitments to be between the upper and lower boundaries, if different from zero.

$$\underline{M}\delta^B_{tscm} \leq w^B_{tscm} \leq \nu^B_{tsc} U_m S_m \delta^B_{tscm} \qquad t \in \mathcal{T}^O, s \in \mathcal{S}, c \in \mathcal{C}_s, m \in \mathcal{M} \qquad (5.14)$$

The sum of the commitments in the markets make up the total production in the system. The market indicator is multiplied with the balancing market commitments, as downward regulation is a repurchase of volumes. The total production in the system equals the production, x_{gtsc}, summarized for all generators, as expressed in (5.15).

$$w_{ts}^D + \sum_{b \in \mathcal{B}_t} w_{bs}^D + \sum_{m \in \mathcal{M}} U_m w_{tscm}^B = \sum_{g \in \mathcal{G}} x_{gtsc} \qquad t \in \mathcal{T}^O, s \in \mathcal{S}, c \in \mathcal{C}_s \tag{5.15}$$

5.4 Hydropower Modeling

For all the variables and constraints concerning the operation of the water system, all hours in the planning horizon, $t \in \mathcal{T}$, are considered. We introduce a set of reservoirs $\mathcal{R} = \{1 \dots R\}$, and a subset $\mathcal{G}_r \subset \mathcal{G}$, which define the generators connected to reservoir r. The reservoir volume, v_{trsc}, at the end of hour t is given by a water balance. All water flowing in or out during hour t, and the reservoir volume at the end of the previous hour, $v_{(t-1)rsc}$, are summarized. The general water balance is given in (5.16). The initial reservoir volume, V_r^0, has to be included in the first hour, as defined in (5.17). The reservoir volume increases due to inflow, I_{tr}, and decreases with discharge d_{gtsc}, spill s_{trsc}, and bypass b_{trsc}. Inflow is modeled as a deterministic parameter due to its low impact for a short time horizon, and the preservation of a simple model. The term o_{trsc}, is defined as the sum of the discharge, spill, and bypass coming from connected reservoirs at a higher level (5.18). Reservoirs are connected using indicator matrices, which defines if water can be sent from reservoir r' to reservoir r. The different matrices are the discharge matrix, $M_{r'r}^D$, the spill matrix, $M_{r'r}^S$, and the bypass matrix, $M_{r'r}^B$. The water balance and the associated variables are illustrated in Figure 5.5.

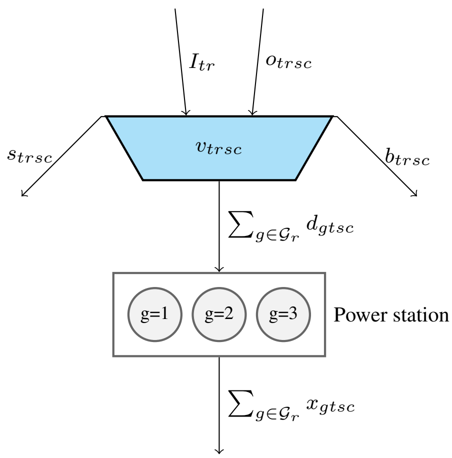


Figure 5.5: Water balance for reservoir r in hour t

$$v_{trsc} = v_{t-1,rsc} + I_{tr} - \sum_{g \in \mathcal{G}_r} d_{gtsc} - s_{trsc} - b_{trsc} + o_{trsc} \qquad t \in \mathcal{T} \setminus \{1\}, r \in \mathcal{R}, s \in \mathcal{S}, c \in \mathcal{C}_s \tag{5.16}$$

$$v_{1rsc} = V_r^0 + I_{1r} - \sum_{g \in \mathcal{G}_r} d_{g1sc} - s_{1rsc} - b_{1rsc} + o_{1rsc} \qquad r \in \mathcal{R}, s \in \mathcal{S}, c \in \mathcal{C}_s \tag{5.17}$$

$$o_{trsc} = \sum_{r' \in \mathcal{R}} \left(M^D_{r'r} \sum_{g \in \mathcal{G}_{r'}} d_{gtsc} + M^S_{r'r} s_{tr'sc} + M^B_{r'r} b_{tr'sc} \right) \qquad t \in \mathcal{T}, r \in \mathcal{R}, s \in \mathcal{S}, c \in \mathcal{C}_s \tag{5.18}$$

The produced power output's dependency on the head level is considered negligible for the short-term bidding problem. Consequently, a linear relationship between the power output, x_{gtsc}, and the discharge rate, d_{gtsc}, is obtained. The production-discharge curve is approximated as a concave piece-wise linear function, which leads to the introduction of a set of discharge segments, $\mathcal{E} = \{1, \dots, E\}$. The relationship is expressed by (5.19). The first term represents the minimum production possible if the generator is running, and is expressed as $\underline{Q}_g \delta^G_{gtsc}$. A segment discharge, d^E_{gtesc}, is introduced for each segment. The segment discharge is restricted by an upper limit, $\overline{D}_{ge}$ (5.20). The total generator discharge, d_{gtsc}, equals the sum of the minimum discharge, $\underline{D}_g$, and the sum of all segment discharges, d^E_{gtesc}, as expressed by (5.21). The minimum discharge corresponds to the minimum production in (5.19). An example of a power-discharge curve with five discharge segments is illustrated in Figure 5.6. As the production function is concave, the discharge in segment e will be at maximum before the discharge in segment $e + 1$ achieves a value greater than zero.

$$x_{gtsc} = \underline{Q}_g \delta^G_{gtsc} + \sum_{e \in \mathcal{E}} R_{ge} d^E_{gtesc} \qquad g \in \mathcal{G}, t \in \mathcal{T}, s \in \mathcal{S}, c \in \mathcal{C}_s \tag{5.19}$$

$$d^E_{gtesc} \leq \overline{D}_{ge} \qquad g \in \mathcal{G}, t \in \mathcal{T}, e \in \mathcal{E}, s \in \mathcal{S}, c \in \mathcal{C}_s \tag{5.20}$$

$$d_{gtsc} = \underline{D}_g \delta^G_{gtsc} + \sum_{e \in \mathcal{E}} d^E_{gtesc} \qquad g \in \mathcal{G}, t \in \mathcal{T}, s \in \mathcal{S}, c \in \mathcal{C}_s \tag{5.21}$$

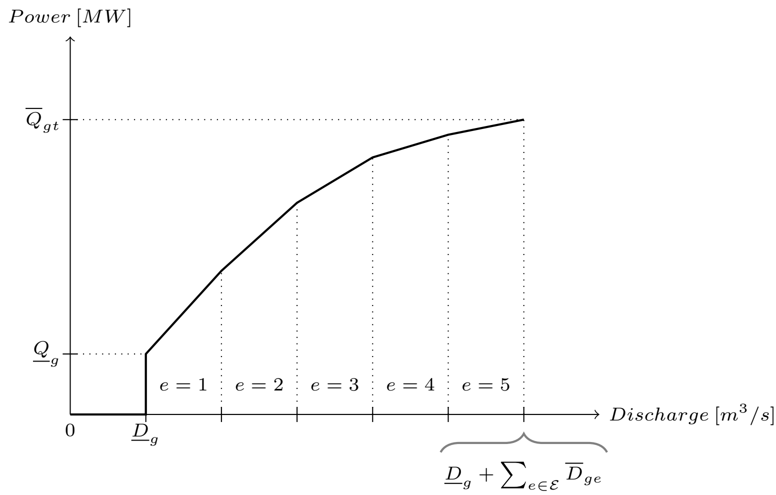


Figure 5.6: Example of a power-discharge curve with five discharge segments

The production, x_{gtsc}, is limited by the maximum and minimum capacity of the generator (5.22). The boundaries are multiplied by the binary variable, δ^G_{gtsc}, indicating if the generator is on or off. When the generator is not running, the upper and lower boundaries will thus be forced to zero. For the first deterministic day, the production is set equal to a given production plan, P_{gt}, as defined by (5.23).

$$\underline{Q}_g \delta^G_{gtsc} \leq x_{gtsc} \leq \overline{Q}_{gt} \delta^G_{gtsc} \qquad g \in \mathcal{G}, t \in \mathcal{T}, s \in \mathcal{S}, c \in \mathcal{C}_s \tag{5.22}$$

$$x_{gtsc} = P_{gt} \qquad g \in \mathcal{G}, t \in \mathcal{T}^P, s \in \mathcal{S}, c \in \mathcal{C}_s \tag{5.23}$$

A unit start-up cost, C^S_g, is induced each time a generator starts after not have been running for one or several hours. Multiplying the unit start-up cost with binary variables indicating a start-up gives the total start-up cost, y_{gtsc}. The start-up constraint is given by (5.24).

$$C^S_g (\delta^G_{gtsc} - \delta^G_{g(t-1)sc}) \leq y_{gtsc} \qquad g \in \mathcal{G}, t \in \mathcal{T} \setminus \{1\}, s \in \mathcal{S}, c \in \mathcal{C}_s \tag{5.24}$$

The reservoir volume and bypass has upper and lower limits as expressed by (5.25) and (5.26), respectively.

$$\underline{V}_r \leq v_{trsc} \leq \overline{V}_r \qquad t \in \mathcal{T}, r \in \mathcal{R}, s \in \mathcal{S}, c \in \mathcal{C}_s \tag{5.25}$$

$$\underline{B}_r \leq b_{trsc} \leq \overline{B}_r \qquad t \in \mathcal{T}, r \in \mathcal{R}, s \in \mathcal{S}, c \in \mathcal{C}_s \tag{5.26}$$

5.5 The Objective

The formal objective of the bidding problem is to maximize the profits from participating in the day-ahead market and the balancing market. The revenue from each market during the hours of operation, is calculated as the market price less the marginal loss cost, C^L_{ts}, multiplied with the commitment in the market. The marginal loss cost is defined by (5.27), as the loss rate, L_t, multiplied by the day-ahead market price. The market indicator, U_m, is included in the calculation of revenues for the balancing market due to opposite contributions. Upward balancing gives a positive contribution to profits, while downward balancing leads to a cost for the hydropower producer.

$$C^L_{ts} = \rho^D_{ts} L_t \qquad\qquad t \in \mathcal{T}, s \in \mathcal{S} \qquad (5.27)$$

A longer planning horizon has to be included in addition to the hours of operation, in order to prevent the model from only seeing opportunities the following day. A set of hours, $t \in \mathcal{T}^H \subset \mathcal{T}$, representing the hours after the hours of operation, is introduced. For the rest of the planning horizon, bidding is relaxed, and the hydropower producer adjusts production after the price path in the day-ahead market. The revenue from this period is included by multiplying the day-ahead market price less the marginal loss cost, by production x_{gtsc}, and not commitments. Including these future profits is not enough to keep the model from producing at full capacity during the whole planning horizon, as it would produce as long as there is enough water in the reservoirs. Thus, the value of the water remaining in the reservoir is taken into account. This value is the volume in the reservoir at the end of the horizon, $v_{|H|rsc}$, less the initial volume, V^0_r, multiplied with the water value, W_r. An energy equivalent, E, indicating how much energy that can be extracted for each cubic of water, is included in the expression to obtain the correct units. Start-up costs, y_{gtsc}, are included for all time intervals, except the first deterministic day. A penalty, Z, for spill is included to make sure that spill is undesired in the system, which also applies in cases where spill ends up in a lower reservoir.

The objective of the three-stage stochastic mixed-integer program, formulated as its deterministic equivalent, is presented in (5.28). As the problem is formulated as a deterministic equivalent of the stochastic program, the probability of each second-stage outcome, π_s, and the probability of each third-stage outcome, π_{sc}, is included in the objective function.

$$\max \sum_{s \in \mathcal{S}} \pi_s \Bigg(\sum_{t \in \mathcal{T}^O} (\rho^D_{ts} - C^L_{ts}) w^D_{ts} + \sum_{b \in \mathcal{B}_t} (\overline{\rho}^D_{bs} - C^L_{ts}) w^D_{bs} + \sum_{c \in \mathcal{C}_s} \pi_{sc} \Big(\sum_{t \in \mathcal{T}^O} \sum_{m \in \mathcal{M}} (\rho^B_{tsc} - C^L_{ts}) w^B_{tscm} U_m$$
$$+ \sum_{g \in \mathcal{G}} \big(\sum_{t \in \mathcal{T}^H} (\rho^D_{ts} - C^L_{ts}) x_{gtsc} - \sum_{t \in \mathcal{T} \setminus \{\mathcal{T}^P\}} y_{gtsc} \big) + \sum_{r \in \mathcal{R}} \big(W_r E \left(v_{|\mathcal{H}|rsc} - \underline{V}_r \right) - \sum_{t \in \mathcal{T}} Zs_{trsc} \big) \Big) \Bigg) \tag{5.28}$$

Chapter 6

Forecasting the Balancing Market

In order to utilize a forecast-based scenario generation method for generating input to the stochastic coordinated bidding model, forecasts for the day-ahead market and balancing market are needed. Forecasting of day-ahead market prices is a widely investigated subject in the literature, and such forecasts are generated daily by market participants. As stated in Chapter 3, no highly successful forecasts have been developed for the balancing market. The balancing market is designed to handle unforeseen events, and the prices and volumes should thus be random. If the balancing market is an efficient market, Klæboe et al. (2015) point out that any predictable event that can cause an imbalance in the system the day of operation, should be incorporated in the day-ahead market settlements. However, in the case of a non-efficient balancing market, speculative possibilities would open for market participants supplying regulation services. The focus of this chapter is the attempt of developing a forecast that can provide any information about the balancing market before the day-ahead market clears. Most of the current literature regarding forecasting of the balancing market is based on linear statistical approaches, such as ARMA and ARX time series models. The alternative of using artificial neural networks (ANNs) is explored in the following chapter. Section 6.1 gives an introduction to ANNs, and how they are designed for forecasting. An empirical analysis of the Nordic balancing market is presented in Section 6.2, in which different properties of the market, and possible explanatory factors are presented. Section 6.3 presents the process of generating the forecasts. Two ANNs are designed and trained to provide hourly predictions regarding the balancing market volume and premium. Finally, the resulting forecasts are presented and evaluated in Section 6.4. In order to evaluate the forecasts, two naive forecasts are used as benchmark. The forecasting procedure is implemented in Python 3.6. The open source framework TensorFlow is utilized, which strongly supports machine learning applications such as the implementation of ANNs.

6.1 Artificial Neural Networks

ANNs are used to represent non-linear relations between variables. They are designed to recognize complex patterns, with a high tolerance of imperfect data. Specific tasks include classification, clustering, and prediction. ANNs are frequently used for prediction in several fields, such as weather and financial forecasting. As discussed in Chapter 3, the method is already widely investigated in order to forecast day-ahead market prices.

6.1.1 Introduction

Several types of ANNs are currently used in machine learning, such as recurrent neural networks and convolutional neural networks. Simple feedforward neural networks are considered in this work. The concept of neural networks is based on individual units of mathematical calculations, representing artificial neurons. Neural networks processes information using a connectionist approach to computation, by using interconnected groups of artificial neurons (Gupta, 2013). Such groups are referred to as sets of layers. A network consists of input and output layers, as well as one or several hidden layers. Figure 6.1 illustrates how neurons are coupled to each other in a network with one hidden layer. All of the input neurons are linked to each neuron in the hidden layer, which again are linked to each of the output neurons.

Neurons in the first hidden layer receive input from the input layer, denoted by the vector X. The input is multiplied by individual weight values, often denoted by the matrix W. The neurons form a linear combination of the input and weights, and a bias vector b is added as an offset. The result is denoted by the vector Z. Further, Z is used as input to an activation function σ, which calculates the output vector A. There are a variety of activation functions which can be used. The easiest example is the Heaviside Step function, which returns 1 if the input is positive and 0 otherwise. The output of an activation function is used as input for the calculations in the next layer. The calculation of the output vector in layer l, is expressed by (6.1).

$$\mathbf{A}^l = \sigma(\mathbf{Z}^l) = \sigma(\mathbf{W}^l \mathbf{A}^{l-1} + \mathbf{b}^l) \tag{6.1}$$

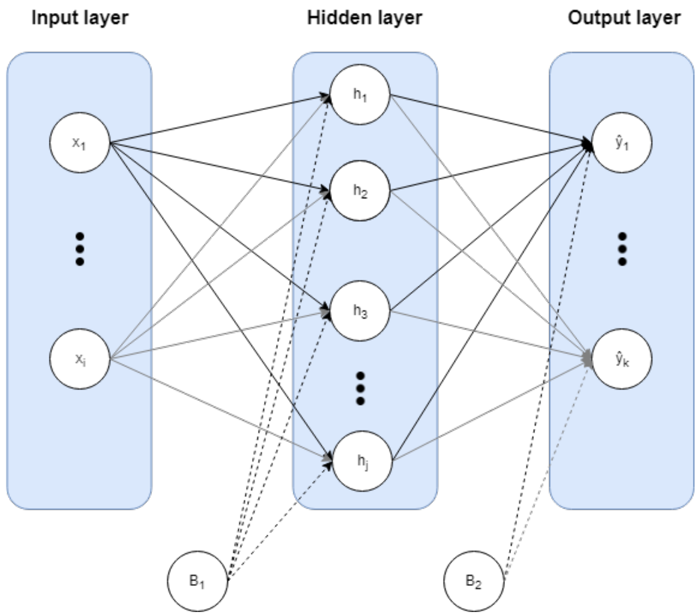


Figure 6.1: Couplings between the neurons in a network with one hidden layer

Although neural networks have been around for some time, it was not until the backpropagation algorithm was introduced, that neural networks could learn fast and solve problems which had not been solvable earlier. The backpropagation algorithm is based on calculating the gradient of the cost function with respect to weights W and bias b. One of the simplest learning strategies for a neural network is called supervised learning, in which the calculated output values are compared to target values. Weights in the layers are adjusted to minimize a given cost function (Kaastra and Boyd, 1996). The cost function measures how well the network is able to match the target values, and at estimating the relation between the input and output.

