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# Using Machine Learning to Improve Hedging of Power Prices in the Nordic Market

*A study of how predictions of the Nordic system price can be used for Norwegian hydropower producer's hedging strategies*

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# Abstract

The prices in the Nordic power market are characterized by high volatility. This creates a demand for securing future power prices. Large hydropower producers use a variety of instruments to predict price changes, and sign derivatives contracts to secure prices for parts of their production. In this thesis, we examined how the introduction of machine learning, in the form of power price predictions, can contribute to risk management for hydropower producers. More specifically, we focused on the following research question:

*How can predictions of the Nordic system price using machine learning methods enhance decision support for hydropower producers when trading medium-term power derivatives?*

To answer this question, we predicted the yearly, quarterly and monthly Nordic system price for 2018. Predictions of each price was made using the programming language R, with historical data from 2013 to 2018 retrieved through open sources and Datastream. We applied eight different machine learning methods, namely linear regression with backwards selection, ridge regression, lasso regression, partial least squares, regression trees, random forests, boosting and support vector regression. In addition, we generated forecasts using ARIMA and NNAR models. To replicate how the decision-making processes of traders would be in real life, the predicted prices by the three best-performing models on data prior to 2018 were compared to contract prices at Nasdaq Commodities. Based on the comparison we determined which futures contracts should be purchased.

The answer to the research question is that machine learning models have great potential to enhance the decision support for hydropower producers when trading power derivatives. Compared to a strategy of securing all prices through futures contracts, using the predictions of the estimated models to decide whether to purchase the contracts led to the same or a higher gain. To mitigate the risk associated with the models and the market in general, the predictions made by the models should be used in combination with existing information and forecasts. The risks associated with the models should also be incorporated into the general risk management strategy.

***Keywords*** – Machine learning, risk management, futures contracts, hydropower producers

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# 1 Introduction

## 1.1 Background

In 2018, 95% of the Norwegian power production was generated by hydropower producers (Statistisk sentralbyrå, 2019a). Given the large share of hydropower, Norway has Europe's largest share of renewable energy sources in its production mix (Norwegian Ministry of Petroleum and Energy, 2019b). Moreover, half of Europe's reservoir storage capacity is made up by Norwegian hydro reservoirs. With such a high storage capacity, most of the Norwegian hydropower production is flexible, as production can be regulated. Flexibility provides operational advantages, however, the production at Norwegian hydropower plants is restricted by license constraints. In addition, the inputs, i.e. inflow to reservoirs, are uncertain.

Although most of the hydropower production can be regulated, risk in the power market is highly associated with price risk, and it is common practice to use power price predictions to manage these risks. The Norwegian power market is integrated with the Nordic market, and the Nordic region operates with a joint price called the Nordic system price, which is a theoretical price set in the equilibrium between supply and demand (Norwegian Ministry of Petroleum and Energy, 2019c). Each country also has its own individual area prices, although these tend to be near the system price. The market integration causes Norwegian prices to be impacted by non-domestic factors, as areas within Norway and neighboring countries are connected through the transmission grid. The grid has physical restrictions of transferring power, causing large price fluctuations (Saakvitne and Bjønnes, 2015). Disturbances in the power supply, combined with inflexible demand and distinct consumption patterns, also contribute to the price fluctuations. As a consequence of these fluctuations, most of the major hydropower producers will typically reduce the price risk by adopting risk management functions (Fleten et al., 2001).

The power price fluctuations of today's market are not likely to diminish in the near future. There is considerable uncertainty associated with the development of the power market towards 2030-2040, and one of the most important drivers for this uncertainty is the global climate challenge (Bøhnsdalen et al., 2016). The EU and individual member states adopt policies to reach climate goals. The goals are prioritized, but weighted against costs and security of supply. To reach the goals, a larger share of the total power production must consist of renewable energy sources. As of today, solar and wind power appear to be the preferred sources of renewable energy. In contrast to the hydropower production, these renewables have intermittent capacity. As a result, in periods with a lot of sunshine and wind, generation could reach high levels and even exceed consumption. As electricity cannot be stored, the high production is balanced through lower prices. Thus, the increase of solar and wind power in the total generation is expected to increase price volatility. Further, the Nordic countries are planned to be closer integrated with the European power market in the coming years (Norwegian Ministry of Petroleum and Energy, 2019a). In total, the transmission capacity out of the Nordic region could increase by 150%. As a result, the European prices and variations will be reflected to a greater extent in the Nordic market. Due to climate policies, there is also significant uncertainty related to future prices of coal, gas and oil, which will impact future power prices as well.

Future uncertainty is also related to the digitalization of today's society and industries, where new business opportunities related to big data, analytics, artificial intelligence and machine learning arise. The pace of change and innovation is high, causing more businesses to either embrace the opportunities or force them to join the developments in risk of falling behind (Schwab, 2015). Also in the power market, digitalization is becoming increasingly important. Thus, hydropower producers have to adopt to the changes as well. Big improvements and innovations on machine learning have evolved in recent years, making the discipline a more common tool in businesses (Datatilsynet, 2018). Along with applications for risk management, and financial and operational purposes, machine learning has proven potential in its predictive functions, and the applicability and importance of the area continues to grow (Krishna et al., 2017). With the uncertainty of both future power prices and technological innovations, machine learning could serve great potential for price prediction applications in the power market.

The Nordic power market is split between the financial and the physical market. Power markets in general differ from standard commodity markets in their limitations of storage (Saakvitne and Bjønnes, 2015). In several commodity markets, producers can hedge against price fluctuations by storing the commodity until prices are favorable. As electricity cannot be stored, hydropower producers rely more on the use of power derivatives in securing future prices. In essence, a power derivative is a contract between a buyer and seller to buy electricity in the future at a given price. The settlement of this contract either involves delivery of physical power, or an exchange of future cash flows. The Nordic power market is one of the most liquid power derivatives markets in the world (Nasdaq, Inc., nd). Most of the financial power trading in the Nordic countries takes place at Nasdaq Commodities, through the Nasdaq Oslo ASA Exchange and Nasdaq Clearing AB. Nasdaq Commodities differs from other exchanges as financial actors without exposure to the underlying asset constitute a minority (Saakvitne and Bjønnes, 2015). Moreover, the trading of power derivatives mainly takes place on the exchange, in contrast to international commodity markets, where trading usually happens outside of the exchange.

On the contrary, there has been a downwards trend in recent years towards less derivatives trading at the exchange, resulting in declining liquidity at Nasdaq Commodities (Finanstilsynet, 2019). A potential future risk is thus an illiquid market where hydropower producers struggle to sell their contracts. The declining liquidity, combined with the expected increase in price volatility and uncertainty of the future market, renders future earnings of hydropower producers with growing uncertainty. There is evidence of widespread risk management practices among Norwegian electricity companies (Sanda et al., 2013). Therefore, with the expected developments in the market, risk management can prove to be increasingly important.

## 1.2 Purpose and research question

The focus of this thesis is on large-scale hydropower producers in Norway. With uncertain factors as those presented in the previous section, price risk management strategies are important for the producers to secure future earnings. The largest hydropower producers in the market manage market risk by securing prices through financial contracts. In this thesis, the financial contracts in focus will be yearly, quarterly and monthly futures contracts at Nasdaq Commodities, as these are some of the most liquid contracts used to secure future prices. We define the contracts in question as medium-term, as opposed to short-term contracts such as daily and weekly futures, and long-term contracts that span over several years. The contracts use the Nordic system price as reference, thus this price will be a recursive factor in this thesis.

Much of the general understanding of market practices for hydropower producers has been introduced through interviews with hydropower producer BKK and the industry leader for Deloitte Norway's activities in the power market, on October 17th and November 25th respectively. Through the interviews, common hedging strategies for hydropower producers, involving general considerations and specific financial instruments, as well as general practices for price prediction have been elucidated. Much is considered sensitive information in the power market. The main focus in the interviews has therefore been on a general understanding of the most common market practice, as much market information is neither published, nor intuitive. Thus, the interviews have been an important source of understanding crucial factors. The second interview, on November 25th, also had a particular focus on transmission costs and taxes. In the sections where information from the two interviews is directly used, they will be referred to explicitly. Otherwise, the interviews in general, function as a background for our understanding of general market practice.

When trading futures contracts, traders use available information to determine whether to purchase or sell contracts. The most vital source of information is predictions of the future system price. Many of the algorithms used for predicting system prices are considered trade secrets and sources of competitive advantage (Krishna et al., 2017). Thus, the exact algorithms used for predicting prices cannot be stated, and usually a consolidated evaluation of many predictions and judgements are used. In our thesis, we consider how standard machine learning methods can be applied to predict future system prices. The accuracy of these machine learning models will be evaluated, and their performance will be tested to see whether the predictions can be used in the context of risk management for purchases of futures contracts. Thus, we provide a simple approach to the power price forecasting and investigate whether this approach can generate value that makes it applicable in practice.

This thesis contributes to price risk management indirectly. Our analyses and recommendations are intended for those in charge of trading futures contracts. The aim is to help them make better decisions, i.e. purchase the correct contracts in a profit maximizing view. More specifically, we aim to increase their decision support for trading futures contracts. Thus, the decisions made by the traders are intended to maximize profit. However, when applied by the business as a whole, the purpose of the trading is to manage risk. Hence, risk management serves as a backdrop for our research question, even though the research question in itself is set to maximize profit. The objective is to introduce the use of artificial intelligence in predicting the Nordic system price and investigate how these predictions can be used in a risk management perspective. The research question that will be discussed is:

*How can predictions of the Nordic system price using machine learning methods enhance decision support for hydropower producers when trading medium-term power derivatives?*

The purpose of this thesis is to evaluate whether applying machine learning can increase decision support for hydropower producers when purchasing financial power contracts for price risk management purposes. To be applied in the risk management function, both the expected earnings and risks of using machine learning are discussed. More specifically, the performance of standard machine learning algorithms in predicting the system price are tested and evaluated. The performance is measured both in terms of prediction accuracy and in their guidance for developing hedging strategies. For testing the performance of the methods, 2018 is used as the year of reference. 2018 was a year with extraordinary power prices and developments, and thus might not be the best year of reference. The reason why the models are still tested on this year is because the data set begins in 2013. Several machine learning methods require large amounts of data to give precise predictions. Hence, 2018 is used as it is the last year in the data set with complete data.