A sufficient amount of data is necessary when forecasting with an ANN. Three data sets are needed; training data, test data, and validation data. The training data is used to train the neural network, and a sufficient amount of data is needed in order to make the network learn properly. Test data is needed in order to adjust design parameters in order to obtain a general network. The validation data is only used to evaluate the performance of the algorithm, and is not included in the training of the ANN.

Training a network can take considerable amount of time and computing power, which is one of the biggest challenges of developing neural networks. Kaastra and Boyd (1996) present other limitations of ANNs, such that solutions may suffer from overfitting, and that multiple parameters have to be experimentally selected. Overfitting occurs when the neural network obtains low cost function values by only memorizing the training data set, instead of finding a general model. Generalization describes the ability of the model to adapt to a data set it has not seen before, and not overrating the details and noise from the training set (Western Washington University). If overfitting occurs in a neural network, it becomes clear by comparing the cost function value of the training data set and the test data set. A small cost function value for the training data and a high cost function value for the test data indicates the problem. Thus, these two accuracies should always be compared to check for overfitting. Designing and training an ANN can be a time-consuming method, with the risk of not giving significant improvements from simpler methods.

6.1.2 Design

The ANNs are designed as multi-layer perceptron models (MLP), which is a class of feed-forward neural networks. Such models are often used in the literature covering electricity price forecasting using neural networks. The general models are created as three-layer networks with one hidden layer, though several hidden layers are tested. In a basic feed-forward network, there are no cycles or loops between the neurons, so the information can only flow in one direction, from input to output. The flow of information in the network is illustrated in Figure 6.2. Weights and biases are varied though the training process to find the best fit to describe the output by the input. For the input and the hidden layers, the activation function is a rectified linear unit function (ReLU), while a pure linear function is used for the output layer. The two activation functions are illustrated in Figure 6.3.

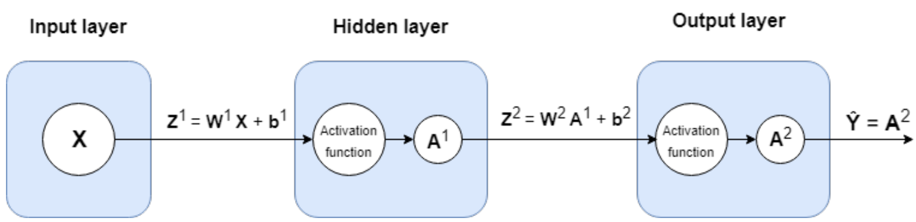
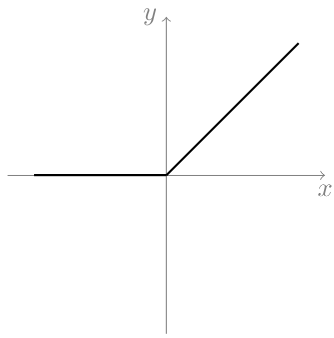
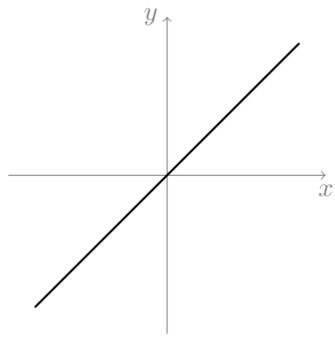


Figure 6.2: The flow of information in the neural networks

Supervised learning is used to train the networks, using a backpropagation network learning algorithm to adjust the weights and biases. The root mean squared error (RMSE) is used to measure the error between the output value and the target value. The error can be measured in a variety of ways. However, RMSE is considered natural when applied to forecasting, as this is a common way of measuring forecast performance. The calculation of the RMSE is expressed in (6.2), in which n is the number of observations, $\hat{y}_t$ is the



(a) Rectified linear unit function



(b) Pure linear function

Figure 6.3: Activation functions used in the ANNs

predicted value, and y_t is the target value. The neural network use the training data set to adjust the weights, such that an optimal forecast is found by minimizing the RMSE. The network returns the corresponding weights and biases, which are used to generate a forecast.

$$RMSE = \sqrt{\frac{\sum_{t=1}^{n}(\hat{y}_t - y_t)^2}{n}} \tag{6.2}$$

A time-consuming part of designing the neural network, is experimentally selecting the parameters listed in Table 6.1 below. The parameters affect the training process in different ways, such as how fast the model converges and how general the model gets. Epoch size represents the number of iterations. Increasing the number of neurons and layers decreases the RMSE, meaning that the performance of the network increase. However, it is important to keep in mind the problem of overfitting. Extensive work is thus put into finding the optimal design parameters such that the performance increase, without overfitting the network.

Table 6.1: Design parameters in the ANN

Number of hidden layers
Number of hidden neurons
Activation function
Evaluation criteria
Learning rate
Epoch size

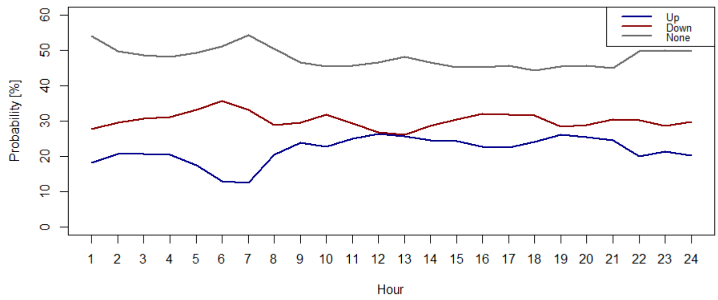
6.2 Analyzing the Balancing Market

An empirical analysis is carried out to identify the characteristics of the balancing market. Historical market data is analyzed, in addition to other physical and economic variables which may influence the balancing market volumes and premiums. The market analysis is used as a decision aid to make informed decisions regarding the input which should be included in the ANN, to increase the performance. Historical data from January 2013 to January 2018 is used in the market analysis, and is chosen due to availability. The market data is retrieved from Nord Pool's database, whereas the historical climate data is downloaded from the Norwegian Meteorological Institute's database eKlima. Forecasts for day-ahead market prices and weather forecasts, are provided by a co-operative hydropower producer. Forecasts for consumption and production are downloaded from Nord Pool's database. The data is mainly based on the NO2 price area, but data for some of the connecting areas such as DK1 is also collected. The borders which make up the price area NO2, has only had minor adjustments in the period considered. The data is thus considered to be comparable for the entire period. The same historical data is used for further analyses and studies throughout the thesis.

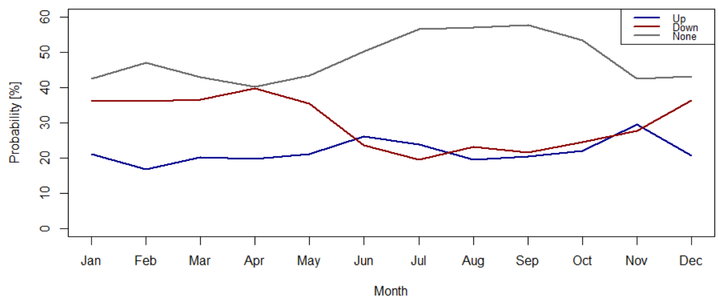
6.2.1 Empirical Analysis

When there are no imbalances in the system, the balancing market volume is equal to zero. This is the case for 48% of the hours included in the analysis. The probability of a balancing market state occurring throughout the day is illustrated in Figure 6.4a. It can be observed that the probability of no regulation always is above 40%. Downward regulation is generally more likely than upward regulation throughout the day, especially during the night hours and early morning hours as illustrated by the increased gap in the plot. The hours in the middle of the day are characterized by a higher share of regulation, as the consumption is less predictable in this period. Figure 6.4b shows that the yearly variations in the probability of balancing market states are quite large, especially for downward regulation. During the summer and autumn months, the probability of no regulation is above 50%, while upward and downward regulation are approximately equally probable. The probability of downward regulation is substantially higher than for upward regulation from December to May.

The descriptive statistics of the balancing market are presented in Table 6.2. The volumes have a larger standard deviation than the premiums, which indicates that the premiums are more stable around its mean. The premium for upward regulation produces the most extreme spikes. Notice that the highest spike is 284 EUR/MWh, while the mean is 1.42



(a) Hourly



(b) Monthly

Figure 6.4: Probability of balancing market states

EUR/MWh. From the skewness and kurtosis, it can be observed that the upward premiums are highly skewed and fat-tailed. This can also be observed by the historical distribution in Figure 6.5. The volumes are more symmetrical around zero. Balancing market volumes and premiums are extremely volatile, as can be seen from the historical data plotted in Figure 6.6. The spiky behaviour of the plots reflects that there are many hours with no regulation, in addition to cases with very high/low volume or premium. The spikes do not seem to occur simultaneously for volume and premium. It is hard to observe any relation between the balancing market volume and premium, or any seasonal patterns.

Table 6.2: Descriptive statistics of the balancing market volumes and premiums

	Mean	SD	Med.	MAD	Min	Max	Skew.	Kurt.	SE
Volume up	17.53	52.74	0	0	0	993	5.18	40.39	0.25
Volume down	-32.32	77.84	0	0	-916	0	-3.72	18.23	0.37
Premium up	1.42	4.89	0	0	0	284	21.73	739.36	0.02
Premium down	-2.30	3.58	0	0	-66	0	-3.34	25.82	0.02

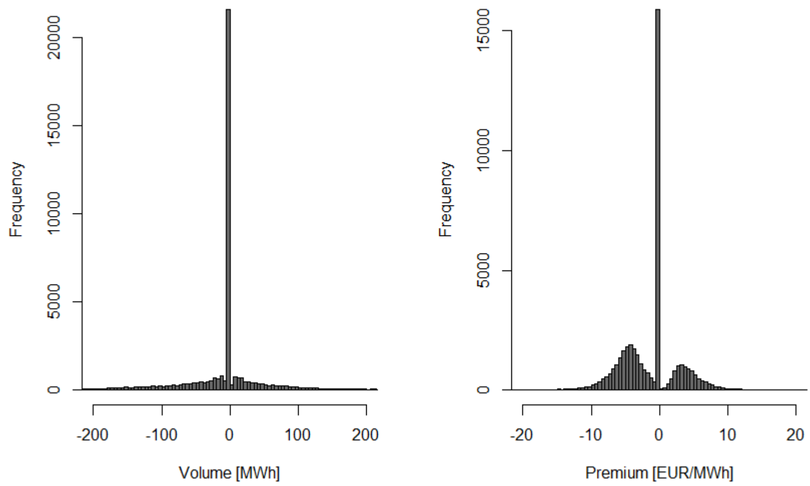


Figure 6.5: Historical distribution of the balancing market volume and premium

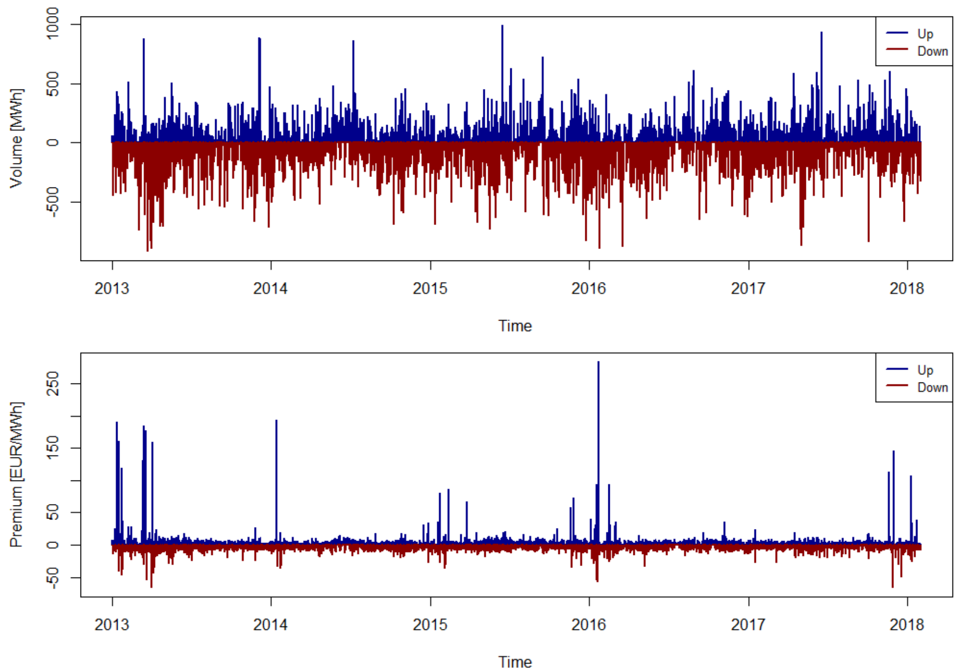


Figure 6.6: Historical volumes and premiums in the balancing market

The scatter plot in Figure 6.7 illustrates that there exists some correlation between volume and premium. The Pearson correlation coefficient for the balancing market is 0.53. If upward and downward regulation is considered separately, the correlations are 0.41 and 0.56 respectively.

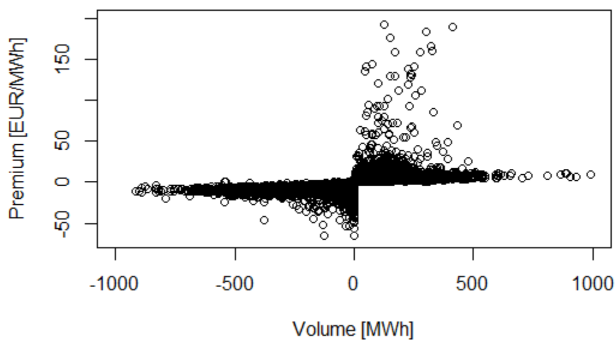
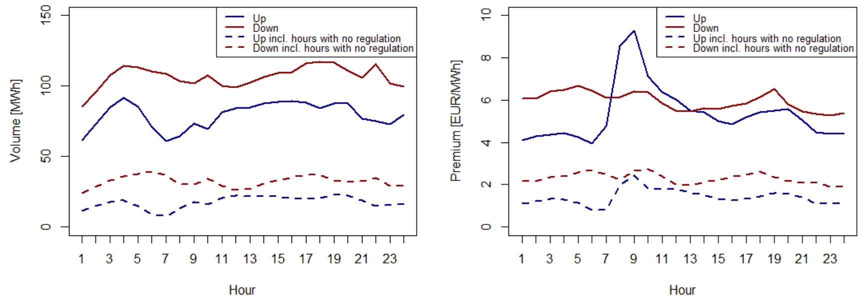
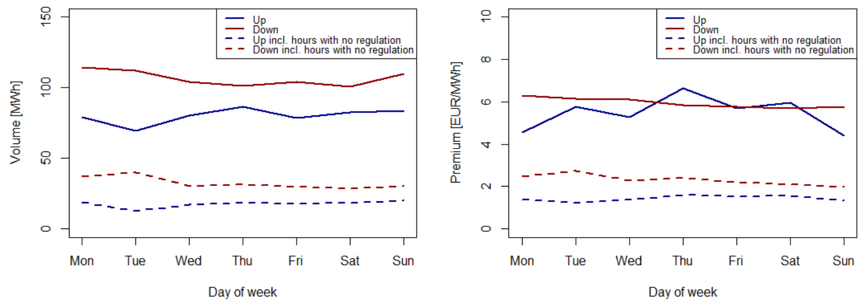


Figure 6.7: Scatter plot of balancing market volume and premium

The hourly and daily average volume and premium are plotted in Figure 6.8, including and excluding hours with no regulation. An hour with no regulation is defined as an hour in which the balancing market volume equals zero. The average values increase substantially when excluding no regulation hours. In Figure 6.8a, it can be observed that the average volume in the upward balancing market rises during the night hours, which is not prominent in the hourly probability of balancing states illustrated in Figure 6.4a. This means that the volumes for upward regulation are higher during the night time, if they occur. It is interesting to observe the spike in the average premium for upward regulation, which exceeds the value for downward regulation in the hours between 08:00 and 14:00. This indicates that suppliers require higher prices for upward regulation during the work day. From Figure 6.8b, it can be observed that the average volume does not vary as much for the different days of the week. The average premium for upward balancing is low on Sundays and Mondays, while the average premium for downward balancing is quite stable around 6 EUR/MWh throughout the week.



(a) Hourly



(b) Daily

Figure 6.8: Average balancing market volume and premium including and excluding hours with no demand

6.2.2 Exogenous Factors

In able to determine if there are any physical or economic variables influencing the balancing market volume and premium, historical data for fundamental factors such as system parameters, loads, and weather conditions, are analyzed.

Market Data

The market parameters investigated include consumption and production in both the NO2 price area and Norway as a whole. The day-ahead market price in the NO2 price area, and wind production in the DK1 price area in Denmark, are also included. There seems to be no or very little correlation between the parameters, as presented in Table 6.3. The balancing market volume do not seem to have any relation to the day-ahead market price at all, while the premium in the downward balancing market has some correlation with the day-ahead market price. Consumption and production are neither affecting volume, while they may have some relation to premium.

Table 6.3: Correlations between the balancing market and market parameters

	DAM price NO2	Cons. NO2	Cons. NO	Prod. NO2	Prod. NO	Wind prod. DK1
Volume up	-0.022	0.018	0.012	0.019	0.045	-0.045
Volume down	-0.038	-0.024	-0.031	0.004	0.059	-0.123
Premium up	0.090	0.102	0.092	0.085	0.101	-0.055
Premium down	-0.197	-0.100	-0.098	-0.054	-0.014	-0.085

As the balancing market is designed for unforeseen events, it is likely that a deviation from expected values affects the balancing market. If Nord Pool or several producers have large forecasting errors, it is reasonable to believe that this causes an imbalance in the system. All of the forecasting errors give higher correlations with the balancing market than the observed value alone, except the forecasting errors for the day-ahead market price. This may be because the forecasts for the day-ahead market price is specific for a producer. The correlations can be seen in Table 6.4. Consumption forecast for the price areas are not available. It can be observed that the forecast error for production, affect the balancing market volume more than the forecast error for consumption. In addition, the premium have higher correlation with the production forecast error. Wind power is known to be hard to predict, but does not seem to have much influence on the balancing market.

Table 6.4: Correlations between the balancing market and forecasting errors for the market parameters

	DAM price NO2	Cons. NO	Prod. NO2	Prod. NO	Wind prod. DK1
Volume up	0.002	-0.141	-0.469	-0.380	0.119
Volume down	-0.012	-0.146	-0.621	-0.491	0.109
Premium up	-0.038	-0.123	-0.206	-0.247	0.070
Premium down	0.086	-0.148	-0.386	-0.428	0.138

Climate Data

The demand for electricity in the Nordic countries is often considered as independent of price, as the price does not affect consumption significantly (Skantze et al., 2000). Due to the wide use of electricity as heating, the demand is however highly dependent on air temperature. Cold winters and mild summers in the Nordic countries, lead to a much higher demand during the winter than during the summer. The effect of temperature is often incorporated in the demand forecast. As the majority of power production in the Nordic countries comes from hydropower production, the supply is also highly weather dependent due to uncertainty in precipitation and snow melting. Even though the balancing market volume and premium have low correlations with consumption and consumption forecast errors, there may be some relation between the balancing market and weather conditions. The climate factors considered are air temperature, solar radiation, wind velocity and wind direction. From the correlations presented in Table 6.5, the weather conditions do not seem to have any effect on the balancing market. The forecasting errors are analyzed in the same manner as for the market data. In addition, the change in weather conditions from the day before is included. A substantial change in the weather conditions from one day to another, may cause an imbalance between supply and demand. However, neither the forecast errors nor the daily changes in weather conditions give any indication of correlation with the balancing market.

Table 6.5: Correlations between the balancing market and the climate parameters

	Temp.	**Solar**	**Wind vel.**	**Wind dir.**
Volume up	0.030	0.030	-0.002	-0.006
Volume down	0.042	0.008	-0.053	-0.040
Premium up	-0.064	0.000	-0.031	-0.039
Premium down	0.101	0.025	-0.010	0.007

Table 6.6: Correlations between the balancing market and the forecasting errors, and daily changes, for the climate parameters

	Temp. error	**Temp. change**	**Solar error**	**Solar change**	**Wind vel. error**	**Wind vel. change**	**Wind dir. error**	**Wind dir. change**
Volume up	0.028	-0.028	0.041	-0.012	0.023	-0.007	0.005	-0.008
Volume down	0.049	-0.036	0.025	-0.005	0.033	-0.017	0.034	-0.017
Premium up	-0.003	-0.020	0.009	-0.005	0.001	0.003	-0.008	-0.001
Premium down	0.047	-0.046	0.044	-0.013	0.048	-0.018	0.038	-0.021

6.3 Selection of Input Variables

The performance of an ANN is highly dependent on the input data (Kaastra and Boyd, 1996). However, the selection of the input variables can often be a difficult part of the implementation process. Hippert et al. (2001) state that few theoretically considerations exist for determining the input data to an ANN, and that it often requires a priori knowledge regarding the problem, and what affects the output. The market analysis in Section 6.2 presents few clear trends and relations in the potential input data, but provides some insight to the balancing market. It is interesting to investigate whether a forecast generated using ANN is able to detect any complex patterns in the data, which have not been found through simpler methods. The potential input variables analyzed in Section 6.2 are further evaluated, in order to determine the input variables to the ANN. In addition to considering the available raw data and their lagged values, processed data such as forecasting errors, changes from day to day, and indicators defining different events, are investigated.

Using large data sets increases the performance of a neural network (Abhishek et al., 2012). However, as market situations changes with time, it is natural to use relatively recent data when forecasting market prices. All of the historical data presented in Section 6.2, is considered relevant as there have not been considerable changes in the market during this period. The data set is divided into training data, test data, and validation data. Minimum a year of validation data should be used in order to evaluate performance, due to seasonal variations in the data. However, the amount of validation data is limited, as sufficient training data is needed. The validation data is thus chosen to be data from July 1, 2017 to January 16, 2018. The rest of the available data, from January 1, 2013 to June 30, 2017, are randomly divided into training and testing data. 80% of the data is assigned to the training data set, and the remaining 20 % is assigned to the test data set. All of the data is analyzed on an hourly resolution, as an hourly forecast is desirable. Due to 2016 being the only leap year in the data set, February 29, 2016 is excluded from the data set in order to retain uniformity. The data is normalized before it is used in the training algorithm, to obtain a better fit and compress the variance.

6.3.1 Forecasting Horizon

When utilizing a coordinated bidding strategy, it is desirable to forecast the balancing market before the closure of the day-ahead market. Figure 6.9 illustrates the time line of the forecasting horizon for the balancing market. Day $d + 1$ is the day to be forecasted, while the day-ahead market closes at 12:00 in day d.

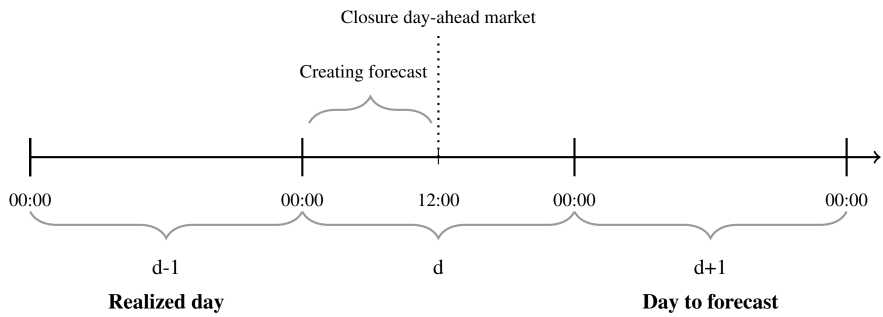


Figure 6.9: Forecasting horizon for the balancing market

Nord Pool publish production and consumption forecasts for day $d+1$ in the morning hours of day d. At the same time, market participants spend time on forecasting parameters such as the day-ahead market prices for $d + 1$. The balancing market forecast should thus be generated after all available information is collected, but before the closure of the day-ahead market in day d. The realized values in the period between 00:00 and the time of forecasting in day d, are not included in the analysis for simplicity. Thus, the data available when forecasting the balancing market, is forecasted values for day d and $d + 1$, and realized values for day $d - 1$.

6.3.2 Method

In addition to the correlation analysis of the potential input presented in Section 6.2, the relationship between the parameters and the balancing market is tested through multiple linear regression. Such analyses are also performed for their lagged values and processed versions. The indicators are calculated using logical statements based on the data. For instance, an expression returning 1 if the temperature is below a certain value, and lower than the day before. Neither the correlation analysis nor the regression analysis proves any significant relations, which leads to the method of trial and error. Trial and error is a common method to determine the input variables to an ANN. Szkuta et al. (1999) apply this method, and validate the selection of input by sensitivity tests. The sensitivity tests are done by varying one variable in the neural network at a time, while holding the remaining variables constant. A sensitivity analysis of including different input variables is conducted systematically, starting with the input which gave the most promising results in the market analysis.

Croston (1972) claims that since the Nordic balancing market has many hours with no imbalances, one should use time series models which distinguish between the occurrence of incidents (regulation or no regulation), and the size of the incidents. However, designing and training neural networks for prediction of the balancing market never has been done before. Thus, modeling the balancing state implicitly is considered as a good starting point for evaluating if ANNs are worth using. A negative volume implies downward regulation, while a positive volume implies upward regulation. The accuracy of the neural networks is tested when considering upward and downward regulation separately, which gives no improvements. In addition, considering the regulation states separately makes it difficult to exclude the possibility of forecasting both upward and downward regulation in the same hour.

To counteract the problem of overfitting when fine-tuning the neural networks, two different methods are used. Early stopping is the simplest method, which implies stopping the training when the cost function value of the training data decreases, and the cost function value for the test data starts to increase. The second method is the use of L2 regularization, which adds a fraction of the sum of the squared weights to the cost function. This is done to prevent large weights that are obtained when overfitting occurs.

6.3.3 Final Design

The input variables which proved to give the best accuracy of the ANNs, are presented in Table 6.7. Six parameters are used to predict the balancing market volume, and five parameters are used to predict the balancing market premium. Adding more input variables did not increase the accuracy.

Table 6.7: Exogenous factors included in the ANNs

Balancing Volume	Balancing Premium
Time and seasonal effects	Time and seasonal effects
Day-ahead market price (d)	Day-ahead market price forecast (d+1)
Consumption forecast NO (d+1)	Balancing volume forecast (d+1)
Production forecast NO (d+1)	Danish wind power forecast (d+1)
Temperature forecast (d+1)	Temperature change
Change in solar radiation	

Including the balancing volume as an explanatory variable in the forecast of the balancing premium, improved the performance of the ANN substantially. Volumes and premiums have a correlation of 0.53, so this was expected. As the volume forecast is not available for the training period, historical values representing a perfect forecast are used to train the network. However, the balancing volume forecasts generated using the ANN are used for validation.

The market analysis in Section 6.2 proves that there are considerable daily and yearly variations for the probability of each regulation state, and for the average level of volume and premium. Time effects are therefore included in the neural networks in multiple ways. In addition to accounting for the hour, the day of the year, and the month, a dummy variable indicating the season is included. No improvements in accuracy are detected by taking the day of the week into account. This is as expected, due to small weekly variations in the historical data.

The day-ahead market price proved to have a small influence on the accuracy of the ANNs, in spite of not showing any relation through the correlation or regression analysis. The realized price for day d affected the balancing market volume the most, while the forecast for day $d + 1$ proved to have the greatest influence on the balancing market premium.

Including forecasting errors gave no increase in performance. As realized data for day d and $d+1$ are not available at the time of forecasting, the most recent data for forecast errors have a lag of two days. The correlations are in that case not as depicted by the market analysis in Section 6.2. It would be interesting to include information about the level of uncertainty in the forecasts, as the forecast error proved to be highly correlated with the balancing market for some of the parameters. However, data regarding uncertainty in forecasts were not available in this analysis.

6.4 Forecasting Results

The design of the ANNs is based on minimizing the cost function represented by the RMSE. The performance of the neural networks described in Section 6.3, is thus measured by analyzing the RMSE of the generated forecasts. In addition, the share of correctly predicted states and the coverage of the forecasts, are analyzed. As mentioned in Section 6.2, the months from June to November have quite equal probability for upward and downward regulation, which makes it hard to predict the state of the balancing market during this period. Conejo et al. (2005) points out that prediction is difficult in periods with high volatility and spikes, such as the winter months.

The generated forecasts are compared to the observed values in the same period, and benchmarked against two naive forecasts; last value and no imbalance. The problem of outperforming naive forecasts is proven to be hard in both the day-ahead market (Conejo et al., 2005), and in the balancing market (Klæboe et al., 2015). The last value forecast uses the most recent balancing market data available as a forecast, which corresponds to the realized values for day $d-1$. The no imbalance forecast predicts that no regulation is needed in the system, leading the volume and premium to equal zero for all hours. The no imbalance forecast is a reasonable forecast in the case of an efficient balancing market, and is hereby referred to as the zero forecast. The evaluation of the forecasts is presented on a weekly basis, due to the large amount of data obtained. Hours with balancing market volumes below 10 MW are considered as hours with no imbalance, as all market participants have to bid at least 10 MW when participating in the balancing market.

6.4.1 State

Table 6.8 presents the historical distribution of balancing market states for the out-of-sample period, and the share of each balancing market state predicted by the ANN. The share of hours with upward and downward regulation are approximately equal in the observed data. The ANN predicts a substantial higher share of downward regulation, while it predicts no imbalance in only 35% of the hours in the period.

Table 6.8: Historical and predicted share of balancing market states

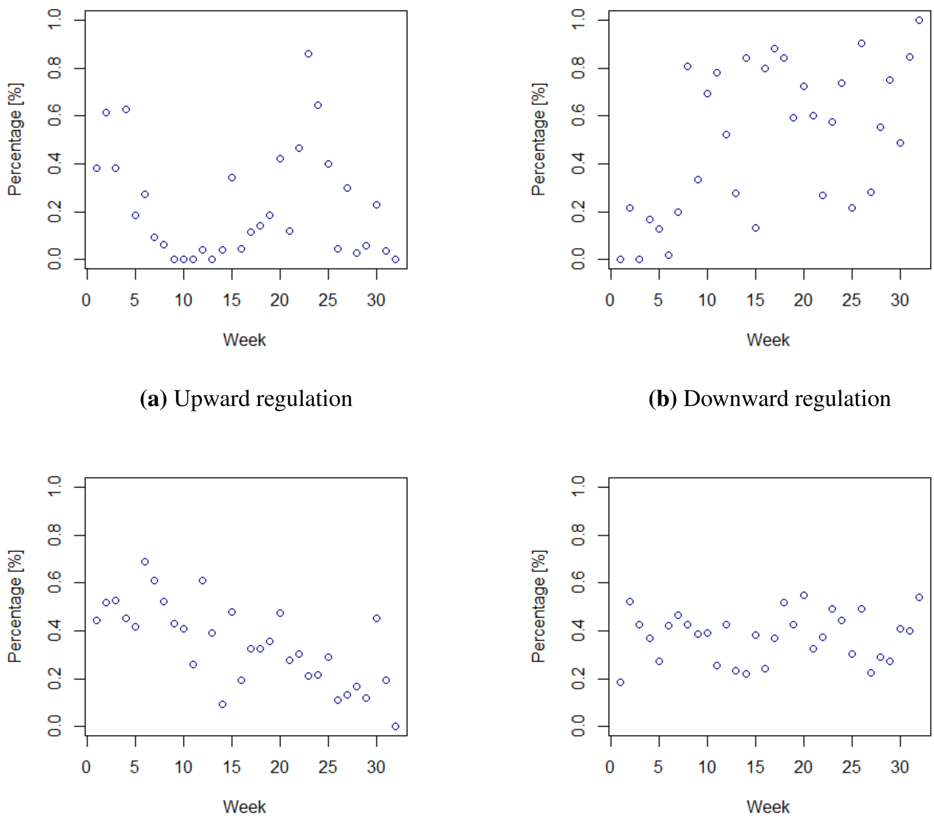
	Up	**Down**	**No**
Observed	24 %	26 %	50 %
ANN	19 %	46 %	35 %

The share of correctly predicted balancing market states for all three forecasts are presented in Table 6.9. The ANN predicts the right state in only 38% of the hours throughout the period, which makes it the least accurate forecast. However, a maximum share of 37% correctly predicted states was obtained in the benchmarking of models presented in Klæboe et al. (2015). The period from January 2, 2013 to March 22, 2013 was used for out-of-sample verification in the article, in which the number of observed downward regulation hours was more than double the number of upward regulation hours.

Table 6.9: Share of correctly predicted balancing market states

	Up	**Down**	**No**	**Total**
ANN	23 %	53 %	37 %	38 %
Zero	0 %	0 %	100 %	50 %
Last value	28 %	26 %	53 %	40 %

The share of correctly predicted states by the ANN per week is plotted in Figure 6.10. The ANN rarely predicts upward regulation correctly, while a positive development in the share of correctly predicted states for downward regulation can be observed. However, the ANN has a negative development in its ability to predict the no regulation state towards the end of the period.