The results of this thesis are mainly meant to be used by hydropower producers in their price risk management strategies. Overall, standard machine learning methods are applied using the programming language and system R (R Core Team, 2013). The specific packages used in R are included in Appendix A5. Data is retrieved through open sources and Datastream. In our approach we attempt to replicate how the decision-making processes of traders will be in real life. When applied to a real-life setting however, hydropower producers can use their own data set in the model estimation. With a few modifications, our results can also be used by and benefit other power producers, power suppliers and large-scale end users.

## 1.3 Structure

The first part of the thesis includes an introduction to the Nordic power market along with theory of risk management, derivatives and machine learning. The thesis begins by presenting the power market in Chapter 2. The main focus is on Norway and Norwegian hydropower producers. However, as Norway is part of the joint Nordic physical and financial market, the joint market is presented. The chapter ends with the current practice for predicting the Nordic system price and an introduction of the particular market situation of 2018. Chapter 3 explains the data collection of variables used in the machine learning methods, before Chapter 4 introduces the theory of these methods. The methodology for training, testing, validating and estimating models is presented step by step, along with reasoning for the choices made in the process.

The second part of the thesis includes the analyses, discussions and conclusions of the subjects introduced in part one. First, we analyze the results of the estimated machine learning models in Chapter 5. The analysis presents the predictions and uses them to develop hedging strategies. In Chapter 6 we discuss the results of the analysis. Both the accuracy of our predictions and the risks associated with the models, hedging strategies and machine learning in general, is elaborated on. Thereafter, we present recommendations for hydropower producers and suggestions for further research. Finally, we present a conclusion of the results, discussions and recommendations of this thesis in Chapter 7.

# 2 The Nordic Power Market

The Nordic power market is split between the physical and the financial market, where trading takes place on separate exchanges (Norwegian Ministry of Petroleum and Energy, 2019c). Nord Pool AS constitutes the physical power trading, while Nasdaq Commodities accounts for the financial trading. In Norway, production and trading of electricity is market-based, while grid operations are strictly regulated, as it is a natural monopoly. Norway, Sweden, Denmark and Finland have a joint Nordic power market, linked both by financial market integration and physical interconnectors. The Nordic power market is further integrated into the wider European power market, in both financial and physical terms. 24 countries are interlinked in the European market which covers about 90% of the European energy consumption. The EU is working on improving integration further, both within and beyond the existing market.

Most of the financial power trading in the Nordic countries takes place on the Nasdaq Commodities exchange (Norwegian Ministry of Petroleum and Energy, 2019c). However, financial power trading also happens bilaterally and on other exchanges. At the Nasdaq exchange, all contracts are settled financially, and do not involve physical power delivery. However, as of early 2019, Nasdaq Commodities has applied for a license to enter the physical market, taking up arms with Nord Pool (Jordheim, 2019). The financial power trading at Nasdaq Commodities is used for risk management purposes as well as speculation.

In a risk management view, predictability of costs and income related to power prices are important both for producers, distributors and large-scale consumers in the Nordic power market. Hence, actors benefit from price predictions to varying degrees. Besides providing benefits connected to risk management for hydropower producers, predictions can contribute in operations such as production planning and budgeting processes. The volatility of power prices often makes accurate predictions difficult. A recent example is the case of 2018, where power prices moved in the opposite direction of what was expected.

In the upcoming chapter, the physical and financial power market is introduced, along with current practices for power price prediction and the special situation of 2018. First, the structure of the Norwegian and Nordic physical market is accounted for in Section 2.1, along with a discussion of pricing of electricity. Section 2.2 describes the financial power market, both in general terms and with a focus on Nasdaq Commodities. Introductions to risk management, hedging and derivatives are included. As a backdrop for the machine learning methods that will be introduced in Chapter 4, Section 2.3 will first describe which prediction methods are used by hydropower producers today. To complete the introduction to the Nordic power market, Section 2.4 concludes with a final remark on the power situation in 2018.

## 2.1 The physical power market

The Norwegian physical power market is part of the Nordic market, which is connected through the power exchange Nord Pool. In this section, we begin by introducing the wholesale and end-user market as well as the different market players. Thereafter, we introduce how electricity is priced and what affects these prices.

**Figure 2.1:** Illustration of the Norwegian power market

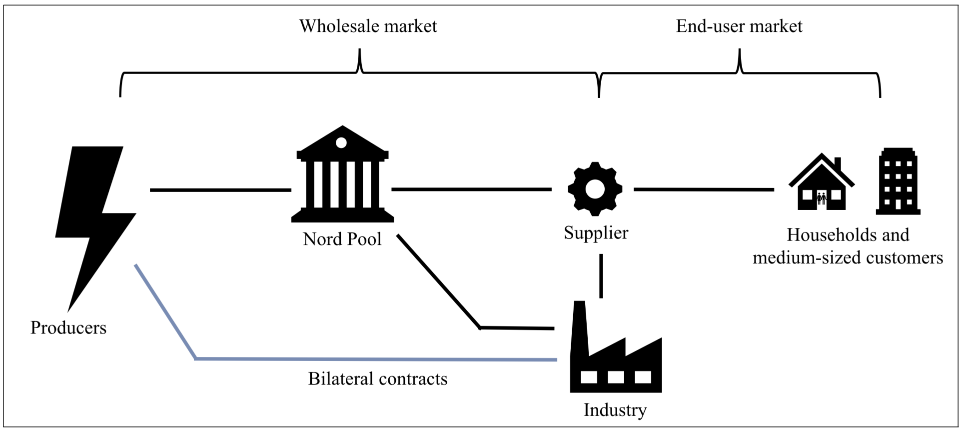



Figure 2.1 shows an illustration of the physical Norwegian power market. The market can be split into the wholesale and the end-user market (Norwegian Ministry of Petroleum and Energy, 2019c). In Norway, the end-user market is mainly split between households, medium-sized customers, such as chain stores and hotels, and the industry. In 2017, the three accounted for respectively 44.4%, 21.3% and 34.3% of the Norwegian power consumption (Statistisk sentralbyrå, 2019a). End users are consumers who purchase power for their own consumption. Power suppliers trade on behalf of these end users. In the wholesale market, larger volumes of power are bought and sold. Participants in this market

include power producers, energy companies, power suppliers, large industrial customers and brokers. Hydropower producers make up the largest share of power producers in the Norwegian market.

The wholesale market consists of three organized markets where participants place bids and the price is determined: the day-ahead market, the continuous intraday market and the balancing market (Norwegian Ministry of Petroleum and Energy, 2019c). For the first two, trading takes place on the Nord Pool exchange, whilst the balancing market is run by Statnett (Flataker and Nielsen, 2018). Market participants can also enter into bilateral contracts, which specify the volume of electricity bought or sold at an agreed price, for an agreed delivery period (Norwegian Ministry of Petroleum and Energy, 2019c).

Nord Pool is an exchange for trading contracts with delivery of physical power (Norwegian Ministry of Petroleum and Energy, 2015). The largest volumes of power in the Nordic region are traded in the day-ahead market (Norwegian Ministry of Petroleum and Energy, 2019c). Volumes are traded in contracts which specify hour-by-hour physical delivery for the next day. The day-ahead market is important for ensuring balance between supply and demand. However, the market participants' actual consumption and production might differ from their position in the day-ahead market. The intraday market is used to balance this difference. From the clearance in the day-ahead market up until one hour before the operation hour, contracts are continuously traded in the intraday market. However, events occur that could disturb the balance within the hour. Through balancing markets, Statnett regulates production or consumption up or down to correct for such events.

Participants in the day-ahead market make bids and offers every day (Norwegian Ministry of Petroleum and Energy, 2019c). Producers submit bids on how much they wish to produce at different prices, their bids reflecting the value they put on their production. On the demand side, actors submit bids that reflect how much they want to consume or provide to end users at specified prices. Every day, Nord Pool use the bids to calculate the system price for the following day. The system price is a theoretical price that is set in the equilibrium between supply and demand. It is set under the assumption that there are no congestions in the Nordic transmission grid and functions as an indicative price. The system price is the same for all geographical areas in the Nordic power market, while the realized price varies between different areas. The Nordic system price is also the reference price used for financial contracts on Nasdaq Commodities (Flataker and Nielsen, 2018).

In addition to the system price, Nord Pool sets area prices (Norwegian Ministry of Petroleum and Energy, 2019c). Norway is divided into five bidding areas, Sweden into four, Denmark into two, while in Finland there is only one bidding area. Norwegian hydropower producers will thus receive their area price in the physical power sale at Nord Pool. However, their income from contracts at Nasdaq Commodities is determined by the realized joint Nordic price. If the grid capacity at the time of transmission is not sufficient, congestions arise, and as a result the prices vary between the areas. The area prices thus take congestions in the grid into account. Without congestions, the power that is supplied to the grid will follow physical laws, flowing down the path of least resistance, so that power is exported from areas with a power surplus to areas with a power deficit. Regions that have a power surplus at a given time, might have a power deficit at another time. These differences could vary between different hours, seasons and years. Moreover, by physical laws, loss of power occurs in transmission of electricity through the grid (Rosvold, 2019). The loss constitutes up to 10% of the total generation.