(a) Upward regulation

(b) Downward regulation

(c) No regulation

(d) Total state accuracy

Figure 6.10: Weekly average share of correctly predicted balancing market states

6.4.2 Volume

Descriptive statistics of the predicted balancing market volumes are presented in Table 6.10, as well as for the historical values in the same period. The observed values have a standard deviation drastically higher than the forecasted values. The observed and predicted volumes are plotted in Figure 6.11. The ANN is not able to capture the extreme spikes seen in the historical data, and a range which is substantially more narrow. From the plot, it can be seen that the yearly variations affect the forecast. A higher share of downward regulation is predicted in the winter months, in addition to larger volumes in both directions. This coincides with the market analysis in Section 6.2, which suggest that downward regulation occurs more often than upward regulation during the winter months. The forecast is able to capture some of the spikes during this period.

Table 6.10: Descriptive statistics of the balancing market volumes

	Mean	SD	Med.	MAD	Min	Max	Range	Skew.	Kurt.	SE
Observed	-2.72	84.70	0	4.45	-832	606	1438	-0.39	11.13	1.18
ANN	-10.94	27.65	0	22.97	-145	136	281	-0.58	2.19	0.39

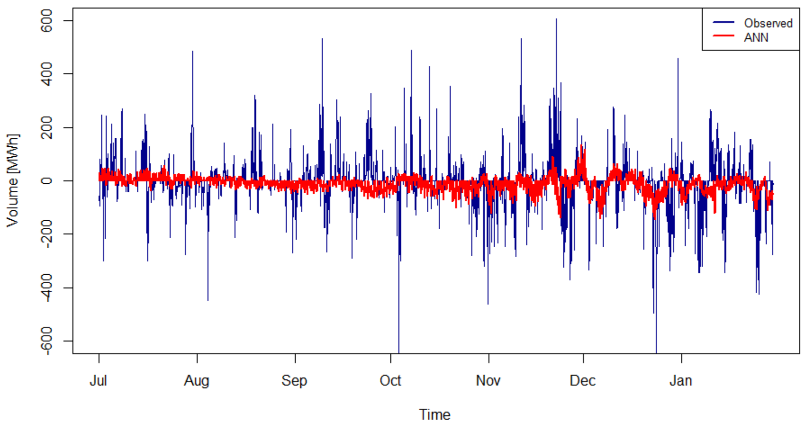


Figure 6.11: Observed and predicted balancing market volume

An important aspect of evaluating the generated forecasts, is measuring its ability to capture the level and distribution of the observed values. This is measured by the share of historical values which falls within given intervals. The intervals are specified by the median of the forecasted values, adding and subtracting half of the range, and multiplying with a given share. The results are presented in Table 6.11. From the table, it is observed that 80% of the data falls within 50% of the range of the forecasted values. When the same analysis is done for the historical range, 99.4% of the values fall within 50% of the range. The generated forecast is hence very narrow compared to the historical range. Only 90.5% of the forecasted values fall within 99% of the range, meaning that the forecast does not capture the spikes well.

Table 6.11: Percentage of observed balancing volumes within intervals specified by the median of the forecasted values and different shares of the range

	50 %	75 %	90 %	99 %
ANN	80.3 %	86.4 %	89.5 %	90.5 %

Table 6.12 presents a weekly comparison of the RMSE for the generated forecast and the two naive forecasts. The last value forecast performs poorly throughout the period, and only outperforms the ANN forecast in week 26 and 38. The ANN forecast produce the lowest RMSE in 9 of 32 weeks, whereas the zero forecast perform best in 23 of 32 weeks. However, the level of the RMSE for the ANN and zero forecast are quite similar. As 50% of the balancing volume throughout the period is equal to zero, it is not surprising that a zero forecast is hard to outperform.

Table 6.12: Weekly root mean square error of the volume forecast compared to naive forecasts

w	ANN	Zero	Last value
26	101.2	92.8	92.8
27	64.3	68.5	99.0
28	79.5	76.6	89.0
29	36.1	35.0	85.7
30	87.8	86.9	104.2
31	61.1	58.9	110.7
32	36.3	34.5	42.4
33	70.0	69.8	84.5
34	34.8	28.6	71.7
35	63.3	61.1	85.1
36	102.9	99.9	118.1
37	86.1	86.4	153.8
38	102.2	90.3	100.9
39	52.8	36.5	81.6
40	130.2	127.3	172.4
41	74.2	66.7	100.6
42	56.6	47.0	71.6
43	53.1	59.9	74.6
44	94.9	99.2	132.3
45	117.3	121.7	161.7
46	51.3	45.5	125.3
47	153.5	147.0	197.2
48	64.9	72.7	109.3
49	61.8	57.3	75.9
50	66.6	58.6	88.4
51	108.2	131.4	139.9
52	129.9	119.0	199.2
1	100.8	99.4	131.0
2	115.7	102.7	145.6
3	51.7	50.2	100.0
4	104.1	115.6	162.5
5	76.4	87.7	90.8

6.4.3 Premium

As explained in Section 6.3, the historical balancing volumes are used as input in the training of the ANN predicting the balancing premiums. However, historical balancing volumes are not available when forecasting the premium. Thus, the balancing volume forecast generated by the ANN is used for out-of-sample verification. The volume highly affects the weights and biases of the resulting ANN, so if the volume forecast performs poorly, the premium forecast performs poorly as well. Table 6.13 presents a comparison of the descriptive statistics of the forecasted values and the historical values for the balancing market premium. Again, the standard deviation for the observed values is clearly higher than for the predicted values.

Table 6.13: Descriptive statistics of the balancing market premiums

	Mean	SD	Med.	MAD	Min	Max	Range	Skew.	Kurt.	SE
Observed	-0.69	6.51	0	4.31	-66	145	211	6.58	136.14	0.09
ANN	-0.89	2.79	-0.21	2.04	-16	11	27	-1.14	2.60	0.04

The observed and predicted balancing market premiums are plotted in Figure 6.12, in which it is clear that the observed values are characterized by much higher spikes than the forecast. However, the forecast seems to be better at matching the highest spikes in the winter months.

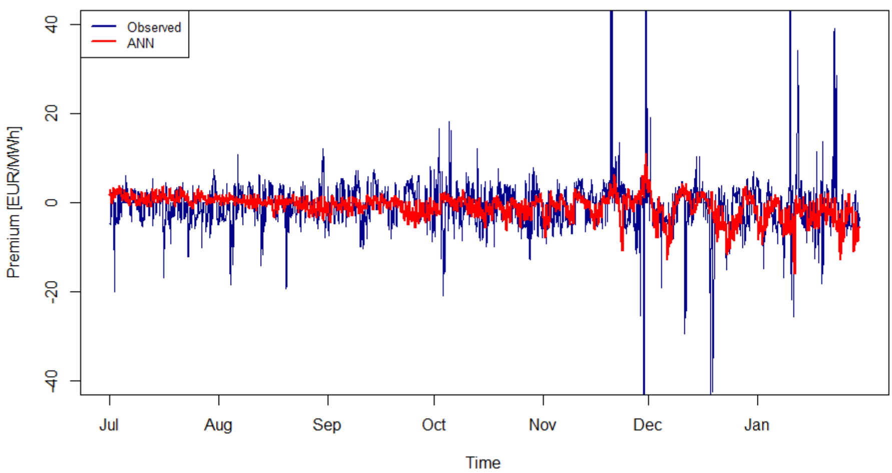


Figure 6.12: Observed and predicted balancing market premium

The predicted premiums are evaluated in the same manner as the balancing volumes, to measure the ability of the forecast to capture the level and distribution of the observed values. The results are given in Table 6.14. Over 90% of the historical premiums fall within 50% of the forecasted range, and almost 98% of the historical values fall within 99% of the range. This means that the forecasted range captures most of the historical data. Extreme spikes are hard to predict, due to the risk of very large RMSE.

Table 6.14: Percentage of observed balancing market premiums within intervals specified by the median of the forecasted values and different shares of the range

	50 %	**75 %**	**90 %**	**99 %**
ANN	91.5 %	96.3 %	97.2 %	97.7 %

Table 6.15 presents the weekly RMSE of the premium forecast and the two naive methods. Again, the last value forecast performs poorly, and is outperformed in most weeks. The zero forecast has the lowest RMSE in 22 of 32 weeks, while the forecast generated by the ANN performs better in 9 of 32 weeks. From Figure 6.12 it is clear that the forecasting method is not able to predict the highest spikes, but also that the forecast captures some of the trends in the market.

Conclusively, the forecast generated by the ANN struggles with outperforming the naive method of predicting zero. However, the last value forecast is outperformed in most weeks. This supports the results in Klæboe et al. (2015), which find that the mean average error of the generated forecasts are on the same level as predicting zero. However, they emphasize that the generation of forecasts is not futile. The forecasts can provide an idea of the shape of the distribution, which is important for making good operational decisions in a bidding situation. The forecast generated by the ANN, and the zero forecast, are further evaluated by using them as input to the stochastic bidding model presented in Chapter 5. The forecasts are used indirectly, as they are input to a forecast-based scenario generation method.

Table 6.15: Weekly root mean squared error of premium forecast compared to naive forecasts

	ANN	Zero	Last value
26	7.16	5.66	5.66
27	2.77	2.41	4.50
28	4.39	3.60	4.37
29	4.12	3.46	4.94
30	3.97	3.42	4.09
31	4.84	4.39	5.95
32	3.45	3.26	4.09
33	4.41	4.32	6.03
34	2.35	2.23	4.91
35	4.49	3.79	5.55
36	4.26	3.95	4.61
37	3.35	3.43	6.00
38	4.58	3.24	4.13
39	4.80	3.82	4.82
40	7.35	6.85	10.49
41	4.80	4.42	5.91
42	4.16	3.40	4.07
43	3.66	4.69	5.24
44	4.15	4.24	5.76
45	3.41	3.85	5.32
46	3.33	3.33	5.56
47	14.40	14.46	19.29
48	16.42	17.18	24.47
49	4.13	4.35	4.96
50	7.26	6.42	9.31
51	10.08	10.87	14.15
52	5.71	4.08	7.87
1	4.75	4.43	6.75
2	13.77	12.99	18.16
3	5.18	5.43	7.39
4	9.61	8.22	11.89
5	3.33	3.97	2.59

Chapter 7

Computational Study

A computational study is carried out in order to evaluate the practical performance of the coordinated bidding model presented in Chapter 5. The performance of an optimization model is difficult to determine based on a single run of the model, so a backtest procedure is implemented to test the performance of a coordinated bidding strategy over time. Section 7.1 presents the implementation of the backtesting procedure, and the process flow indicating how the different steps of the process interact with each other. Scenario trees for the stochastic parameters are generated by the method presented in Section 7.2, in which the number of scenarios needed to ensure a stable solution is determined. Section 7.3 describes the topology of the water system used as a basis for the case study, and the determination of other input data. Performance measures and different cases which are tested are explained in Section 7.4. The results are presented in Section 7.5, and further discussed in Section 7.6.

The optimization models are implemented in Xpress-IVE 64 bit using Xpress-Mosel, and solved with Xpress-Optimizer. The backtesting procedure is implemented using Python 2.7, and run on computers with an Intel Core i7-7700 3.60GHz CPU and 32.0 GB installed RAM.

7.1 Implementation

The following section describes the implementation of the backtesting procedure. The backtest simulates the real-life performance of a bidding strategy over time, without any risk of loss for the hydropower producer in the case of a poor strategy.

7.1.1 Framework

When evaluating performance of an optimization model, one should look at the consequences of following the model decisions. The evaluation of a decision made under uncertainty is dependent on the stochastic processes, which can have an infinite number of realizations. An optimal solution of the bidding problem is only optimal given that the market prices follow the discrete stochastic process given by the scenario tree. The main output from the models are the bids, so the performance is evaluated using the obtained bid curves, and calculating the resulting commitments and profits when applying the historical realizations of the market prices.

To test the practical performance of the model with realized market prices, the model is executed in three parts. The first model is the exact model as described in Chapter 5, for which all market prices and balancing market volumes are uncertain. To mimic the sequential clearing of the markets, the day-ahead market decisions are the first to be submitted. The day-ahead bid curves are thus saved as output from the first model. To calculate the commitments in the day-ahead market, these bid curves are used as input in the second optimization model, along with the realized day-ahead market prices. If interpolation with the realized market prices leads to commitments which are lower than the minimum production capacity, the commitments are set to zero. This is due to the solution in such cases are being infeasible. By setting the commitments to zero, this is considered as a penalty of committing an infeasible volume, by not being able to produce. The bid curves for the balancing market are then re-optimized according to the commitments in the day-ahead market, and further saved as output. The last deterministic run of the optimization model uses the balancing market realizations, in addition to the day-ahead commitments and balancing bid curves as input. This is used to calculate the commitments in the balancing market, in addition to optimizing the production allocation.

A similar model is also implemented for a sequential bidding strategy. When using a sequential bidding strategy, the markets are considered in the same order as they are cleared. As the day-ahead market clears first, the first model optimizes the bid curves for the day-ahead market without considering the opportunities in the balancing market. The second and third model are the same as for the coordinated bidding strategy explained above. When including realizations of the uncertain parameters, it can be random which of the models that perform best. Evaluation over time gives more informed results, as it is easier to excludes wrong conclusions regarding bidding strategies based on random luck. The framework used in the case study for both bidding strategies is illustrated in Figure 7.1. The input with a dashed perimeter is specific for each of the strategies, while the other input is the same in both strategies. The two bidding models are hereby referred to as the

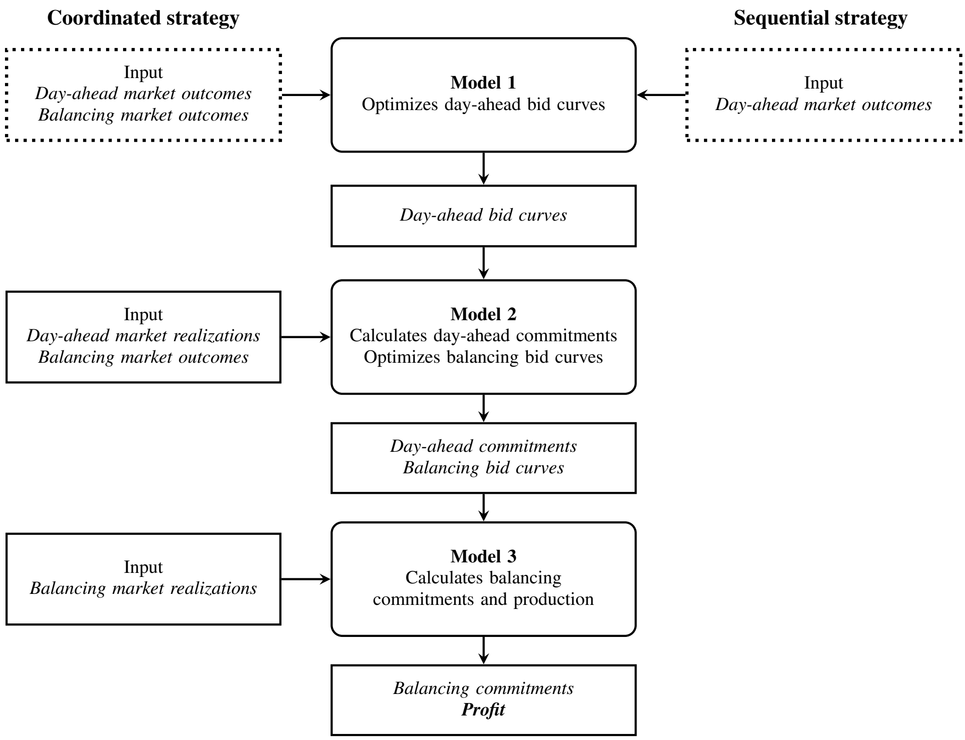


Figure 7.1: Case study framework for a coordinated and sequential bidding strategy

coordinated and the sequential model.

7.1.2 Procedure

The backtesting procedure consists of several steps in which different programs are used. The fundamental feature of the backtest is to simulate the performance of the bidding strategies for several consecutive days, when applying historical data. For each day in the sample period, the optimization models are run in three parts as described above. The results are saved, and the day counter is incremented by one, before the procedure is repeated for the next day. Some of the results from the third model are used as input for the next day in the sample period, such as production plan for the bidding day and reservoir levels. The water value is updated every Tuesday in the period, which is considered as the start of a new week in the backtesting procedure. The input with a dashed perimeter is updated every day of the sample period. The daily updated input includes the market prices, balancing market volumes, and inflow, which are time series shifted one day ahead according to the range of the planning horizon of the model. The flow chart for the simulation procedure is illustrated in Figure 7.2.

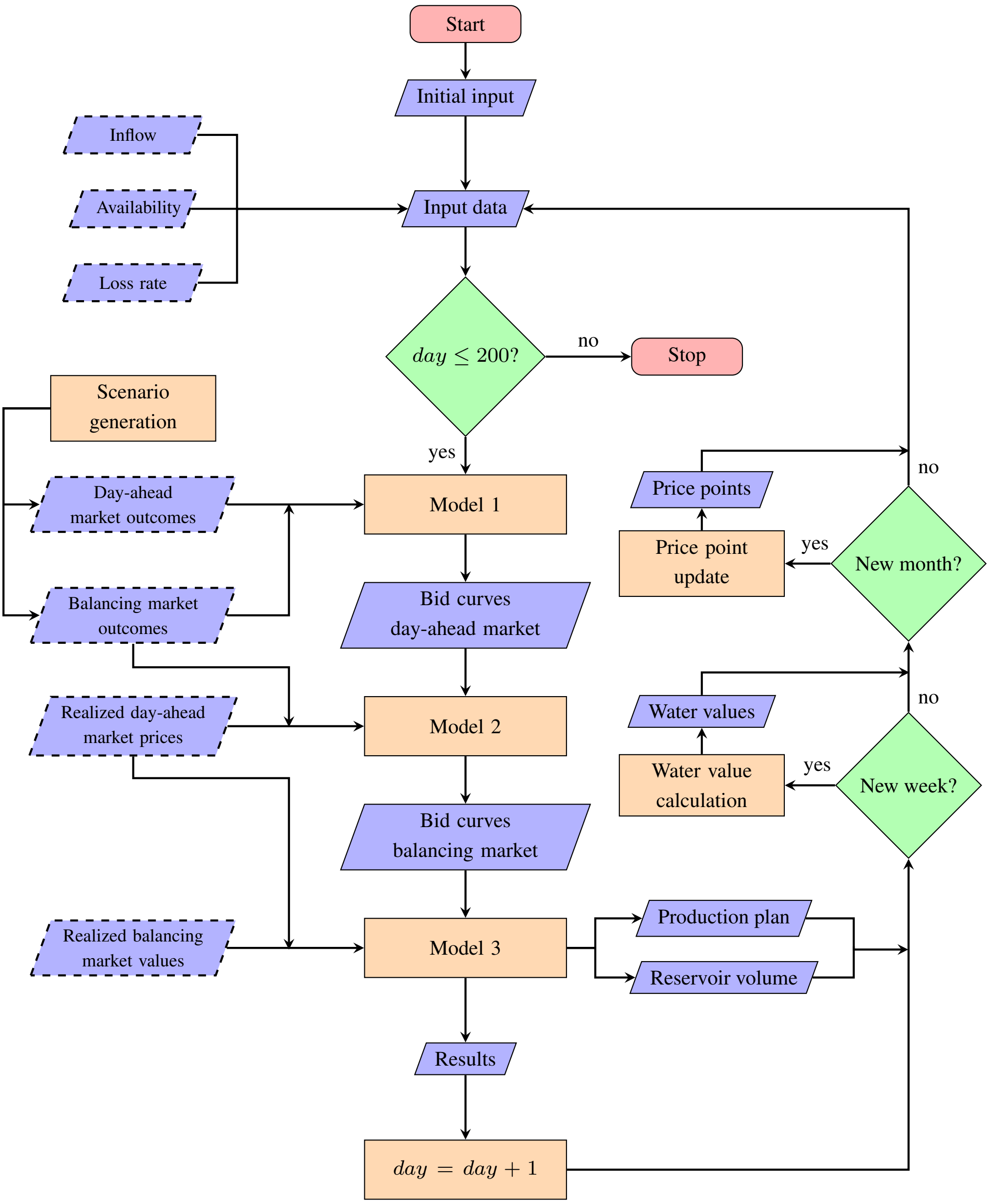


Figure 7.2: Flow chart for the backtesting procedure

7.2 Scenario Generation

Most of the standard scenario generation methods today require a substantial amount of input data to describe the stochastic parameters. Kaut (2017) recently introduced a method that uses a single forecast for the uncertain future to generate scenarios, in combination with historical forecasts and realized data. The historical error between the forecast and the realization is used to generate scenarios, with a distribution that covers the actual observed uncertainty. As day-ahead market price forecasting already is a natural decision aid for hydropower producers, such forecasts can be obtained by an industrial partner. Thus, only a balancing market forecast is needed in order to utilize this method in the thesis. The forecasts developed in Chapter 6 is used.

The process of generating the range of outcomes for both the second- and third-stage nodes are throughout this section referred to as scenario generation, despite that a node formulation is used. The scenario generation tool is developed by Michael Kaut at NTNU/SINTEF, and has been provided to us by NTNU in the form of an EXE file that uses JSON files as input. The reader is referred to Kaut (2017) for details of the method.

7.2.1 Initialization

The period chosen as the validation data in Chapter 6, is further used as the period of the future forecast in this chapter. In addition, forecasts are developed in the same manner for the historical period, as the scenario generation tool requires historical forecasts to calculate the forecast errors. The length of the period with historical forecasts is limited due to the need of training data for the ANN. However, 18 months are considered more than sufficient for the method. Historical market prices and volumes from the same period are used to calculate the forecast errors.

In the forecasting of the balancing market, a version of the day-ahead market price is used as an explanation factor in both the premium and volume forecast. This dependence should also be included in the scenario generation, by making the possible outcomes of the balancing market dependent on the possible outcomes of the day-ahead market. However, the scenario generation tool is not able to capture such dependencies, which is a limitation of the tool. The only way to overcome this problem, is to create a balancing market forecast and than scenarios, for each possible outcome of the day-ahead market. The dependency of the scenarios is thus neglected, as it leads to an impracticable run time. However, the sum of the balancing premium and the day-ahead market price yields different balancing market prices for every day-ahead outcome. The balancing volume outcomes are however equal for each of the day-ahead market price outcomes. As the dependency seems to be small, it is assumed to be a reasonable assumption.

As explained in Chapter 5, this is a three-stage stochastic problem. The number of possible outcomes for the second-stage and third-stage nodes are used as input in the scenario generation procedure, such that $|\mathcal{S}| \cdot |\mathcal{C}_s|$ number of scenarios is obtained. The first 24 hours of the coordinated model are considered deterministic with a predetermined production, so the branching in the scenario tree begins the first hour of the bidding day. Possible outcomes of the day-ahead market price are generated for thirteen days forward. All generated outcomes for the day-ahead and balancing market are equiprobable. Figure 7.3 illustrates the scenario tree which is developed for each day in the backtesting period. One dot represents 24 hours, where the first 24 hours are deterministic. The next 24 hours represents the bidding day, where both day-ahead market outcomes and balancing market outcomes are included. For future days, only day-ahead market outcomes are present.

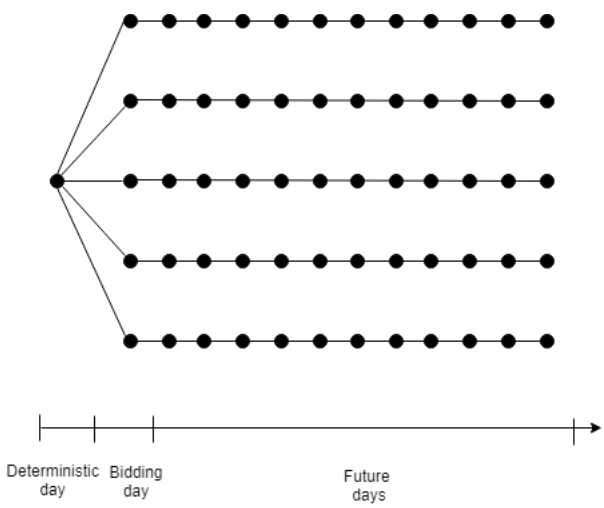


Figure 7.3: Scenario tree illustrating each day of the backtesting period

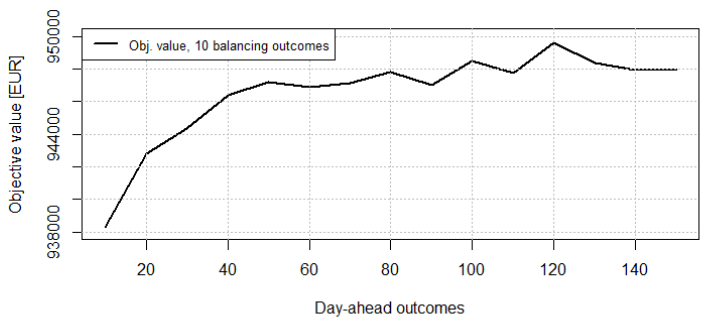
7.2.2 Evaluation

Kaut and Wallace (2007) point out that when evaluating scenario generation methods for stochastic programs, the focus is on the practical performance of the scenarios. The goal is not necessarily to search for a discretization of a continuous distribution that is good in a statistical sense, but which performs well in real-life problems. If the discretization leads to good decisions in the model, it is not that important how well the scenario generation method approximates the true distribution. The error of approximating a random vector with a discretization is given by the optimality gap (Kaut and Wallace, 2007). The gap is defined as the difference in the objective function values for the true and approximated problems, and is approximately zero for a scenario generation method that performs well. Testing this requirement is in most practical problems impossible, so weaker requirements for the scenario generation method are used.

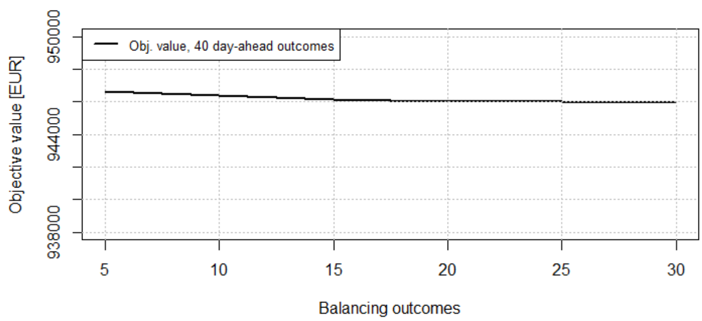
A common requirement for a scenario generation method is stability, which implies obtaining approximately the same objective value if the problem is solved several times with different scenario trees generated from the same input. The scenario generation method should in other words not affect the solution of the model, as it should be the model, and not the discretization of probability distributions, that drives the results (King and Wallace, 2012). The requirement of stability is based on the assumption that many common scenario generation methods are random, and generate different scenario trees if run several times with the same input. The scenario generation method presented here is not itself random, which means that the exact same scenario tree will be produced each time the method is run with the same data. The only source of instability with methods that does not include randomness, is the number of scenarios (Kaut and Wallace, 2007). Stability can thus be evaluated by comparing the objective values when running the model with two different scenario trees $\hat{\xi}_k$ and $\hat{\xi}_l$, as described by (7.1). Varying the number of scenarios is a test for in-sample stability, as the solutions are evaluated on the sample (tree) they came from (Kaut and Wallace, 2007). The requirement of in-sample stability is a test of internal consistency (King and Wallace, 2012).

$$\hat{F}_k(\hat{x}_k^*) \approx \hat{F}_l(\hat{x}_l^*) \tag{7.1}$$

The coordinated model is run for many different scenario sets, and both the number of day-ahead market outcomes and the number of balancing market outcomes are varied. The objective value for different numbers of day-ahead market outcomes is plotted in Figure 7.4a. The objective value seems to stabilize around 140 day-ahead market outcomes when using 10 balancing market outcomes. However, the objective value does not change much going from 40 to 140. Thus, the number of day-ahead outcomes is set to 40 for computational tractability. The number of balancing market outcomes have a negligible effect on the objective value, as can be seen from the plot in Figure 7.4b. Due to computational reasons, 10 balancing market outcomes is chosen. This is also used in several other studies (Faria and Fleten, 2011; Klæboe et al., 2018).



(a) Varying the number of day-ahead market outcomes



(b) Varying the number of balancing market outcomes

Figure 7.4: Stability evaluation by measuring the objective value for varying number of scenarios

7.3 Case Description

The case study is based on a specific watercourse located in the southern parts of Norway. Technical and historical data for the system is provided by the industrial partner.

7.3.1 Topology

The water system consists of four reservoirs in cascade. Figure 7.5 illustrates the topology of the system. Water may be released from reservoirs either as production discharge through the power stations, as bypass, or as spill. In this system, there is only one power station, which is located at the lowest reservoir. The power station contains one generator, with a given efficiency curve and production capacity. The remaining reservoirs are not connected to power stations, so these are modeled as dummy stations with zero efficiency and zero production capacity. Water can be sent as discharge without producing power, which corresponds to bypass. For reservoir four, there is no option of bypass.

Spill occurring in the upper reservoirs is led to the reservoirs below, while spill in the last reservoir is considered lost from the system. The maximum discharge for each of the upper reservoirs is set equal to the discharge in the situation with a reservoir volume which corresponds to 50% of the highest regulated water level, and wide-open sluice gates. The generator has a minimum and maximum capacity of 16 MW and 80 MW, and a best efficiency point of 60 MW. The corresponding discharge for each production point is given by the production-discharge curve, illustrated in Figure 7.6. The effects of elevation are as mentioned neglected. The production-discharge curve is thus based on the historical average water level, instead of using different curves for different levels.

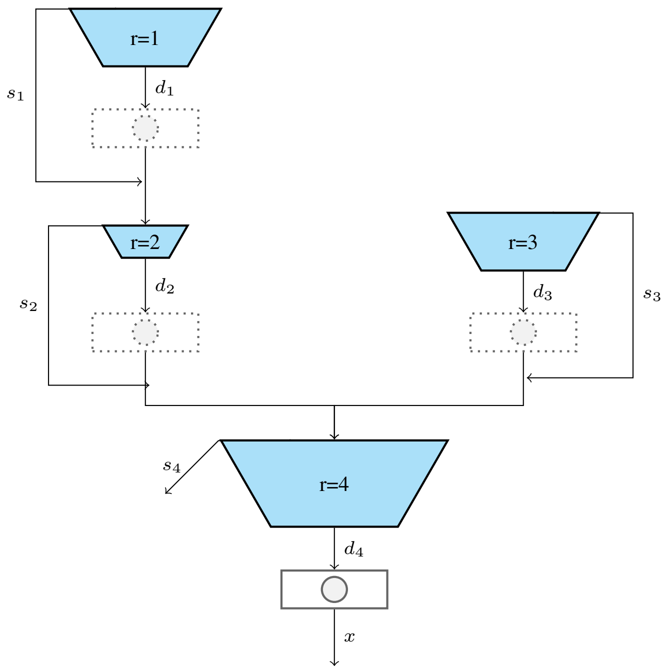


Figure 7.5: Topology of the water system

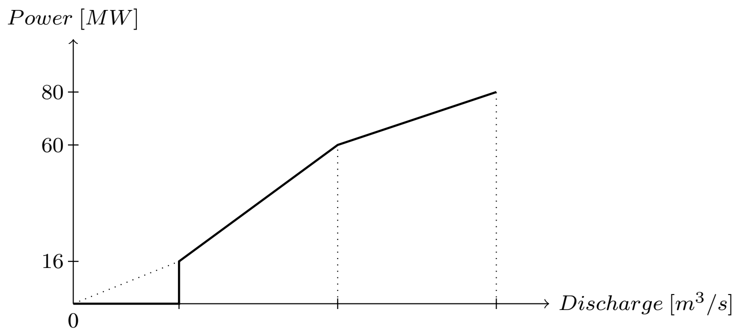


Figure 7.6: Power/discharge curve at the historical average water level in reservoir four

7.3.2 Input data

The backtest is run with the setup described in Section 7.1. Before the backtesting can begin, the time span for the test needs to be decided. The sample period should be long enough to fulfill the criteria of being representative statistically, so that the evaluation of the model performance is not too affected by seasonal effects or random events. Ideally the period should include all possible variations. Due to computational reasons, a sample period of 200 consecutive days is considered sufficient, from July 1, 2017 to January 16, 2018. This period does not include aspects such as dry and wet years, but most other seasonal variations. The procedure starts by initializing a day counter to zero for the first day of the sample period.

Scenario trees are used as input to the backtesting procedure, and are generated as presented in Section 7.2. Scenario trees for every day of the test period are generated in advance, as the scenario generation is not dependent on output from the models. When the realizations of the uncertain day-ahead market prices are revealed, the actual market prices replace the part of the forecast that represents the next day. As the scenario generation procedure is carried through, the planning horizon is rolled 24 hours forward. Each scenario tree for the test days represents the possible outcomes throughout the planning horizon of the model, including the first deterministic day in each run. The scenario trees are saved as input files for each day, both before and after the realized day-ahead market price is known.

As the first day of the testing period is deterministic, the historical reservoir levels and the industrial partner's production plan for the first day, are used for initialization. For the remaining period, historical values for inflow, water values, and feed-in fees are used in the models. The historical weekly water values in the period are extrapolated to fit the water level in the given case situation. The water values are updated every Tuesday during the backtesting period, as they do in the industry.

Due to computational tractability, only three blocks ($B = 3$) are included in the case study. The hours in the day are divided into blocks in the following manner: $b_1 = \{1, \ldots, 8\}$, $b_2 = \{9, \ldots, 16\}$, and $b_3 = \{17, \ldots, 24\}$. The choice of these hours in particular is due to the industrial partner using these three blocks for most hours. The hours in block b_1 are characterized by low day-ahead market prices and higher chances of downward balancing. By a coordinated bidding strategy, it can be profitable to commit high volumes in the day-ahead market, in order to be able to regulate down in the balancing market. This is not taken into account in a sequential bidding strategy, and it is thus interesting to evaluate the gain of coordinated bidding while including block bids. The hours in block b_2 are characterized by high day-ahead prices, while the day-ahead market price decreases again in b_3.