With an open market, Norway has a high trading capacity with other countries (Norwegian Ministry of Petroleum and Energy, 2019c). As a result, Norwegian power prices are strongly affected by the cost of electricity production and consumption in other countries. Therefore, the price of coal, natural gas and emission allowances has an impact on the electricity price. In the Nordic region renewable energy sources, such as hydropower and wind power, constitute a relatively large amount of the power supply. Norway, Sweden and Finland have large hydropower resources, while wind power makes up a large part of Danish power production. In this way power prices in the Nordic region are affected by the variation in water inflow to storage reservoirs and the wind force near turbines. In years with high inflow, the power supply is high, and thus prices are pushed down. However, with low precipitation and lower inflow, prices rise. In windy and less windy periods we see similar effects. On the demand-side, temperature fluctuations also influence market prices, as it affects how much energy is used for warming houses. The factors that affect electricity prices will be elaborated on in Chapter 3.

Spot prices are volatile for different reasons (Falbo et al., 2010). In the short run, power demand is extremely inelastic, so unexpected shocks in demand, for example due to extreme weather conditions, are regulated through price spikes. Similar outcomes can be seen with disruption in transmission and unexpected outages. Electricity cannot be stored, and thus the typical volatility reduction that can be achieved through storage cannot be applied in this market. As discussed in Chapter 1, power producers' earnings rely heavily on power prices. Due to the volatility of prices, most hydropower producers hedge against price uncertainty (Norwegian Ministry of Petroleum and Energy, 2019c). It is common in electricity markets to sign contracts before the spot market trading occurs to hedge against this price uncertainty (Wu et al., 2002). In Section 2.2 such contracts and the financial market will be further explained.

## 2.2 The financial power market

In the following, we will present the basic functions of the Nordic financial power market. First, we will define and discuss risk management and hedging as a risk management strategy. Consequently, we introduce reasons for why hydropower producers choose to hedge power prices. Section 2.2.1 presents derivatives, which is the most common form of hedging. Benefits, criticism and pricing of derivatives follow the presentation. The focus of Section 2.2 will be on price risk and the Nordic power derivatives at Nasdaq Commodities, primarily futures contracts, which are the derivatives we focus on in this thesis.

*Hedging*

Before discussing specific strategies, we start by defining risk management and hedging. Risk management is the process where an individual or organization first defines which level of risk they wish to take, and thereafter measure and adjust their current risk level to equal their preferred level (Pirie, W. L. (Ed.)., 2017). Hedging is a risk management strategy that can be used to limit or offset the probability of loss from price fluctuations (Edwards, 2014). The strategy can help protect from uncertainty, so in effect, a hedge is a way to transfer risk. The downside is that hedging could involve a high cost or a reduction of the expected profit. Both situations could render a worse outcome than an unhedged position. Hydropower producers seeking to transfer risk, need to take their current market situation and environment into account.

When water inflow is high, the water levels in hydro reservoirs increase. To avoid spillages or low realized prices, hydropower supply increases and prices decrease. On the contrary, if water inflow is low, supply goes down and power prices rise. In other words, the power price and the water inflow are negatively correlated and by default risk is limited (Bråthen et al., 2010). However, Bråthen and Nissen-Meyer (2009) found that there are significant benefits connected to using hedging strategies that include electricity contracts compared to solely relying on the negative price correlation between power prices and the water inflow. They show that hedging electricity can reduce risk significantly with only a minor reduction in the mean revenue.

While hedging is done to reduce the volatility associated with a potential price change of a security, there are also speculators in the market that try to profit from these price changes (Edwards, 2014). The distinction between hedging and speculation can be subtle. A speculator in the power market could make a speculative bet that power prices will fall. This bet involves using the same transaction as the electricity producer who is hedging to reduce their price exposure. Thus, the difference between a hedge and speculation could be purely the intent of the trade.

Most of the major hydropower producers use hedging for portfolio- and risk management to cope with price fluctuations (Fleten et al., 2001). Hydropower producers experience large fluctuations in production revenues, caused by changes in factors such as the power price and inflow. Sanda et al. (2013) found evidence that about 90% of aggregate electricity production in Norway is subject to hedging policies. This indicates that producers are risk averse decision-making units, willing to pay to reduce risk. In the interview with BKK, the demand of risk management policies was discussed. As most Norwegian hydropower producers are fully or partially publicly owned, stable returns are important to ensure a predictable allocation of funds to public services. As such, risk management policies are important for producers. In order to control the risk in the total portfolio, producers are willing to start and maintain more or less costly risk management functions in the company (Fleten et al., 2001). In standard financial theory, investors can diversify this risk on their own, and the risk management functions will not be necessary (Copeland et al., 2013). In practice however, there are reasons for risk management within companies (Fleten et al., 2001). For instance, economies of scale in the risk management function could make it cheaper for producers than for individual owners to operate in the derivatives market.

Summarized, hydropower producers can use hedging to reduce their exposure to power prices, by securing a price for some of their future production. The producers are dependent on prices that are high enough for their production to be profitable, while buyers need to ensure that prices remain low enough. As hydropower producers and end users have different price interests, they can hedge by agreeing on a contract that binds the future price at a level acceptable for both contract parties, thereby eliminating the risk of unprofitable power prices. Alternatively, both entities can secure prices by purchasing power derivatives on Nasdaq Commodities. Further, this thesis will look closer into some of the financial contracts offered at Nasdaq Commodities, and discuss differences between these and long-term contracts.

### 2.2.1 Derivatives

In the investment world, the most common way of hedging is through derivatives (Reiff, 2018). Derivatives are financial contracts that derive their performance from the performance of an underlying asset or reference price (Rahman, 2015). The underlying asset is the source of the risk (Pirie, W. L. (Ed.)., 2017). However, the underlying does not need to be an asset itself. It is common to use currencies or equities as underlyings, but other derivatives have underlyings that in general are not thought of as assets, e.g. energy and weather. Derivatives are widely used in the Nordic power market and the Nordic market is one of the most liquid derivatives markets in the world (Nasdaq, Inc., nd). At Nasdaq Commodities, the underlying asset for Nordic power derivatives is the Nordic system price. Instead of physical delivery, there is a cash settlement of the futures contracts. Settlement is the process where the actual exchange of money or physical delivery of an asset takes place. Derivatives are similar to insurance, considering that both enable transferring risk, have a definite life span and an expiration date (Pirie, W. L. (Ed.)., 2017).

Two parties are involved in a derivative contract, a buyer and a seller (Cohan, P. S. and Capstone Press Staff, 2003). The buyer of the derivative takes a long position, they own or hold the derivative, and will profit when the value of the instrument they own increases (Johnson, 2017). On the other end, the seller of the derivative holds a short position on the derivative, and will gain profit from decreases in the value of the instrument he or she has sold. A hydropower producer who wants to secure a sales price for their production would thus sell a derivative, taking a short position. On the other side, an end user or distributor who wants to lock in a price to ensure their electricity price will not get too high would buy a derivative, taking a long position. The rights and obligations of each contract party are defined in the derivatives contract.

In the Nordic power market, derivative contracts can be traded on the over-the-counter (OTC) market or on the exchange Nasdaq Commodities (Norwegian Ministry of Petroleum and Energy, 2015). OTC-derivatives are customized contracts that are transacted bilaterally between parties. These contracts provide tax benefits that we will return to in Section 2.2.2, but involve the risk that the counterparty fails to meet their obligations under the contract (Rahman, 2015). However, by using a central counterparty clearinghouse that clears the transaction, this risk can be mitigated. At Nasdaq Commodities the derivative contracts are cleared and standardized. Clearing is the process where an exchange verifies the execution of a transaction and records the identities of the participants. Standardization implies that contracts follow specified terms and conditions stated on the exchange, and the possibility for altering those terms is very limited. The standardization of contracts also makes the transactions easier to analyze analytically, which will be exploited in Chapter 5.

The liquidity of power derivatives is driven by trading interest, and the standardization of contract terms on Nasdaq Commodities facilitates the creation of a more liquid derivatives market. The creation of a clearing and settlement operation is also facilitated by standardization (Pirie, W. L. (Ed.)., 2017). Altogether, settlement, clearing and standardization ensures that money is collected and disbursed efficiently, which is a critical element of derivatives trading.

Derivatives are divided into two general classes (Chen, 2018). The first class provides the right but not the obligation to purchase or sell the underlying at a predefined price and is called contingent claims. Options are the primary contingent claims (Pirie, W. L. (Ed.)., 2017). The other derivatives class provides the ability to lock in a price that the underlying might be bought or sold for. These are called forward commitments as they force both contract parties to go through with the transaction at the price agreed upon previously (Chen, 2018). On Nasdaq Commodities one can find both forward commitments and options. This thesis focuses on forward commitments as it is the most used derivatives class for electricity contracts (Fleten et al., 2001).

Forward commitments include forward contracts, swaps and futures contracts (Chen, 2018). In standard financial theory, a forward contract is a derivative contract that is traded over-the-counter (Pirie, W. L. (Ed.)., 2017). Two parties agree that the buyer will purchase the underlying from the seller at a later date, for a price agreed upon when the contract was initiated. Another form of OTC-contracts is swaps, where the two parties make an agreement to exchange a series of cash flows. One party will pay a variable series that is determined by either an underlying asset or rate, while the other party will pay either a variable series that is determined by another underlying asset or rate, or a fixed series. Unlike forwards and swaps, futures contracts are not traded over-the-counter, they are created and traded on an exchange. Futures are standardized derivative contracts where two parties agree that the buyer, at a later date, will purchase the underlying asset from the seller. It will be sold at a price the parties agreed upon when they signed the contract and will have daily settling of gains and losses. The futures exchange also gives a credit guarantee through its clearinghouse. For the remainder of the thesis, we will focus on futures traded at Nasdaq.