The number of bid points highly affect the run time of the model. Due to computational tractability, ten bid points are chosen. This is also the number used by Boomsma et al. (2014). The price points are set to represent the historical distribution of the market prices, and are calculated by dividing the historical data into eight quantiles. In addition, minimum and maximum points are set according to the market rules, which gives ten bid points in total. As the market prices varies throughout the year, the quantiles are recalculated monthly based on the historical data.

As explained in Chapter 5, the demand in the balancing market is limited. The forecasted balancing market volume is further restricted by the hydropower producer's market share, which is introduced as a parameter. In the case study this market share is set to 100%. As explained in Chapter 6, the volumes forecasted are relatively small compared to the realized volumes.

7.4 Analyses

The performance and behavior of the coordinated model is compared to the sequential model, and historical data provided by the industrial partner. Several measures for bidding model performance are used. During a backtesting procedure, the daily results depend highly on the decisions from the days before. Even if two cases have the same starting point the first day, big variations in the results can arise during the backtesting procedure. The two cases will therefore not have the same premises on a daily basis. Thus, the evaluation of the models is mostly based on the results from the entire backtesting period as a whole. The coordinated model is run with the scenarios described in Section 7.2, which is referred to as the base case. The model is also run with different degrees of information regarding the balancing market.

7.4.1 Gains of Coordinated Bidding

A major part of the objective value from the coordinated model consists of the revenues from future production, and the value of the remaining water in the reservoirs after the short-term horizon. The inclusion of these end-of-horizon terms, is mainly to ensure that the model also sees opportunities in the future. Otherwise, the production would be at maximum capacity throughout the day of operation. However, these terms are not realistic data which should be included in the evaluation of the practical performance of the coordinated model. The gains of coordinated bidding is thus quantified by considering the accumulated profits in the hours of operation for the whole testing period, and the calculation of this measure is presented in equation (7.2) below. The total value obtained is defined in (7.3). Note that the marginal loss cost is taken into account in the market revenues. The value of the water remaining in the reservoir in the last hour of operation, is included in the calculation of the total value. The water can be seen as the stock for the hydropower producer, and represents the possible earnings in the future for each of the models. The value of the water is calculated as the sum of the reservoir volumes, multiplied with their respective marginal water values and the energy equivalent. To have a comparable measure, the historical marginal water values are used for this calculation.

$$Accumulated\ Profits = Sum\ of\ Market\ Revenues - Start\ Costs \tag{7.2}$$

$$Total\ Value = Accumulated\ Profits + Water\ Value \tag{7.3}$$

A common measure of bidding model performance is the obtained average price, which is calculated by dividing the sum of market revenues by the total production in the period (7.4). While the total value and accumulated profits illustrate the ability of the model to utilize the water in the best possible way, the obtained average price is a measure of how well the bidding strategy adjusts the production allocation according to the market prices. Producing at high prices in the day-ahead market, and utilizing high premiums in the balancing market, increases the obtained average price.

$$Obtained\ Average\ Price = \frac{Sum\ of\ Market\ Revenues}{Total\ Production} \tag{7.4}$$

The same measures are used to compare the results from the sequential model, and historical data from the industrial partner. The industrial partner use a sequential bidding strategy, and include block bids in the day-ahead market. However, more aspects are considered in the planning of real-life operation than what is included in the implemented models. The historical data is thus not completely comparable to the results from the coordinated and sequential model, but is included as a way to validate the results from the models.

When evaluating the coordinated model, it is interesting to evaluate in which cases coordinated bidding is most valuable. Kongelf and Overrein (2017) discuss the effects of the deviation between the water value and the realized day-ahead market price, when evaluating the gains of coordinated bidding. They define a measure referred to as absolute price-water-value squared deviation (PWSD), which is calculated as described by (7.5). The realized day-ahead market price in hour t is denoted $\tilde{\rho}_t^D$, and the water value is represented by W. Evaluating this measure, they find that the gains of coordinated bidding are higher for days in which the day-ahead market price approaches the water value. This measure is further analyzed, and compared to the results of Kongelf and Overrein (2017).

$$PWSD = \sqrt{\frac{1}{24}\sum_{t=1}^{24}(\tilde{\rho}_t^D - W)^2} \tag{7.5}$$

7.4.2 Information Regarding the Balancing Market

A great amount of effort has been put into developing an hourly forecast for the balancing market volume and premium. Such information is essential for a coordinated bidding strategy to perform well, but has been proven to be hard to generate. To evaluate the effect of having a balancing market forecast, the results from the coordinated model are compared with two other cases. The same performance measures as described above, are compared for the different cases.

The first case is based on using the zero forecast described in Chapter 6, as input to the scenario generation tool in Section 7.2. Using this forecast gives no new information about the future, but provides a scenario tree with the historical distribution of the volumes' and premiums' deviations from zero. As described in Chapter 6, the zero forecast is reasonable, as there often are no imbalances in the system. The value added of taking the time to develop a balancing market forecast can thus be evaluated. The other case considered in this study, has perfect information regarding the balancing market. Hence, the added value of knowing the exact outcome of the balancing market, before bidding in the day-ahead market, is evaluated. The possible day-ahead outcomes remains the same for all cases, to evaluate the effect of the balancing market only. The base case with scenarios generated using the ANN forecast, is referred to as the ANN case. The two other cases are referred to as the zero case, and the perfect information case.

7.5 Case Results

The results are presented in three parts. First, the evaluation of the base case based on the different performance measures is presented. The results are compared to the corresponding sequential model, and a simpler version of the coordinated model which excludes the option of block bids. No significant gain is observed by including block bids, thus block bids are excluded for the rest of the case study due to computational reasons. Second, the performances of the implemented models are compared to the historical behavior of the industrial partner. During the historical period which the backtest corresponds to, the generator was unavailable for larger time intervals. Thus, the historical availability is taken into account in the models. In this analysis, a comparison of the performance for the base case, the zero case, and the perfect information case is presented. Availability is reset to 100% in all hours when evaluating the effect of different degrees of information about the balancing market, as the goal is to evaluate as many days as possible for each run of the backtest.

7.5.1 Evaluation of the Coordinated Bidding Model

The resulting total value, accumulated revenues, accumulated costs, and the end-of-horizon water value, are presented in Table 7.1. An insignificant gain of 0.07% in total value is obtained when comparing the coordinated model with the corresponding sequential model. It can be observed that the coordinated model utilizes the balancing market more. Thus, it obtains higher revenues from upward regulation, but also higher costs from downward regulation. The sequential model obtains higher revenues in the day-ahead market, which is not surprising. It allocates the optimal amount of capacity for the day-ahead market first, thus there is a restriction on the idle capacity which can be used in the balancing market. The results show that the sequential model obtains lower start-up costs than the coordinated model, which is somewhat unexpected for a coordinated strategy which takes both markets into account during the bidding process.

Table 7.1: Total value, accumulated revenues/costs, and water value for the base case

	Total value [EUR]	Total DAM [EUR]	BM Up [EUR]	BM Down [EUR]	Start-up costs [EUR]	Water value [EUR]
Coord.	8 989 317	5 689 961	310 103	-202 947	-22 750	3 214 950
Seq.	8 982 848	5 748 011	211 139	-176 254	-21 775	3 221 726
Gain [%]	0.07					

The gain from the coordinated model is more pronounced in the comparison of obtained average prices. The coordinated model has 0.17% higher obtained average price than the corresponding sequential model, as presented in Table 7.2. This difference indicates that the coordinated model is slightly better at adjusting the power production according to the market prices which maximizes the total revenues.

Table 7.2: Obtained average prices for the base case

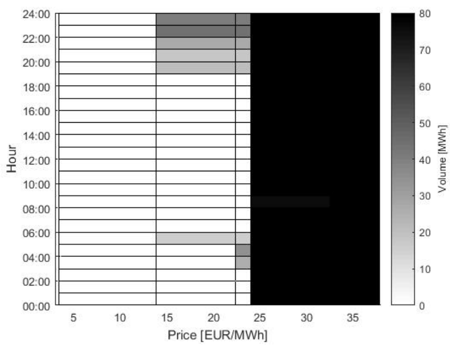
	Obtained average price [EUR/MWh]
Coord.	30.63
Seq.	30.57
Gain [%]	0.17

The resulting total production for both models, and the commitments in each market, are presented in Table 7.3. The results show that the coordinated model produces more than the sequential model, which coincides with the lower end-of-horizon water value. Hourly bids make up most of the production for both models, but block bids are also used to some extent. The sequential model has the highest volume of block commitments, which may explain the lower start-up costs presented in Table 7.1. The largest deviation registered is between the commitments for upward regulation in the balancing market. The coordinated model may hold back capacity in the day-ahead market in order to provide regulation services in the upward balancing market.

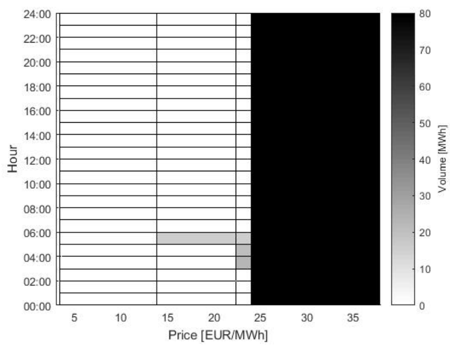
Table 7.3: Total production and commitments in each market for the base case

	Total production [MWh]	Total DAM [MWh]	DAM hourly [MWh]	DAM block [MWh]	BM up [MWh]	BM down [MWh]
Coord.	189 275	189 753	144 281	45 472	8 769	9 247
Seq.	189 139	190 566	142 610	47 956	6 487	7 913

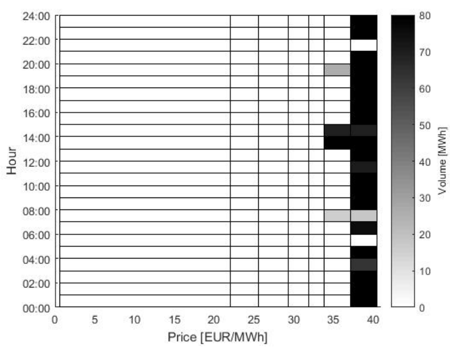
Optimal bid matrices in the day-ahead market are presented in Figure 7.7. The matrices in the figure are divided into columns representing price points, and rows representing the hour of the day. The color intensity represents the size of the bid volumes. Remember that the bid volumes are represented as accumulated values for a given price. From the figure, it can be observed that the bid curves are qualitatively different in the two models. In day 84 of the backtest, the outcomes for the balancing market imply that there is a possibility for downward regulation. From Figure 7.7a and Figure 7.7b it can be observed that the coordinated model bids at lower prices than the sequential model, most likely in order to provide regulation services in the downward balancing market. Conversely, upward regulation is expected in day 99. The sequential model does not see this expectation when placing bids in the day-ahead market. Figure 7.7c and Figure 7.7d illustrate that the sequential model bids at lower prices in the day-ahead market, while the coordinated model holds back capacity in order to provide upward regulation. Note that the models do not represent the exact same case, as the results are dependent on decisions in previous days. The differences in bidding behaviour can thus also be caused by variations in reservoir volume and water value, in addition to different bidding strategies.



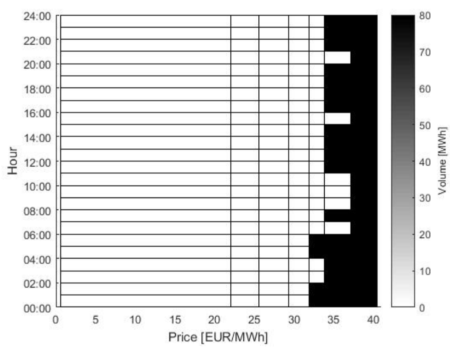
(a) Coordinated, day = 84



(b) Sequential, day = 84



(c) Coordinated, day = 99



(d) Sequential, day = 99

Figure 7.7: Comparison of optimal bid matrices in the day-ahead market for days with different expectations regarding imbalances

Evaluation of Price-Water Value Deviation

The days of the backtesting period are divided into three intervals depending on the value of the squared deviation (PWSD) between the realized day-ahead market prices and the water values. The water values from the coordinated model are used in the evaluation, for the reservoir connected to the power station. The sum of profits in each interval for both of the implemented bidding models are presented in Table 7.4. The division of the intervals are such that approximately 50% of the days fall within the first interval, and approximately 25% in each of the two other intervals. Kongelf and Overrein (2017) also use three intervals, with the first having an upper limit of 20 for the PWSD. Such high deviations are rarely achieved during the backtest, thus more narrow intervals are chosen. Most of the days have a PWSD below 5, which implies that the backtesting period is characterized by a high share of hours in which the water values and the realized day-ahead market prices are quite similar.

In the interval in which the value of PWSD is below 5, one can observe that the coordinated model achieves a gain in profits of 5.3% compared to the sequential model. However, it can be observed that the largest part of the profits for both models are obtained for days when the PWSD is outside this interval. The average profit increases substantially with the size of the PWSD, as can be seen from the increase in sum of profits. The sequential model outperforms the coordinated model for the intervals in which the PWSD is larger than 5, as a negative relative change in profits occurs. However, keep in mind that the results from each day of the backtest are dependent of the results from the previous days. The profits from the coordinated and sequential models are thus hard to compare on a daily basis, as the sequential model have different water values which is not accounted for. Hence, this test only gives an indication of the performance at different PWSD levels. To make sure that the results are reasonable, the same test is done considering the water values from the sequential model. The same conclusions regarding the effect of PWSD are obtained, thus the results are not presented.

Table 7.4: Percentage change in profits when dividing the days into intervals depending on the PWSD

	PWSD $<$**5**	**PWSD** **5 - 10**	**PWSD** $>$**10**
Number of days	102	50	48
Sum profits coord. [EUR]	1 916 708	1 295 603	2 562 055
Sum profits seq. [EUR]	1 823 722	1 335 992	2 601 407
Change [%]	5.1	-3.0	-1.5

The results mainly coincide with the results of Kongelf and Overrein (2017), as they also achieve the highest gain in the interval in which the PWSD is lowest. They also find that the gain of their coordinated model decreases as the PWSD increases, but never obtain negative relative changes from the sequential model. As they do not simulate the management of the water system over time, their coordinated and sequential model have the same starting point for each of the test days. The different daily starting point of the models implemented in the backtesting procedure, can thus be the reason for the negative relative change.

Excluding the Option of Block Bids

The inclusion of block bids in the coordinated bidding problem considering the day-ahead market and the balancing market, has never been tested before to our knowledge. Thus, it is interesting to evaluate the difference in performance between the base case, and a coordinated model not having the option of block bids. Table 7.5 presents the percentage change in total value, accumulated revenues and costs, and water value, from a coordinated model excluding block bids. Block bids increase the total end-of-horizon value obtained during the backtesting period by 0.03%. The changes show that the base case has higher revenues for upward regulation, and lower costs for downward regulation. The main reason for the use of block bids is to ensure that the bid is either fully accepted or rejected for a block of consecutive hours, and thus reducing the risk of many start-ups. As expected, block bids decrease the start-up costs substantially.

Table 7.5: Percentage change in total value, accumulated revenues/costs, and water value from the coordinated bidding model excluding block bids to the base case

	Total value [EUR]	DAM [EUR]	BM Up [EUR]	BM Down [EUR]	Start-up costs [EUR]	Water value [EUR]
Coord. excl. block	8 986 624	5 789 960	290 637	-262 443	-27 950	3 196 420
Change [%]	0.03	-1.73	6.70	22.67	18.60	0.58

To further investigate if there are any effects of using block bids in a coordinated strategy, the gains of a coordinated model over a sequential model when excluding block bids is evaluated. Table 7.6 shows that a coordinated model achieves 0.11% higher total value, and 0.25% higher obtained average price, than a sequential model excluding block bids. Note that these values are higher than the gains of coordinated bidding in the base case. However, there is no change in obtained average price between the coordinated models when including and excluding block bids, they both achieve 30.63 EUR/MWh. Additionally, a positive gain in total value in using block bids is found from Table 7.5. Thus, the reason for the increased gain of coordinated bidding when excluding block bids, is due to poor performance of the corresponding sequential model. These results indicate that the sequential model in the base case perform better than a sequential model excluding block bids. However, the sequential model in the base case does not perform better than a coordinated model excluding block bids.

Table 7.6: Percentage change in total value and obtained average price from a sequential model excluding block bids to the corresponding coordinated model

	Total value	**Obtained avg. price**
Change from sequential model [%]	0.11	0.25

7.5.2 Comparison with Industrial Partner

The results from the backtest are compared to the operation and behavior of the industrial partner, which uses a sequential bidding strategy. Keep in mind, that the generator of the industrial partner is fully or partly unavailable in some days of the backtesting period, so the historical unavailability is included in the models in the following section. Table 7.7 presents the total value, accumulated revenues and costs, and end-of-horizon water value for the coordinated model and the industrial partner. This is given for both the coordinated model and the industrial partner. The table presents a gain of 4.19% for the model, which is very high compared to the gain presented in the previous section. Note, that the total value for the industrial partner is not quite comparable to the implemented model. This is due to simplifications in the model, in addition to the industrial partner having other aspect to take into consideration. The industrial partner may have obtained revenues from other markets, which is not accounted for in the calculation of total value. The table shows that the balancing market is highly used by the coordinated model compared to the industrial partner. In addition, the market share used in the models for the balancing market, may be a bit high compared to the market share for the industrial partner. The industrial partner has a substantial lower start-up cost than the coordinated model, even though the same unit cost for each start-up is considered.

Table 7.7: Total value, accumulated revenues/costs, and water value for the coordinated model and the industrial partner

	Total value [EUR]	**DAM [EUR]**	**BM Up [EUR]**	**BM Down [EUR]**	**Start-up costs [EUR]**	**Water value [EUR]**
Coord.	8 980 611	5 860 641	290 070	-343 614	-28 275	3 201 790
Partner	8 619 511	5 404 426	188 224	-126 386	-9 425	3 162 673
Change [%]	4.19	8.44	54.11	- 171.88	- 200.00	1.24

Table 7.8 shows the percentage change in obtained average price. Unlike the total value, the obtained average price is more comparable, as it includes production and revenues

in the day-ahead market and balancing market only. The coordinated model achieves an obtained average price which is 1.61% above the industrial partner. This implies that the coordinated model exploits high market prices in a more optimal manner than the industrial partner.

Table 7.8: Percentage change in obtained average price from the industrial partner to the coordinated model

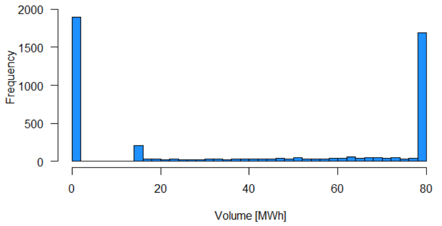
	Obtained average price
Change [%]	1.61

Table 7.9 presents the total production volumes and the commitments in each market for the coordinated model, sequential model, and the industrial partner. Keep in mind that the model results deviate from the results in the previous section, as the days of unavailability is taken into consideration. It is clear that the coordinated model has the most aggressive bidding behavior, with substantially larger commitments in the balancing market. Notice that the industrial partner has the lowest production level, and commits much lower volumes in the downward balancing market than the implemented models. The industrial partner may not be willing to risk producing at a higher level in the day-ahead market, in order to be able to regulate down later. The commitments for upward regulation are quite similar for the sequential model and the industrial partner, which both use a sequential bidding strategy.

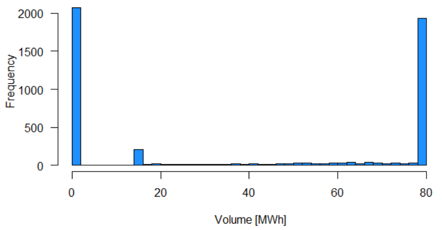
Table 7.9: Total production and commitments in each market in the case including unavailable days

	Total production [MWh]	**DAM [MWh]**	**BM Up [MWh]**	**BM Down [MWh]**
Coord.	188 900	195 893	8 142	15 135
Seq.	189 267	198 016	6 291	15 040
Partner	180 683	178 593	6 585	4 495

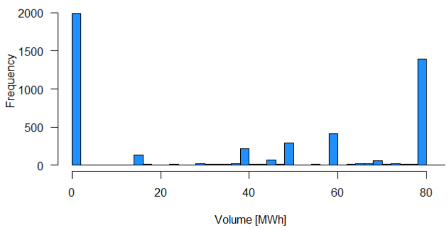
The distribution of the production volumes for the implemented models, and the historical commitment data from the industrial partner, is illustrated in Figure 7.8. It is evident from the plot that the industrial partner exploits the best efficiency point of 60 MW in many hours, while the implemented models mostly produce at minimum or maximum production capacity. However, the coordinated model utilizes more of the volume levels in the range between minimum and maximum capacity than the sequential model. The form of the distributions may be due to the fact that the implemented models use the balancing market more, and thus regulate up to maximum capacity, or regulate down to either minimum capacity or zero.



(a) Coordinated bidding model



(b) Sequential bidding model



(c) Industrial partner

Figure 7.8: Comparison of production distributions for the implemented models and the industrial partner

The total volume in the reservoirs throughout the backtesting period is plotted in Figure 7.9. Except for a period in mid-October to mid-November, the total volume is higher for the two implemented models. It is clear that there are small differences between the coordinated and the sequential model throughout the period. Some of the gap between the models and the industrial partner may be due to production in other markets, as discussed above. It is important to note that the industrial partner experience uncertainty in inflow, while the implemented models knows the exact amount of water coming into the reservoirs the next thirteen days. The industrial partner thus experience a higher risk of spill when having high reservoir volumes, which can explain the generally lower reservoir volume.

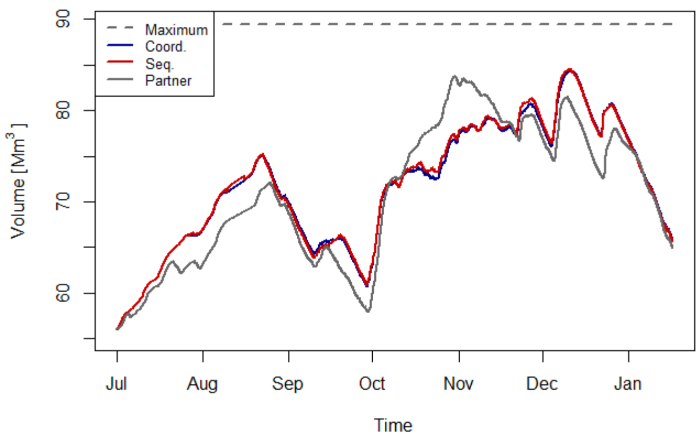


Figure 7.9: Total volume for all reservoirs for the implemented models and the industrial partner

Table 7.10 presents optimal bid matrices for the upward balancing market determined by the coordinated and sequential model for a day in July 2017, as well as the historical bid matrix submitted by the industrial partner. The commitments in the day-ahead market are represented in the columns with the label DA, while the other columns represent the bid volumes for different price points. From the bid matrix of the industrial partner, it is obvious that they require a high market price to start the generator in the case when it is not already running. This careful behavior towards start-ups is further evident in the low start-up costs from Table 7.7.

7.5.3 Value of Balancing Market Forecast

The following section presents the results of running the backtesting procedure for the coordinated model, with different expectations regarding the balancing market. The aim is to quantify the added value of developing a forecast of the balancing market. The results of utilizing the generated forecast is compared to having no information, and having perfect information.

Table 7.10: Comparison of bid matrices for upward regulation July 28, 2017 for the implemented models and the industrial partner

	Coordinated model				**Sequential model**				**Industrial partner**			
		Bid price [EUR/MWh]				*Bid price [EUR/MWh]*				*Bid price [EUR/MWh]*		
Hour	*DA*	*26.8*	*30.7*	*34.5*	*DA*	*26.8*	*30.7*	*34.5*	*DA*	*30.9*	*32.5*	*46.3*
1	75	0	0	0	0	0	0	0	0	0	0	80
2	68	0	0	0	0	0	0	0	0	0	0	80
3	54	0	0	26	0	0	0	55	0	0	0	80
4	33	12	29	47	0	0	29	80	0	0	0	80
5	22	0	30	58	0	0	30	80	0	0	0	80
6	19	0	32	61	0	0	32	80	0	0	0	80
7	48	15	32	32	66	14	14	14	0	0	0	80
8	17	13	36	63	64	13	16	16	0	0	0	80
9	31	0	25	49	69	0	11	11	0	0	0	80
10	49	0	0	31	72	0	0	0	0	0	0	80
11	40	17	40	40	73	0	0	0	0	0	0	80
12	40	0	39	40	73	0	0	0	0	0	0	80
13	46	11	11	34	56	11	11	24	0	0	0	80
14	33	13	47	47	39	13	41	41	0	0	0	80
15	28	18	52	52	35	18	45	45	0	0	0	80
16	22	23	58	58	26	23	54	54	0	0	0	80
17	35	26	26	45	40	26	26	40	0	0	0	80
18	17	15	48	63	61	15	19	19	0	0	0	80
19	16	31	46	46	50	12	12	12	0	0	0	80
20	48	11	23	32	62	11	18	18	0	0	0	80
21	30	11	36	50	59	11	21	21	0	0	0	80
22	43	0	35	37	59	0	21	21	0	0	0	80
23	40	11	30	40	58	11	22	22	16	44	64	64
24	47	0	0	0	47	0	0	0	16	44	57	57

No Information

Utilizing a scenario tree which is generated based on forecasting errors when predicting zero demand in the balancing market for all hours, provides qualitatively different results of the backtesting procedure for the coordinated model. The resulting percentage changes are presented in Table 7.11. Comparing the coordinated model and the sequential model which both uses the zero forecast, no gain in total value is obtained. The coordinated model based on no information about the balancing market, gave a percentage change of -0.44% compared to the ANN case. The zero case has -0.77% lower obtained average price than the ANN case.

Table 7.11: Percentage changes in total value and obtained average price for the zero case

	Total value	**Obtained avg. price**
Change from sequential model w/ zero forecast [%]	0.00	0.08
Change from coordinated model w/ ANN forecast [%]	- 0.44	- 0.77

Perfect Information

When having perfect information regarding the balancing market, the performance of the bidding models increases substantially. Table 7.12 presents the percentage changes for the perfect information case. The perfect information case obtains 4.27% higher total value, compared to the ANN case. The obtained average price has a relative increase which is even higher. The percentage change from the sequential model to the coordinated model when having perfect information regarding the balancing market, is quantified to be 3.8%. Keep in mind that the outcomes of the day-ahead market are not perfectly known.

Table 7.12: Percentage changes in total value and obtained average price for the perfect information case

	Total value	**Obtained avg. price**
Change from sequential model w/ perfect information [%]	3.80	5.60
Change from coordinated model w/ ANN forecast [%]	4.27	6.35

Comparison

To further evaluate the performance of the three cases considered, the results for each of them are compared. The total production and market commitments are presented in Table 7.13. The ANN case has the highest total production, which means that it has used more water than the other cases. In addition, Table 7.14 shows that the ANN case has the highest number of start-ups. However, the ANN case obtains a higher total value at the end of the horizon than the zero case, due to a higher obtained average price. The available water in the reservoirs is thus used in a more profitable manner in the ANN case. The case with perfect information has less commitments in the day-ahead market, and substantially more commitments in the upward and downward balancing market. Knowing exactly when high premiums occur, it is as expected that the balancing market is used more frequently.

Table 7.13: Total production and market commitments for the ANN case, the zero case, and the perfect information case

	Total production [MWh]	**DAM [MWh]**	**BM Up [MWh]**	**BM Down [MWh]**
ANN	189 968	193 465	8 255	11 752
Zero	189 536	191 207	6 062	7 733
PI	189 443	182 910	40 706	34 173

Table 7.14: Number of start-ups for the ANN case, the zero case, and the perfect information case

	Coordinated	Sequential
ANN	86	77
Zero	71	63
PI	43	76

The accumulated profits for the coordinated model in each of the three cases considered, are plotted in Figure 7.10. The perfect information case obtains accumulated profits which is 366 000 EUR higher than for the ANN case, which again is 53 000 EUR higher than the zero case. As the profits for the ANN and zero case are quite similar, their difference from the case of perfect information are included in the plot as dashed lines. The zero case has higher accumulated profits than the perfect information case for 9 days in the first half of the backtest, while the ANN case has higher accumulated profits for 3 days in the second part of the backtesting period. However, the trend in the differences between the perfect information case and the two other cases is mainly an increase throughout the period. When the accumulated profits for the perfect information case is close to the two other cases, the perfect information case has low production and saves water.

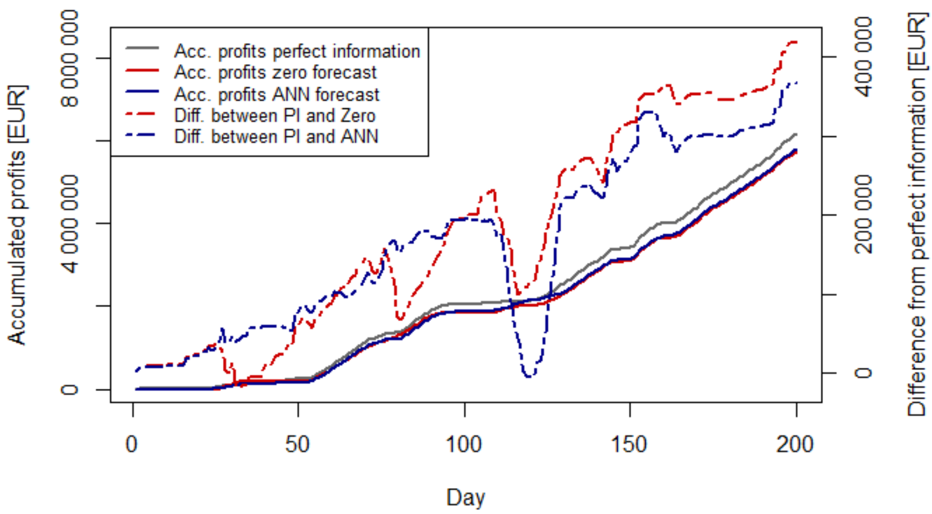
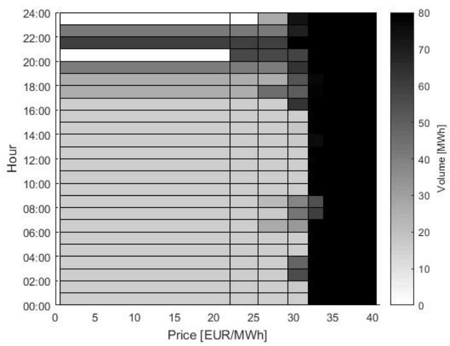
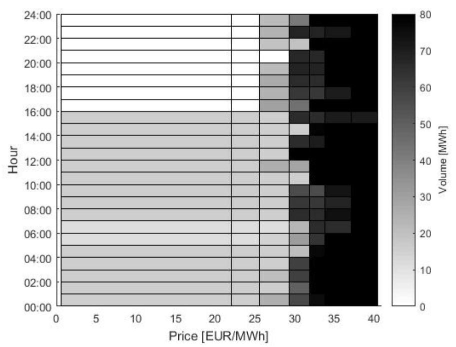


Figure 7.10: Accumulated profits for the ANN case, zero case, and perfect information case

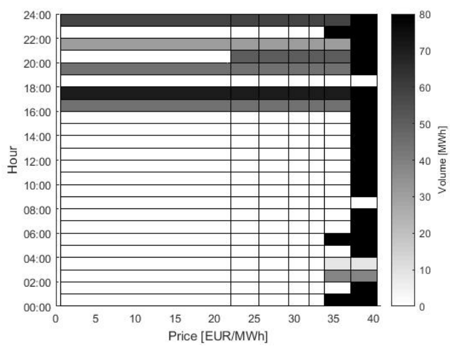
Figure 7.11 presents the bid matrices for day 115 of the backtesting period, which is in the interval when the differences in accumulated profits decrease. Even if the three cases have the same scenario tree for the day-ahead market outcomes, the resulting bid matrices for the day-ahead market are significantly different. This is due to different expectations regarding the balancing market, but also because of different input, such as water values. The zero case has the lowest water value, while the perfect information case has the highest. From the figure, it is clear that the ANN case has the most aggressive bidding behavior, while the perfect information case has a more careful bidding behavior. The premiums in the balancing market are quite low, though there are some possibilities for upward regulation in the morning and evening hours.



(a) ANN case



(b) Zero case



(c) Perfect information case

Figure 7.11: Optimal bid matrices for the ANN case, zero case, and perfect information case in the day-ahead market for day 115 of the backtesting period

7.6 Discussion

The main findings from the analyses are presented in Table 7.15, along with main findings from comparable studies also evaluating the gains of a coordinated bidding strategy. The estimated gains found in this work are moderate compared to Boomsma et al. (2014), which find gains up to 2% for a producer without market power. As described in Section 3.1, they do not use an upper limit for the balancing market demand. The gains of coordinated bidding found in this work are not significant, but in the same range as found in other studies which also includes an upper bound on balancing market demand (Faria and Fleten, 2011; Kongelf et al., 2018; Fodstad et al., 2017; Klæboe et al., 2018).

Table 7.15: Comparison of main findings in studies considering the gains of a coordinated bidding strategy

Study	Main findings
This work	No significant gain in total value (0.07% when including block bids, 0.11% otherwise). A good forecast can increase the gains substantially
Faria and Fleten (2011)	No significant increase in profits (less than 0.65%)
Boomsma et al. (2014)	Gains up to 2% with no market power, and up to 1% with price response in the BM
Kongelf et al. (2018)	Gains decline when increasing the portfolio size, but there is a tendency towards stabilization (0.47%)
Fodstad et al. (2017)	Increases the relative profits by 0.8 % for NO5 and 1.7 % for SE
Klæboe et al. (2018)	No significant gain in the current market situation (0.1%), but can increase with increased market volume and asymmetric pricing (3.9%).