#### 2.2.1.1 Advantages and criticism of derivatives

In contemporary finance there are several reasons why derivative markets have an important and useful purpose (Pirie, W. L. (Ed.)., 2017). Before derivatives markets existed, risk management was cumbersome, it could be disruptive for portfolios and usually involved high transaction costs. Derivatives solve the problem of risk allocation, transfer and management very effectively, both for companies and economies. Using derivatives allows trading the risk without trading the instrument itself. However, derivative markets have also been criticized. Critics argue that derivatives are speculative devices that allow for legalized gambling. They also argue that derivatives could lead to major financial crises (CFA Institute, 2017). Further, we will discuss the benefits and the criticism connected to derivatives.

*Benefits of derivatives*

One advantage of derivative markets can be found in the predictive function posed by futures prices (Pirie, W. L. (Ed.)., 2017). Futures prices could hold some information about the future, as they reflect the market's expectation of how the underlying prices will develop. The fundamental value of the underlying is likely to be reflected in the derivative markets before the underlying market is adjusted. Thus, it could provide information of future power prices for hydropower producers. Another advantage with derivatives is that it opens up for exposure in instruments that cannot be purchased directly (CFA Institute, 2017). An example of this is weather. Such derivatives could provide an advantage for hydropower producers who want to hedge against volume risk related to the uncertainty of water inflow.

Derivatives also provide operational advantages (CFA Institute, 2017). The transaction costs of derivatives tend to be lower than for the underlying. Therefore, trading derivatives requires less capital than an equivalent exposure in the underlying asset directly. Such trade advantages further lead to a higher liquidity in the derivatives market than in the underlying spot market. In addition, derivative markets have the operational advantage that shorting is very easy, in contrast to underlying assets where it is usually more difficult to go short than long.

All the stated advantages of derivatives markets contribute to financial markets functioning more effectively (Pirie, W. L. (Ed.)., 2017). The advantages attract investors, increasing the number of market participants. The operational advantages of low transaction costs, more market participants and easier short selling enables exploitation of mispricing at a lower price, increasing liquidity and market efficiency further (CFA Institute, 2017). The increased market efficiency posed by derivatives markets simplifies the process for hydropower producers as well as other market participants to purchase and sell power contracts. The stated benefits are thus factors that favor the use of futures contracts over OTC-contracts.

*Criticisms and misuses of derivatives*

For hedging to work efficiently, speculators are needed, as someone has to accept the posed risk (Pirie, W. L. (Ed.)., 2017). Derivative markets are attractive for speculators, and more speculators in the market increases liquidity of contracts, making hedging cheaper. Critics have found the growth in speculative investments alarming, although it has proved to be beneficial for investors. Speculators are often accused of participating in price manipulation and trading at extreme prices. Particularly speculators operating in the electricity market have often been questioned by politicians and regulators. As a recent example, Nasdaq Commodities was under supervision by The Financial Supervisory Authority of Norway after the announced default of trader Einar Aas on September 11th 2018 (Finanstilsynet, 2019). The sum of negative factors causes critics to view speculation as a legal form of gambling (Pirie, W. L. (Ed.)., 2017). However, in contrast to gambling, trading derivatives benefits financial markets by increasing liquidity and market efficiency, and thus also society as a whole (CFA Institute, 2017).

Arguments against speculation go further, and it is claimed that it is not merely speculation or gambling in itself that is the problem, but that it has destabilizing consequences on the financial markets (CFA Institute, 2017). The critics claim that the benefits of hedging lead to excessive speculative hedging which can further lead to default of speculators (Pirie, W. L. (Ed.)., 2017). This in turn can make their creditors default, and spread further throughout markets, an economy, or even the entire world. Such effects were for example seen in the financial crisis of 2008, where many of the problem entities traded derivatives. However, speculative hedging is not the only cause of financial crises. Financial crises have existed since the occurrence of capitalism, such as the stock market crash of 1929 and the South Sea and Mississippi bubbles. Many of these crises happened before the introduction of modern derivatives markets, while others had no relation to the use of derivatives.

To conclude, there are both benefits and disadvantages connected to derivatives markets. Derivatives contribute to a more efficient and liquid market, but also introduce dangers of destabilizing the financial market. Having respect for the danger power derivatives pose is important for using and understanding derivatives (Pirie, W. L. (Ed.)., 2017). In total, derivatives could improve financial markets and the risk management for hydropower producers, but it is important to know how to use them safely.

### 2.2.2 Derivative pricing and costs of hydropower producers

As introduced in Chapter 1 and earlier in this chapter, the electricity market has special characteristics that differs from all other commodity markets. Electricity is not storable, hence power prices are very volatile. Moreover, electricity is lost when transmitted through the grid, and as a consequence there is an imbalance between production and consumption (Rosvold, 2019). The standard pricing of power derivatives and hydropower producers' transmission costs will be elaborated in this section. In addition, this section includes a brief look on the effect of taxes.

#### 2.2.2.1 Pricing of power derivatives

Due to the peculiarities of electricity markets, pricing of power derivatives is different than for other commodities (Vehviläinen, 2002). As electricity is not storable, there is no point in pricing power derivatives based on standard storage cost arguments or product arbitrage. Peaks in the demand and shortages in the generation of electricity results in spikes, jumps and volatility in the spot prices. Further, no analytical connection between the forward prices and the spot price has been established.

Prices of power derivatives are determined by the supply and demand of price hedging and speculation. Producers are on the supply side, power suppliers and large-scale end users, such as actors in the power-intensive industry, are on the demand side, and speculators are found on both sides. Some speculators are international financial actors, which gives reason to believe the contract prices are eventually determined by the correlation with macroeconomic factors such as the oil price (Pirie, W. L. (Ed.)., 2017). Still, the most important factor for pricing of futures- and forward contracts is the expectations market participants have of future system prices.

#### 2.2.2.2 Taxes and transmission costs

Hydropower producers feed power into the main grid and receive the spot price as income. However, producers have to pay a charge for each MWh they feed into the grid, hereby referred to as transmission costs. The transmission costs are determined by and paid to the distribution companies and consist of a fixed and a variable charge (Norwegian Ministry of Petroleum and Energy, 2014). These charges are based on how much power disappears from the grid along the way to consumers. Power producers cover part of the fee, while consumers pay the other part through network tariffs. How high the realized fee becomes depends on where and when the power is produced. As an example, if transmission costs at a given time amount to 10% of the spot price, hydropower producers will be left with 90% of their initial income. At times, transmission costs may even be negative in certain geographical areas. In the eastern part of Norway, producers have occasionally been paid to keep the voltage in the grid up, while in the western part of Norway, there is often a power surplus, as the market is made up of many hydropower producers and a smaller population. Thus, the transmission costs in the west are practically always positive. When developing hedging strategies, hydropower producers have to take transmission costs into consideration in the decision of how much of their future income they should secure.

Another factor that is decisive for the proportion of electricity hydropower producers should hedge, is the taxation of electricity in Norway. Contracts purchased at Nasdaq Commodities are taxed based on the hour-by-hour spot price. This implies a risk for the purchased financial contracts as hydropower producers will have to pay taxes on an amount unknown until the actual delivery date, i.e. the system price. Thus, if a power producer has secured the price of their entire production for a given period, they are in high risk of a tax shock. In contrast to the contracts purchased at Nasdaq, the tax for bilateral contracts is based on the contract price. This removes the risk of taxes increasing relative to the contract price, and thus, signing contracts bilaterally provides a tax advantage for hydropower producers compared to signing financial contracts at Nasdaq Commodities.

### 2.2.3 Concluding remarks on the financial power market

As introduced in Chapter 1, the liquidity in the financial market at Nasdaq Commodities has been going down in recent years. Moreover, the liquidity of long-term contracts is particularly low. The power market is not the customary market for speculators and has generally been characterized by few actors trading large volumes. As the overall discussion of this chapter has stated, most power producers adopt hedging policies. This creates an imbalance between the supply and demand side of the market, as there are more actors on the short-side of the financial contracts. Especially after the default of Einar Aas, who was one of the most successful speculators in the market, there has been a substantial decline in power trading (Finanstilsynet, 2019). A decrease in the demand of contracts could increase the premium power producers have to pay when securing future power prices. In that case, producers would find the contracts less attractive as the transaction costs reduce their expected revenue.

However, the benefits of the markets, including Nasdaq Commodities, exceed the drawbacks, and it is in the interest of all market participants to sustain a liquid and effective financial market for trading power derivatives. The goal should therefore be to turn the downward trend and increase market liquidity. However, the market is still one of the most liquid power derivatives markets in the world, and there are many available tools and approaches to maintain and improve a well-functioning market. One is to address the uncertainty and provide a good decision basis that facilitates well-informed trading.

## 2.3 Current practice for predicting power prices

For hydropower producers, predictions of power prices are important for making well-informed decisions of how much power should be produced at different times, and how much of the production should be hedged. The largest players in the market today use a wide variety of tools to predict future prices. One of the most common models used for hydropower producers' decision making is the Grid Simulation Model (Samkjøringsmodellen). In addition, producers benefit from expert views, self-produced prediction models, publicly available forecasts and reports supplied by external providers, e.g. consultancy firms. The specific algorithms used by producers and other businesses to predict future electricity prices are usually proprietary and not shared with third parties. Further in this section, some of the predictive sources used by hydropower producers for decision making will be discussed. These sources are the ones the machine learning models we estimate in Chapter 5 are ought to supplement.

### 2.3.1 The Grid Simulation Model

In the Nordic power market, the Grid Simulation Model (GSM) is one of the most widely used energy models (SINTEF, nd). The GSM was developed by SINTEF and is a data program used for simulation and optimization of hydrothermal power systems. Detailed descriptions of wind power, hydropower, thermal power plants and consumption need to be included as inputs to the model (Norges vassdrags- og energidirektorat (NVE), 2016a).

The model takes limitations in transfer capacity and geographical hydrological differences into account (SINTEF, nd).