An unexpected result from the analyses, is that a coordinated bidding strategy gives higher accumulated start-up costs than a sequential bidding strategy. As a coordinated bidding strategy takes both markets into account simultaneously, it should minimize the number of start-ups according to the expectations in the balancing market. However, if the realization of the demand in the balancing market turns out to be in the opposite direction of the expectation, it is natural that the number of start-ups increase. The ANN case has a higher number of start-ups than the zero case. As presented in Chapter 6, the ANN forecast is more often wrong about the dominating direction in the market. From the case with perfect information, it is clear that the number of start-ups decrease substantially when the expectations of the balancing market are correct. In this case, a sequential bidding strategy leads to a substantial higher number of start-ups than a coordinated bidding strategy. However, the number of start-ups for the case with perfect information is still quite high compared to the industrial partner. Although the value of the unit start-up cost is based on information provided by the industrial partner, the question arises whether this estimation may be too low for the models implemented.

The gain of a coordinated bidding strategy is highest when the realized day-ahead market prices does not deviate much from the water value, which coincides with the results of Kongelf and Overrein (2017). However, if the deviation is large, a sequential bidding strategy may be optimal. A hydropower producer can use this observation to determine daily if a coordinated bidding strategy should be used, as forecasts for the day-ahead market prices are quite accurate. Consequently, the obtained gains of the coordinated model analyzed in this thesis, are very sensitive to the modeling of the water values. The coordinated and sequential model will have different water values during the backtest, due to decisions from previous days affecting the reservoir volumes. The estimated gain is thus also dependent on the water value for the sequential model, which makes it hard to evaluate daily performance.

Simplifications are made in the models regarding different aspects of hydropower scheduling. Whereas the coordinated and sequential models are given the inflow as a deterministic parameter, the inflow is uncertain for the industrial partner. This simplification is considered reasonable for a short-term horizon, but may lead to big differences in behavior between the models and the industrial partner in periods with high reservoir levels. The models know exactly how much it needs to produce in order to avoid spill. In addition, the models do not consider head effect. This is also considered as a neglectable effect in problems with short-term horizons, but affects the behavior compared to the industrial partner. The industrial partner desires to have high reservoir levels to maximize the head and efficiency, but have to be more careful to avoid spill due to uncertain inflow. The implemented models do not seem to take the best efficiency point into account when operating the water system. The power-discharge curve indicates the marginal increase in discharge level, coming from a unit increase in power production. A unit increase in power production for production levels above 60 MW leads to higher resource usage, than for production levels below 60 MW.

Including the option of block bids in the coordinated model, reduces the gains of coordinated bidding somewhat. However, this reduction is mainly because the sequential model including block bids performs better than the sequential model without this option. The total value increases somewhat by including block bids, compared to the same model without this option. Using block bids also decrease the number of start-ups drastically. However, regardless of including block bids or not, a coordinated bidding strategy always achieves a gain in total value compared to a sequential strategy. Note that these gains are not significant, and that other results could have been obtained by analyzing a larger number of days.

Analyzing the effect of having a forecast for the balancing market, other than predicting no imbalances, proves that making an effort in developing a balancing market forecast is not futile. Using the forecast from the ANN to generate scenario trees for the coordinated model increases the total value obtained by 0.44%, compared to the case of predicting no imbalances in the system. In addition, it is not identified any gains of coordinated bidding when predicting no volumes in the balancing market. The gains of coordinated bidding in the case of perfect information is estimated to 3.8%. This is in the same range as Klæboe et al. (2018) estimate for a future case with increased market volume in the balancing market. Thus, there seems to be a potential for added value of coordinated bidding if an improved forecast is developed and the size of the market increases. It has however been proved hard to say much about the balancing market before the closure of the day-ahead market, as Klæboe et al. (2015) also point out.

Chapter 8

Concluding Remarks

The coordinated bidding problem for a hydropower producer considering the day-ahead market and the balancing market, is presented. The problem is formulated and implemented as the deterministic equivalent of a three-stage stochastic mixed-integer program. In order to utilize a forecast-based scenario generation method for the stochastic parameters, an artificial neural network is developed to forecast the balancing market. An extensive backtesting procedure is implemented. The gains of a coordinated bidding strategy are evaluated against a sequential bidding strategy, over 200 simulated days of bidding and operation.

8.1 Conclusion of Case Results

By comparing the results of the coordinated model to the corresponding sequential model, only moderate improvements in total value are found. For hydropower producers using both hourly bids and block bids in the day-ahead market, a gain of 0.07% in total value is reported. If only hourly bids are used, the coordinated bidding model achieves an increase of 0.11% in total value compared to the corresponding sequential model. Although these numbers are not significant, coordinating bidding may still be worthwhile for a profit maximizing hydropower producer. Including the option of block bids did not have a great effect, as it increased the obtained total value by 0.03%. The gains of coordinated bidding are greatest when the squared deviation between the day-ahead market price and the water value is low. When this deviation is high, the coordinated model is outperformed by the sequential model.

To the authors' knowledge, using artificial neural networks to predict the balancing market has not been evaluated before. The balancing state forecast performed reasonable well compared to other methods in the literature. The added value of using scenario trees based on forecasts generated by the artificial neural network is analyzed. The results are compared with the case using scenario trees based on forecasts predicting no imbalance in the system. The increase in total value is estimated to 0.44%, which indicates that making an effort in developing forecasts for the balancing market is worthwhile. A gain in total value of 4.3% is observed, when comparing the case of perfect information to the case with forecasts generated by neural networks. The gain of a coordinated bidding strategy is in that case estimated to be 3.8%, which indicate that a substantial gain in profits can be obtained by coordinated bidding in the case of a well performing forecast. However, forecasts for the balancing market have been proven hard to improve.

The assumptions and simplifications for the model makes it possible to develop a linear model, and thus solving it with a direct solution method. The results presented indicate that the implemented models behave reasonable, compared to the behavior of the industrial partner. However, the induced start-up costs is proved to be substantially higher for the implemented models.

8.2 Future Research

The question whether a coordinated bidding strategy is worthwhile, remains somewhat uncertain in the current market situation. To further evaluate the gains of a coordinated bidding strategy, it would be favorable to run the backtesting procedure over a longer period of time. In that way, other effects such as dry and wet years can also be included. Uncertainty in inflow should in that case be considered, as it affects the system highly over a longer time horizon.

The case study considers a hydropower producer with a single power station containing one generator. The backtesting procedure can be tested with a more complicated water course with several power stations, to evaluate if it affects the gain of coordinated bidding. The implemented models can be expanded to take additional markets into consideration, such as the intraday market.

As the gains of a coordinated bidding strategy have been proved to be dependent on the deviation of the day-ahead market price and the water values, it would be interesting to run the procedure with a different modeling of the marginal water values. A scheduling model calculating marginal water values, such as EOPS, could easily be integrated in the current backtesting framework. This would also make the simulated operation of the water system more realistic.

Designing and training a neural network takes a great deal of time and effort. As time has been constrained in this work, the alternative of using machine learning for forecasting of the balancing market can be further investigated. The neural network developed was not able to predict high spikes, which may be improved by separating the arrival of the incident and the size of the incident. Developing a separate neural network for balancing market states can be interesting to evaluate. Furthermore, other explanation factors can be tested. Uncertainty in the forecasts for the explanation factors are of special interest.

Appendix A

Model Presentation

max

$$\sum_{s\in\mathcal{S}} \pi_s \Bigg(\sum_{t\in\mathcal{T}^O} (\rho^D_{ts} - C^L_{ts}) w^D_{ts} + \sum_{b\in\mathcal{B}_t} (\overline{\rho}^D_{bs} - C^L_{ts}) w^D_{bs} + \sum_{c\in\mathcal{C}_s} \pi_{sc} \Big(\sum_{t\in\mathcal{T}^O} \sum_{m\in\mathcal{M}} (\rho^B_{tsc} - C^L_{ts}) w^B_{tscm} U_m$$

$$+ \sum_{g\in\mathcal{G}} \big(\sum_{t\in\mathcal{T}^H} (\rho^D_{ts} - C^L_{ts}) x_{gtsc} - \sum_{t\in\mathcal{T}\setminus\{\mathcal{T}^P\}} y_{gtsc} \big) + \sum_{r\in\mathcal{R}} \big(W_r E\,(v_{|\mathcal{H}|rsc} - \underline{V}_r) - \sum_{t\in\mathcal{T}} Zs_{trsc} \big) \Big) \Bigg)$$

s. t.

$$w^D_{ts} = u^D_{t(i-1)} + (u^D_{ti} - u^D_{t(i-1)}) \frac{\rho^D_{ts} - P^D_{i-1}}{P^D_i - P^D_{i-1}}$$

$$\text{if } P^D_{i-1} \leq \rho^D_{ts} < P^D_i, \qquad t \in \mathcal{T}^O, s \in \mathcal{S}, i \in \mathcal{I} \setminus \{1\}$$

$$u^D_{ti} \geq u^D_{t(i-1)} \qquad t \in \mathcal{T}^O, i \in \mathcal{I} \setminus \{1\}$$

$$w^D_{bs} = u^D_{b(i-1)} \qquad \text{if } P^D_{i-1} \leq \overline{\rho}^D_{bs} < P^D_i, \qquad b \in \mathcal{B}, i \in \mathcal{I} \setminus \{1\}, s \in \mathcal{S}$$

$$u^D_{bi} \geq u^D_{b(i-1)} \qquad b \in \mathcal{B}, i \in \mathcal{I} \setminus \{1\}$$

$$\sum_{b\in\mathcal{B}_t} u^D_{b|I|} + u^D_{t|I|} \leq \sum_{g\in\mathcal{G}} \overline{Q}_{gt} \qquad t \in \mathcal{T}^O$$

$$w^B_{tsc1} = u^B_{ts(i-1)1} \qquad \text{if } P^B_{(i-1)1} \leq \rho^B_{tsc} < P^B_{i1}, \qquad t \in \mathcal{T}^O, s \in \mathcal{S}, c \in \mathcal{C}_s, i \in \mathcal{I} \setminus \{1\}$$

$$w^B_{tsc2} = u^B_{ts(i-1)2} \qquad \text{if } P^B_{(i-1)2} \geq \rho^B_{tsc} > P^B_{i2}, \qquad t \in \mathcal{T}^O, s \in \mathcal{S}, c \in \mathcal{C}_s, i \in \mathcal{I} \setminus \{1\}$$

$$u^B_{tsim} \geq u^B_{ts(i-1)m} \qquad t \in \mathcal{T}^O, s \in \mathcal{S}, i \in \mathcal{I} \setminus \{1\}, m \in \mathcal{M}$$

$$u^B_{ts|I|1} \leq \sum_{g \in \mathcal{G}} \overline{Q}_{gt} - (w^D_{ts} + \sum_{b \in \mathcal{B}_t} w^D_{bs}) \qquad t \in \mathcal{T}^O, s \in \mathcal{S}$$

$$u^B_{ts|I|2} \leq w^D_{ts} + \sum_{b \in \mathcal{B}_t} w^D_{bs} \qquad t \in \mathcal{T}^O, s \in \mathcal{S}$$

$$\underline{M}\delta^B_{tscm} \leq w^B_{tscm} \leq \nu^B_{tsc} U_m S_m \delta^B_{tscm} \qquad t \in \mathcal{T}^O, s \in \mathcal{S}, c \in \mathcal{C}_s, m \in \mathcal{M}$$

$$w^D_{ts} + \sum_{b \in \mathcal{B}_t} w^D_{bs} + \sum_{m \in \mathcal{M}} U_m w^B_{tscm} = \sum_{g \in \mathcal{G}} x_{gtsc} \qquad t \in \mathcal{T}^O, s \in \mathcal{S}, c \in \mathcal{C}_s$$

$$v_{trsc} = v_{t-1,rsc} + I_{tr} - \sum_{g \in \mathcal{G}_r} d_{gtsc} - s_{trsc} - b_{trsc} + o_{trsc} \qquad t \in \mathcal{T} \setminus \{1\}, r \in \mathcal{R}, s \in \mathcal{S}, c \in \mathcal{C}_s$$

$$v_{1rsc} = V^0_r + I_{1r} - \sum_{g \in \mathcal{G}_r} d_{g1sc} - s_{1rsc} - b_{1rsc} + o_{1rsc} \qquad r \in \mathcal{R}, s \in \mathcal{S}, c \in \mathcal{C}_s$$

$$x_{gtsc} = \underline{Q}_g \delta^G_{gtsc} + \sum_{e \in \mathcal{E}} R_{ge} d^E_{gtesc} \qquad g \in \mathcal{G}, t \in \mathcal{T}, s \in \mathcal{S}, c \in \mathcal{C}_s$$

$$d^E_{gtesc} \leq \overline{D}_{ge} \qquad g \in \mathcal{G}, t \in \mathcal{T}, e \in \mathcal{E}, s \in \mathcal{S}, c \in \mathcal{C}_s$$

$$d_{gtsc} = \underline{D}_g \delta^G_{gtsc} + \sum_{e \in \mathcal{E}} d^E_{gtesc} \qquad g \in \mathcal{G}, t \in \mathcal{T}, s \in \mathcal{S}, c \in \mathcal{C}_s$$

$$\underline{Q}_g \delta^G_{gtsc} \leq x_{gtsc} \leq \overline{Q}_{gt} \delta^G_{gtsc} \qquad g \in \mathcal{G}, t \in \mathcal{T}, s \in \mathcal{S}, c \in \mathcal{C}_s$$

$$x_{gtsc} = P_{gt} \qquad g \in \mathcal{G}, t \in \mathcal{T}^P, s \in \mathcal{S}, c \in \mathcal{C}_s$$

$$C^S_g(\delta^G_{gtsc} - \delta^G_{g(t-1)sc}) \leq y_{gtsc} \qquad g \in \mathcal{G}, t \in \mathcal{T} \setminus \{1\}, s \in \mathcal{S}, c \in \mathcal{C}_s$$

$$\underline{V}_r \leq v_{trsc} \leq \overline{V}_r \qquad t \in \mathcal{T}, r \in \mathcal{R}, s \in \mathcal{S}, c \in \mathcal{C}_s$$

$$\underline{B}_r \leq b_{trsc} \leq \overline{B}_r \qquad t \in \mathcal{T}, r \in \mathcal{R}, s \in \mathcal{S}, c \in \mathcal{C}_s$$

$$u^D_{ti} \geq 0 \qquad t \in \mathcal{T}^O, i \in \mathcal{I}$$

$$w^D_{ts} \geq 0 \qquad t \in \mathcal{T}^O, s \in \mathcal{S}$$

$$u^D_{bi} \geq 0 \qquad i \in \mathcal{I}, b \in \mathcal{B}$$

$$w^D_{bs} \geq 0 \qquad s \in \mathcal{S}, b \in \mathcal{B}$$

$$u^B_{tsim} \geq 0 \qquad t \in \mathcal{T}^O, s \in \mathcal{S}, i \in \mathcal{I}, m \in \mathcal{M}$$

$$w^B_{tsc1} \geq 0 \qquad t \in \mathcal{T}^O, s \in \mathcal{S}, c \in \mathcal{C}_s \mid \nu^B_{tsc} > 0$$

$$w^B_{tsc2} \geq 0 \qquad t \in \mathcal{T}^O, s \in \mathcal{S}, c \in \mathcal{C}_s \mid \nu^B_{tsc} < 0$$

$$\delta^R_{tscm} \in [0,1] \qquad t \in \mathcal{T}^O, s \in \mathcal{S}, c \in \mathcal{C}_s, m \in \mathcal{M}$$

$$x_{gtsc} \geq 0 \qquad g \in \mathcal{G}, t \in \mathcal{T}, s \in \mathcal{S}, c \in \mathcal{C}_s$$

$$d_{gtsc} \geq 0 \qquad g \in \mathcal{G}, t \in \mathcal{T}, s \in \mathcal{S}, c \in \mathcal{C}_s$$

$$\delta^G_{gtsc} \in [0,1] \qquad g \in \mathcal{G}, t \in \mathcal{T}, s \in \mathcal{S}, c \in \mathcal{C}_s$$

$$y_{gtsc} \geq 0 \qquad g \in \mathcal{G}, t \in \mathcal{T}, s \in \mathcal{S}, c \in \mathcal{C}_s$$

$$d^E_{gtesc} \geq 0 \qquad t \in \mathcal{T}, t \in \mathcal{T}, e \in \mathcal{E}, s \in \mathcal{S}, c \in \mathcal{C}_s$$

$$v_{trsc} \geq 0 \qquad t \in \mathcal{T}, r \in \mathcal{R}, s \in \mathcal{S}, c \in \mathcal{C}_s$$

$$s_{trsc} \geq 0 \qquad t \in \mathcal{T}, r \in \mathcal{R}, s \in \mathcal{S}, c \in \mathcal{C}_s$$

$$b_{trsc} \geq 0 \qquad t \in \mathcal{T}, r \in \mathcal{R}, s \in \mathcal{S}, c \in \mathcal{C}_s$$

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