The GSM divides the hydropower reservoirs into sub-areas, and in the optimization process, the water value in the reservoirs is estimated for each area (Norges vassdrags- og energidirektorat (NVE), 2016a). Restrictions on the reservoir capacity, the minimum water flow, and consumption that needs to be covered are included in the model. The output is a strategy for how hydropower resources should be allocated throughout the analyzed period. The hydropower producer will produce as long as the spot price is higher than the water value in their sub-area.

After the strategy is determined, temperature and inflow scenarios are used to observe how the different sub-areas in the power market respond to changes in price and consumption, and how supply changes with different levels of inflow (Norges vassdrags- og energidirektorat (NVE), 2016a). Finally, the model opens for trading between areas through a detailed description of the power grid. The model can be used to forecast future electricity prices, electricity production, reservoir filling, water supply and for investment analysis (SINTEF, nd).

### 2.3.2 Other methods for price prediction

Hydropower producers can also benefit from price predictions offered by external businesses, such as data and consultancy firms. Examples include Wattsight, who provides short- to long-term power price forecasts (Wattsight, nd) and Nena who provides price prognoses for years, quarters, months, upcoming weeks and the day ahead (Nena, nd). Many of these firms also offer support for risk management, hedging and production planning.

In addition to predictions generated by statistical models, expert and analyst views, as well as the expertise and knowledge of the business itself, can be thought of as judgmental forecasts. Judgmental forecasts are common in practice, where forecasters with important domain knowledge and more timely up-to-date information make forecasts using subjective judgment (Hyndman and Athanasopoulos, 2018). The normal application of judgmental forecasts is to either adjust already generated statistical forecasts or combine the two after both are generated separately.

Through the interview with BKK, the general practice of the largest hydropower producers was discussed, and their methods for price prediction appeared to involve a combination of a variety of tools for prediction purposes. The practice is to base hedging strategies and investment decisions on an overall assessment of different models and sources. Their decisions are based on predictions by the models they have at hand, judgmental forecasts, as well as expected outcomes of variables associated with power prices. These variables include prices such as oil, coal, gas and carbon prices, weather forecasts provided by weather services and expected developments in production and consumption.

Most of the major market participants have employees that are responsible for portfolio- and risk management (Fleten et al., 2001). The employees controlling the portfolios are referred to as traders. The traders use of price predictions in investment decisions include both the statistically generated predictions and judgments. However, the exact strategies and considerations are proprietary. Considering the variety of sources used for predictions of the Nordic system price to optimize investment decisions, it seems natural to address whether machine learning methods can be used as a supplement. As we will evaluate the machine learning alternative by predicting prices in 2018, we will in the following introduce the market developments of this year.

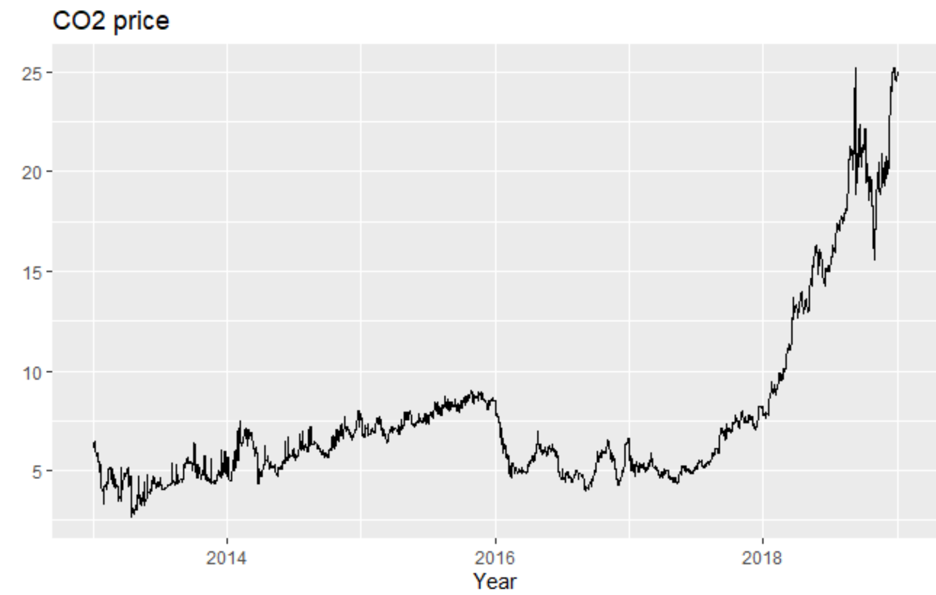
## 2.4 Power situation of 2018

The period of analysis in this thesis is 2018. Before the year begun, experts anticipated a year with lower Nordic system prices than in 2017. However, the development went the complete opposite direction (Svorka, 2018). Prior to applying machine learning models to predict the prices of 2018, we will introduce some of the main characteristics of this year.

The winter of 2017/2018 in the Nordic countries was cold, which led to a high electricity consumption (Energi Salg Norge, 2018c). In the beginning of 2018, there was much snow, which would normally result in a high inflow to the water reservoirs during the summer. However, the Norwegian temperatures in 2018 increased rapidly and stayed high (Fjeld et al., 2018). The result was high inflow into the reservoirs in May (Norges vassdrags- og energidirektorat (NVE), 2018). Hence, hydro reservoir stocks increased above average. Nevertheless, towards the end of the second quarter the inflow to reservoirs flattened out, as precipitation was extremely low and there was little snow left in the mountains. The inflow into Swedish reservoirs had the same development, with a sharp increase in May followed by a flattening towards the end of the quarter. Finnish reservoirs followed a normal trend. In the Nordic market in general, the Danish wind power production was low, and Swedish nuclear power production was reduced as the seawater used for cooling was too warm (Hovland, 2018a). All these factors contributed to increased Nordic prices.

In addition to the high temperatures, there was a drought in the summer (Skaland, R. G., Colleuille, H., Andersen, A. S. H, Mamen, J. Grinde, L., Tajet, H. T. T.,..., Hygen, H. O., 2019). The most unusual with the drought in 2018 was how long it lasted and how large areas it affected. Temperatures from May throughout July were record high in Norway, with an average temperature of 3.1 °C above normal temperatures. On top of this, the low downfall in the same period caused the fourth driest period of May through July since measurements started in 1900, with only 74% of the normal downfall. Large parts of Europe were affected by the drought, and the unusually dry and warm weather lasted for five months in Central Europe.

**Figure 2.2:** Development of CO2 prices




Another price factor other than the weather, was the dramatic development of CO2 prices, which can be seen in Figure 2.2. After being relatively stable in the years prior, the CO2 price increased exponentially in 2018. At the same time, prices of coal increased, making electricity production in Europe more costly and thus European power more expensive. Due to the connection of the Nordic and European market through import and export of electricity, the increased costs further contributed to augmenting Nordic system prices. The sum of the factors mentioned above was a 50% increase in the Nordic system price from the foregoing year.

The Nordic prices in 2018 were not only higher than in 2017, the Norwegian electricity prices for households were also the highest prices that have been registered (Statistisk sentralbyrå, 2019b). Consultant firms were far off in their price predictions. For example, Thema Consulting Group (2017) predicted that the Norwegian electricity price would be about 26 øre per kWh. The average electricity price for households in 2018, excluding taxes and grid rent, was 48.6 øre per kWh (Statistisk sentralbyrå, 2019b). In order to find Norwegian power prices near this level, we have to go back to 2010/2011.

The developments are also reflected in the prices on December 1st 2017, which is the date where predictions and decisions regarding whether a futures contract should be purchased or not are made. At this date, the futures prices for a yearly contract at Nasdaq Commodities was 26.90 euros, while the actual system price ended up being 43.99 euros. This is the highest system price that has been registered since 2011. The time horizon for the data collection in this thesis is from the first day of 2013, up until the end of 2018. The Nordic system price in 2018 was thus the highest registered price in the analyzed data set. The reasoning for choosing 2018 as the test set, despite its extreme values, is the argument of having enough observations to train machine learning models on. Moreover, we want to build a model that works every year, even when prices are peculiar, which is often the case for Nordic power prices. In Section 6.4 we discuss the robustness of using 2018 as the test set as opposed to other years in the data set. All variables and considerations of the data set are introduced in the following chapter.

# 3 Data

The aim of the imposed methodology in Chapter 4, is to introduce and test machine learning methods that can provide increased decision support for the decision of whether or not to purchase a futures contract at a given date. The decision support we wish to add will be in the form of predictions of the prices the futures contracts are settled against. As the reference price for futures contracts at Nasdaq Commodities is the Nordic system price, this is the price we wish to predict. The decision of whether or not to purchase the contract will be made based on a comparison of the predicted price and the contract price for the futures contracts at a given date. For monthly futures, we wish to predict the average monthly system price for the upcoming month, while for quarterly and yearly contracts we wish to predict the average quarterly or yearly price respectively, for the period in question. For this purpose, we use observations of the Nordic system price and associated variables gathered through different sources. Observations have been registered daily from January 1st, 2013.

In the following sections, we first introduce the Nordic system price and how we treat this to use it as the dependent variable. Thereafter, the different predictors are introduced along with a discussion of their relationship to the system price. Lastly, we include a discussion of other possible predictors and the treatment of missing values. The descriptive statistics of all variables are included in Appendix A2.

## 3.1 Dependent variable

Our dependent variable is the average Nordic system price for the period corresponding to each futures contract. In this thesis, the focus is on three different futures contracts, namely monthly, quarterly and yearly contracts. Therefore, we develop different models for each of the three terms, with dependent variables corresponding to the average yearly system price, the average quarterly system price and the average monthly system price respectively. The point in time of prediction is the first day of the month prior to the term of the contract in question. Thus, all predictors are lagged so that the dependent variable for the first day of a given month, will be the average price for the next month, quarter or year, depending on the contract. Table 3.1 shows the point in time when predictors and the dependent variable are registered in the first observation of the data set, namely January 1st, 2013.

**Table 3.1:** Registration time for variables at the first observation (January 1st, 2013)

| Model | Dependent variable (avg.) | Predictors |
|---|---|---|
| Monthly | 2013/02/01 - 2013/02/28 | 2013/01/01 |
| Quarterly | 2013/02/01 - 2013/04/30 | 2013/01/01 |
| Yearly | 2013/02/01 - 2014/01/31 | 2013/01/01 |

Table 3.1 shows that in the monthly model, all predictors are registered on January 1st, 2013, while the dependent variable is the average of Nordic system prices from February 1st to February 28th 2013. The quarterly and yearly models use the predictors observed at the same date, but the dependent variable is either the average of values the next three months or the average of values a year ahead. The registration time for variables follow the same pattern at each observation as shown in Table 3.1. The daily observations of system prices are gathered from the historical market data registered at Nord Pool (Nord Pool, 2019). The official day-ahead market currency is euros, which implies that both actual system prices and the financial contract prices are given in euros per MWh.

## 3.2 Predictors

The predictors used in our model are gathered through different sources. All predictors are observed daily, except for hydro reservoirs, which are registered weekly. The different predictors are chosen based on the assumption that they are associated with the Nordic system price. Some will indirectly impact the price, by affecting the power demand or consumption, while other predictors are assumed to have a direct effect on the pricing.

In the case where the predictors are prices themselves, the currency conversion has to be taken into account. Several predictors in the model are retrieved from Datastream (Thomson Reuters Datastream, 2019). Datastream is a historical financial database provided by Refinitiv, previously Thomson Reuters. Datastream uses the World Market Reuters series to recalculate and download data in a specific currency. Predictors from other sources are loaded in their local currency. The assumed relationships between predictors and the dependent variable, reasoning for selections and sources from which we gather the data, will be elaborated on in the following subsections.

### 3.2.1 Production and consumption

The assumptions of price effects caused by changes in power production and consumption follow standard economic theory. With increased production, prices are expected to decrease, while increased consumption will have the opposite effect. Daily production and consumption of electricity by country is gathered from the historical market data at Nord Pool. The data is given in MWh. Both figures are registered in Norway, Sweden, Finland, Denmark, Estonia, Latvia and Lithuania, as the Baltic countries are closely connected to the Nordic power market. Because of transmission losses, as accounted for in Section 2.1, consumption will not equal production.

In addition to daily aggregated production by country, Nord Pool also provides numbers of daily wind power production in Denmark, Sweden, Finland, Estonia, Latvia and Lithuania. Wind power production in Norway is loaded from NVE (Norges vassdrags- og energidirektorat (NVE), 2019b). Altogether, the total production and consumption, as well as the wind power production amounts to 21 variables.

### 3.2.2 Temperature

The Norwegian power consumption, and thus also the power prices, are highly dependent on the temperature. With low temperatures, consumption increases, while the opposite is true for high temperatures. The temperatures will also affect the spring thaw, and hence the inflow into Norwegian hydro reservoirs. An early arrival of the spring will therefore expedite snowmelt and increase reservoir stocks. Normally, snow melting leads to a larger inflow to hydro reservoirs, however the effect can also be negative. As in the case of spring of 2018, as introduced in Section 2.4, the rapid arrival of the warm weather caused less inflow. Another reason why temperatures are important for the power price is in the case of damages inflicted by low temperatures. Very low temperatures can cause congealing of pipes in hydropower plants, potentially leading to shutdowns and lower production.

The power consumption in the Norwegian end-user market can be divided between three parties, as stated in Section 2.1. These three are the industry, the service sector and households and agriculture. The industry power consumption is not very dependent on the temperature, as electricity is used as an input factor in production (Statistisk sentralbyrå, 2018b). Thus, consumption depends more on the product demand. As opposed to the industry, temperature is an important explanatory variable for the consumption in the service sector, households and agriculture. In the service sector, a large part of the consumption goes toward heating of offices and buildings, and economic activity and power prices in itself are important explanatory variables for the development in power consumption. For households, heating amounts to 70-80% of the power costs (NorgesEnergi, 2018).

Statistisk sentralbyrå (2018a) publishes yearly statistics of power consumption divided by entity. Numbers from 2017 show that nine municipalities constituted roughly 30% of the consumption in the service sector, households and agriculture. The municipality of Oslo accounted for 11.55% of the consumption, while Bergen and Trondheim respectively accounted for 4.97% and 3.20%. The respective shares decrease as the municipalities consume less. Thus, the marginal increase of accumulated consumption gets smaller the less the municipality consumes. As a result, the use of time compared to the obtained value by adding variables of each Norwegian municipality is too large. After the last included municipalities, the marginal increase of accumulated consumption starts falling below one percentage point. As a result, we include the nine municipalities amounting to 30% of the accumulated consumption.

Using the Frost API by the Norwegian Meteorological Institute Norway (see Frost API, 2019), historical temperature data from weather stations across Norway are loaded. The average daily temperature is read daily at 12 pm. Following the nine municipalities, we choose weather stations in Oslo (Blindern), Bergen (Florida), Trondheim (Værnes), Stavanger (Utsira fyr), Bærum, Tromsø, Kristiansand (Oksøy fyr), Fredrikstad and Asker for downloading the temperature data. The only retrievable source of temperature data in Bærum from the Frost API has a total of 1358 missing values in the period in question. Bærum is located closely to both Oslo and Asker, hence the correlation between temperatures at the stations are very high. Therefore, this variable is dropped from the data set. The daily temperatures in Celsius from each of the remaining stations are included as predictors.

### 3.2.3 Hydro reservoirs

As mentioned in Section 3.2.1, increased production is associated with lower system prices. The willingness and ability of hydropower producers to produce is determined by the reservoir levels in their magazines. The producers can regulate and transfer their production to other periods by controlling the level of their magazines. A common approach, as introduced in Section 2.3.1, is to calculate the water value in the magazines, compare this to spot prices and based on this determine whether to produce or not. If levels are too high, producers are forced to produce anyway, as spillage is worse than low prices.

Norway, Sweden and Finland generate the most hydropower production in the Nordic market. From the historical market data at Nord Pool, we find weekly observations of hydro reservoirs measured in GWh for each of the three countries. Assuming that the weekly data can be used for each day of the corresponding week, we assign each day with that value.

### 3.2.4 Precipitation

Hydropower production is determined by water levels in hydro reservoirs, which again are determined by the inflow. In periods with much precipitation near reservoirs, reservoirs fill up. This forces hydropower producers to increase production to avoid spillage and loss of inputs, as this leads to financial losses. With lower precipitation, reservoir stocks shrink, and producers decrease their production. Lower production is again associated with higher prices.

Following the logic in the previous paragraph, the precipitation amounts near Norwegian hydropower plants will be important factors in production planning. As was the case for the temperature data, the marginal increase of accumulated hydropower production gets smaller the less a hydropower plant produces, and compared to obtained value by including production of each plant as a variable, the time used will be futile. In years of normal inflow, the hydropower plant of Tonstad accounts for the largest share of the total Norwegian hydropower production at 3.22%, while the corresponding figure for runner-up Kvilldal is 2.66%. Roughly 20% of the average yearly hydropower production in years of normal inflow is attributed to 11 hydropower plants. After these 11 plants, the marginal contribution becomes lower. Thus, we choose to focus on these plants when considering precipitation amounts. The hydropower plants are at Tonstad, Kvilldal, Aurland I, Svartisen, Tokke, Rana, Sy-Sima, Nedre Røssåga, Aura, Brokke and Vamma (Norges vassdrags- og energidirektorat (NVE), nd). Again, using the Frost API, we retrieve the weather station located closest to these power plants and load their registered precipitation amounts, rendering 11 new predictors. The precipitation amount is registered daily at 6 am, and given in mm.

The loaded precipitation amount at Rana stops being registered on October 31st, 2018. The same applies to Vamma, where the observations stop even earlier, namely June 29th 2018. For the remaining dates, observations are thus instead loaded from seNorge, an online data service provided through a collaboration between The Norwegian Water Resources and Energy Directorate (NVE), Norwegian Meteorological Institute (MET) and the Norwegian Mapping Authority (seNorge.no, 2019). Precipitation amounts at Vamma for the remaining period is retrieved from the station in Askim, while the station used for precipitation at Rana is Skamdal.

### 3.2.5 Water equivalent of surface snow

In addition to precipitation amount, the inflow to hydro reservoirs is impacted by the amount of snow in Norwegian mountains. The water equivalent of surface snow tells how much water in mm the snow amounts to as it melts (Norges vassdrags- og energidirektorat (NVE), 2016b). Around one third of the yearly precipitation amount in Norway is stored in the snow magazine during winter. The measure is calculated by multiplying the snow depth by the density of the snow. Daily observations of the water equivalent of surface snow is loaded from all available stations using seNorge (seNorge.no, 2019). This amounts to 20 different stations and variables.

### 3.2.6 Wind speed

As opposed to hydropower, where production is flexible, the production of wind power is intermittent. Hence, the wind speed determines the wind power production at a given time. As most wind power production is subject to government subsidies, and marginal costs of production is close to zero, power prices can reach very low levels before a wind power producer chooses to shut down a turbine. In periods with strong wind force and low demand, power prices in particular areas can become very low, and even reach negative levels (Buli, 2019). A more complete description of how prices become negative is included in Appendix A1.

Germany is the largest European producer of wind power, while Denmark has the largest share of wind power production in its energy mix (Andersen, 2019). To take the wind speed into consideration when predicting the Nordic system price, the average daily wind speed observations from Denmark and Germany are included. The Danish and German observations are given in m/s and collected from Danmarks Meteorologiske Institut (DMI) (2019) and Climate Data Center (CDC) (2019), respectively.

### 3.2.7 Gas price

In 2016, 20% of the European power generation was made up by natural and derived gas (European Environment Agency, 2018). As opposed to hydro- and wind power, where the factor input is practically free, gas-fired power stations are largely affected by the gas price. As gas prices increase, so does the operating costs. As a result gas prices are key factors for the power prices (Bøhnsdalen et al., 2016). The close linkage between Nordic and Continental prices makes the gas prices key drivers for Nordic power prices as well.

The European market does not have one common reference price, but instead operate with fragmented hub pricing points (Chen, 2019). Natural gas prices will often be indexed to commodities such as crude oil, introducing other factors to affect the natural gas price. Further, we use the Natural Gas Henry Hub Spot Price as the reference price for natural gas. The Henry Hub Spot Price is a market clearing pricing concept based on supply and demand of natural gas as a stand-alone commodity. Although based in the United States, the price is also used in liquid natural gas-delivery contracts on a global basis. By its wide use, Henry Hub has a large trading volume, clear pricing transparency and high liquidity. The price is measured in U.S. dollar per 1 Million British thermal unit (Btu). Historical prices are loaded from U.S. Energy Information Administration (EIA) (2019).

### 3.2.8 Coal price

Coal is the world's largest source of electricity, and accounted for 21% of the European power production in 2016 (European Environment Agency, 2018). Similar to producers of gas-fired power, the operating costs of producing coal-fired power is largely determined by the coal price. The effect on the Nordic prices will be similar - higher coal prices will lead to higher European power prices, and thus also Nordic power prices.

As for gas prices, there are several ways to price coal. For this analysis, we have chosen to retrieve the API 2 index by The Argus/McCloskey's Coal Price Index Service (Argus Media group, 2019). The reasoning is that the API 2 functions as the industry standard reference price used for coal imported into northwest Europe. Historical coal prices per Metric Ton are loaded from Datastream. All prices are converted to euros.

### 3.2.9 Oil price

Oil and electricity are two forms of energy, but apart from this they have little in common (Myhre, 2016). Nevertheless, there is correlation between oil prices and power prices. The oil price affects the coal price, and as discussed, coal prices impact Nordic power prices. Therefore, the oil price will also correlate with the Nordic power price. With increases in oil prices, coal prices increase, leading power prices to increase. Again using Datastream, we load daily observations of the Brent Crude Oil price. The prices are registered in dollars per barrel.

### 3.2.10 U.S. dollar exchange rate

Coal is priced in U.S. dollars, thus the dollar price will affect the operating costs, and therefore the production at coal-fired power stations (Skagerak Kraft, nd). Favorable exchange rates render better circumstances for the producers. More specifically, an increase in the dollar exchange rate relative to the euro will cause more expensive coal. For other power producers importing American inputs priced in dollars, such an increase will have a similar effect. Ultimately, the increased cost is associated with decreased production, and thus higher system prices. All prices in our data set are as yet either given in euros or U.S. dollars. Thus, the USD/EUR cross is included as the chosen predictor in the data set. The source of retrieval is yet again Datastream.

### 3.2.11 CO2 price

In 2005, carbon emission allowances were introduced, forcing power plants to pay for their emissions (Skagerak Kraft, nd). Today, these allowances are traded in a separate market and represent the cost of emitting one ton of carbon dioxide (CO2). When the prices of these allowances increase, the production at fossil-fueled power stations becomes more costly. Similar to the price of gas and coal, CO2 prices are thus also key factors for the power prices (Bøhnsdalen et al., 2016). As such, an increase of the CO2 price leads to an increase of the Nordic system price. The CO2 prices are retrieved in euros from Investing.com, a global financial portal owned by Fusion Media Ltd (Fusion Media Limited - Investing.com, 2019).

### 3.2.12 Periodical predictors

In addition to the fluctuating predictors introduced in the previous sections, we include periodical predictors whose value will depend on the date and hence be known in advance. For the models rendering monthly and quarterly predictions, we include a dummy variable indicating the observation period, i.e. either a monthly or a quarterly dummy. Years are not registered as dummies because a given year will only be observed once, and hence out of sample predictions will not work. In addition, there is no unambiguous increasing or decreasing yearly trend in the sample, so an increase or decrease of a year is not believed to have a particular association with the yearly price.

### 3.2.13 Nordic stock exchange indices

The Nordic power exchange is affected by fluctuations at other exchanges (Skagerak Kraft, nd). Moreover, the state of the economies as a whole will also impact power consumption and production. The performance of the stock market in a country can give an indication of the state of the economy (Masoud, 2013). This performance can be summarized in the stock exchange indices, as they reflect investor sentiment of the country's economy. For the Nordic system price, set by the Nordic consumption and production, the state of the economies in these countries are deemed important. An increase in the stock market index of a country is associated with a positive development in that economy, implying an increase in consumption. The increased consumption again results in higher Nordic system prices. Through Datastream, we retrieve daily observations of the stock market indices in Sweden, Norway, Denmark and Finland, namely OMX Stockholm PI, OSEBX, OMX Copenhagen PI and OMX Helsinki PI.

### 3.2.14 Other possible predictors

As discussed, the goal of the data collection is to find predictors assumed to impact future values of the Nordic system price. Nevertheless, there are presumably other predictors that could have been included in addition to or instead of the chosen data set. Each time choices regarding the data collection are made, we risk biasing the data. Particularly omitted variable bias could pose a challenge. Omitted variable bias is the case when a variable that influences the dependent variable is not included as an independent variable (Barreto and Howland, 2006). As such, we risk missing important information that helps determine the Nordic system price. Another potential hazard is selection bias, where the sample is not representative of the population (Šimundić, 2013). In this case, the selection bias would involve that the Nordic system prices observed in the data set do not represent the general movements of prices. Although we attempt to mitigate the biases of the data set, in effect, the data is already biased by being a sample. Thus, we should be aware of the biases and problems these might pose on the estimated models.

One such challenge could involve the regional predictors. Several predictors in our data set are registered for a specific country. The focus is on the Nordic countries, while the Baltic countries are also included due to their close connection to the Nordic market. In the case of system prices, production, consumption, hydro reservoirs and wind data, aggregate or average values have been used for each country in total. An alternative approach could have been to split the observations by areas in the given countries. Moreover, although the prediction is of the Nordic system price, there has been a particular focus on Norway. While we realize the potential bias, the reason for more variables on Norwegian conditions compared to the other Nordic countries is the study's focus on Norwegian hydropower producers. In addition, when retrieving temperature and precipitation data in Norway, the narrowed choice of predictors might also bias the data set. This could be affiliated with problems considering urban versus rural temperatures, or a focus on too few drainage basins.

With an awareness of the potential biases of the model, it is also relevant to discuss independent variables that could have been included, but were not. All retrieved weather data are historical observations. However, in practice a more common approach would be to include weather forecasts. Weather is one of the least predictable factors in the model, and an important reason why the power price is highly volatile. Thus, using weather forecasts to predict the system price, instead of relying on historical data, could be deemed a better approach. At present, hydropower producers pay to get these forecasts from providers of weather services.

Observations of the hydro reservoir stock are the only included variables that are registered weekly and not daily. Optimally, we would include daily fluctuating observations. However, such observations are not registered or are not publicly available. Hydro reservoir stocks are calculated for each magazine, but the public data is only given by area, as particular and recently updated observations are considered sensitive information (Norges vassdrags- og energidirektorat (NVE), 2019a). We find no information pointing towards a specific trend over the week. Thus, the daily values of a given week are set to equal the weekly value. For further testing, daily fluctuating values or information of weekly trends could prove useful.

Moreover, as power prices are affected by the general state of the economy, stock exchange indices are included as independent variables. However, there are other indicators of economic health that could have been included instead. The consumer price index and

GDP give fair pictures of a given country's economy. Additionally, population growth has an effect on production and consumption. On the other hand, these figures are not recorded daily. As stock exchange indices are recorded on a daily basis, these variables are believed to be the best fit. Other stock exchange indices could also have been included, though the Nordic stock exchange indices seem most obvious in predicting the Nordic system price.

## 3.3 Treatment of missing values

The data set has several occurrences of missing values. Missing values occur for precipitation and temperatures in Norway, as well as for wind power production in Sweden and Finland. Latvia was first connected with the Nordic power market the 3rd of June 2013, which means registrations of Latvian production and consumption at Nord Pool begins this day. The missing data is treated differently, depending on the variable. The methods used are insertion of the mean and linear regression to predict the variable. In instances where a large portion of the data is missing, the variable itself is excluded from the data set. The treatments are summarized in Table 3.2 below.

**Table 3.2:** Treatment of missing values

| Variable | Missing value handling | Observations missing |
|---|---|---|
| Temperature in Asker<br>Precipitation amount<br>- *Aura*<br>- *Aurland*<br>- *Nedre Røssåga*<br>- *Tonstad* | Insert mean of current period | 4<br><br>7<br>1<br>3<br>2 |
| - *Brokke* | Predict through linear regression, using Tokke as predictor | 49 |
| - *Vamma* | Insert mean of corresponding period previous years | 36 |
| Wind prod. Finland<br>Wind prod. Sweden | Remove variable from data set | 1882<br>1121 |
| Latvia<br>- Production<br>- Consumption<br>- Wind production | Predict through linear regression | 153 |

As accounted for in Section 3.2.4, precipitation amounts at Rana and Vamma stops being registered during 2018 and are replaced by observations from seNorge.no. The cause of the missing data is not stated, and there is no particular reason why the data should be missing. In addition, Vamma is missing 36 more observations in April and May 2014. To deal with the missing values, the average precipitation of April and May 2013 is used as insertion. There is no clear pattern for the few missing precipitation amounts at Aura, Aurland, Nedre Røssåga or Tonstad, nor the temperatures from Asker. The observations appear to be missing at random. Hence, these values have been replaced by inserting the mean of the current month.

Neither in the case of precipitation amounts from Brokke has there been found a clear reason for the missing values. In replacement of the missing data, a linear regression model is estimated using the observations from Tokke as the independent variable. Tokke is located the closest to Brokke, thus precipitation amount here is assumed to be its best predictor. The linear regression returns a coefficient of determination of 30%, implying that the precipitation amount at Tokke explains 30% of the variation in precipitation amount at Brokke. As 21 of the missing observations are from 2013, there are no averages of corresponding periods previous years in the data set. Nevertheless, as the precipitation amounts of Brokke and Tokke correlate, the linear regression using Tokke as predictor is viewed as a better alternative to insert the missing values.

Linear regression is also used to predict the production, consumption and wind power production in Latvia until the 2nd of July 2013. As there are no retrieved daily records of the actual numbers and no prior observations, the best approach is to predict these numbers. The consumption in Latvia correlates with consumption in the neighboring countries of Lithuania and Estonia. Using the consumption of these two countries as independent variables in a linear regression with consumption in Latvia as the response, renders a coefficient of determination of 89%. Consumption is thus predicted using the model. Following the same approach, looking for the highest possible coefficient of determination, production in Latvia is predicted using production in Estonia, Norway, Sweden, Finland and Denmark as predictors, while wind power production is predicted using wind power production in Lithuania, Estonia, Norway and Denmark as predictors. The coefficients of determination in the linear models are 44% and 81%, respectively.

Lastly, some variables contain too many missing values and will therefore be removed from the data set. The variables in question are wind power production in Finland and Sweden. Nord Pool does not begin registering the wind power production in Finland before late February 2018, hence including the variable will be pointless. In the case of Sweden, registration begins late January 2015. In addition, missing values occur frequently after the registration starts.

# 4 Methodology

With the collected data introduced in Chapter 3, we seek to generate predictions of the Nordic system price through machine learning. In a predictive model, the applied learning algorithms seek to discover and model relationships between the target variable, i.e. the system price, and its features, i.e. the predictors (Boehmke and Greenwell, 2019). Section 4.1 introduces the approach used in the methodology section, along with reasoning for choices that are made. In Section 4.3, we present characteristic of eight different machine learning algorithms along with their strengths and weaknesses. Thereafter, the eight different methods are tested through time series cross-validation to find the method with the highest prediction accuracy. Accuracy is measured through test MSE, given in Equation 4.1. The most accurate methods are finally used to predict Nordic system prices for different time horizons in 2018.

The machine learning methods used for prediction are backward stepwise selection, ridge regression, lasso regression, partial least squares, random forests, regression trees, boosting and support vector regression. As an alternative approach to the machine learning predictions, one could also use machine learning forecasts of the price using historical observations of the dependent variable itself. Along with a discussion of prediction versus forecasting, we will introduce forecasts of the system price using ARIMA and Neural Network Autoregressive models (NNAR).

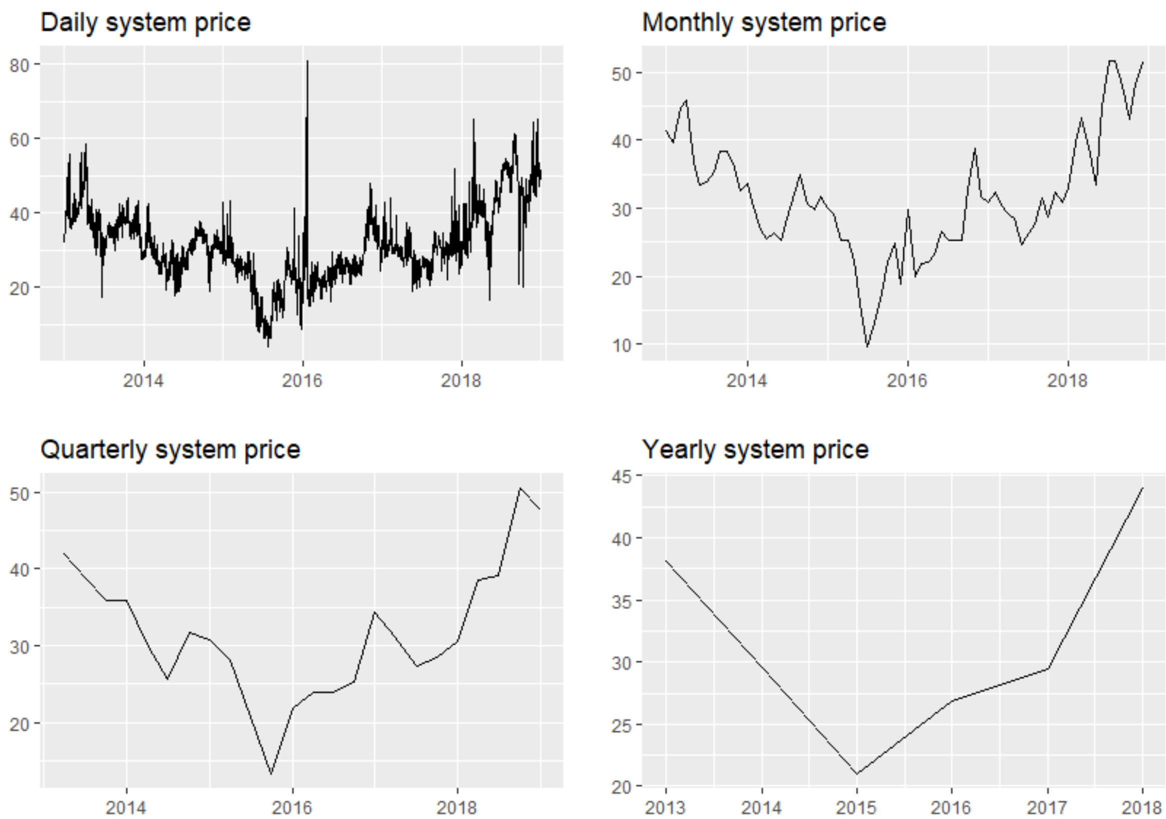
The focus of this thesis will be on prediction and not inference. Hence, the main concern is to provide the most accurate prediction possible, rather than commenting on the true relationships between predictors and response.

## 4.1 Approach

The approach when predicting the yearly, quarterly and monthly system prices is to estimate a model for each of the responses. For each of the three horizons, data sets are initially split in two sets. On the first set, referred to as the training set, we will train and test the performance of the models. The actual predictions will be made on the test set, consisting of prices in 2018. All predictions of 2018 begin at December 1st, 2017. Thus, the training set cannot include the actual system price later than this date and has to stop one period minus one month before. This follows the logic of how dependent variables in the different models are created, as can be seen in Table 3.1. For the first prediction made December 1st, 2017, the training set thus has to stop October 2nd, 2017 for monthly predictions, August 2nd, 2017 for quarterly predictions and November 2nd, 2016 for yearly predictions. The quarterly predictions are made on the first day of each month before a beginning quarter. The training set will include an additional three months of observations for each prediction. Accordingly, monthly models are re-estimated each month, and the training set includes one additional month of observations.

Figure 4.1 shows scatterplots of the average Nordic system prices from 2013 to 2018 on a daily, monthly, quarterly and yearly basis. The lower the time level, the higher the volatility of prices are. As power prices are highly affected by the weather, seasonality has to be taken into account when studying power prices. However, as discussed in Chapter 3, power prices are impacted by many other factors as well.

**Figure 4.1:** Scatterplots of system prices



The dependent variable, or response, is denoted by $Y$. The assumption is that the response and the $p$ predictors are related by $X = (X_1, X_2, ...X_p)$ (James et al., 2013). The relationship can be written in the form of $Y = f(X) + \epsilon$, where $f$ is an unknown function of X, and $\epsilon$ is a random error term, independent of $Y$ with a mean of zero. The estimated methods to find $Y$ all take the form $\hat{Y} = \hat{f}(X)$. $\hat{f}$ is thus the estimate of $f$, and $\hat{Y}$ is the prediction of $Y$. Prediction accuracy will depend on two quantities, namely the reducible and the irreducible error. As $Y$ is also a function of $\epsilon$, variability of $\epsilon$ will also affect the prediction accuracy. This is referred to as the irreducible error, as it cannot be predicted using $X$, and thus the error cannot be reduced. Our further aim with testing models is to minimize the reducible error by using the most appropriate statistical learning method.

### 4.1.1 Forecast vs. prediction

Before considering actual methods used for price prediction, the initial distinction between time series forecasting and standard prediction will be addressed. Both alternatives can be thought of as supervised learning techniques. According to James et al. (2013, p. 1): "supervised statistical learning involves building a statistical model for predicting, or estimating, an output based on one or more inputs". In the event-based predictions, the inputs are the variables other than $Y$, while in the univariate time series forecasts, past values of $Y$ constitute the inputs.

In supervised learning, the objective is to predict $Y$, using $\hat{Y} = \hat{f}(X)$. How well the machine learning methods fit the data and perform in prediction will thus depend on the true functional form of $f$. Hence, the aim is to find the machine learning method that best replicates the functional form of $f$. Time series forecasting can be thought of as a subcategory of prediction. It aims to estimate how the sequence of observations will continue into the future (Hyndman and Athanasopoulos, 2018). As future values of the predictors introduced in Chapter 3 are unknown, and separate forecasts of each predictor will not be made in this thesis, only univariate time series forecasts will be considered.

Prediction accuracy of future prices can be impacted by factors such as our understanding of contributing variables and the available data. A time series forecast, or an event-based prediction could be applied to predict the Nordic system price. To decide which path to follow, we present two different hypotheses of the performance of both methods:

1. The Nordic system price is affected by numerous variables, leading to its volatile behavior. Therefore, machine learning models that take all these variables into account will be the best approach for predicting future values of the price.
2. Observations of the Nordic system price are not independent, and seasonal variations and autocorrelation lead to volatility. Therefore, time series forecasting that make use of lagged observations of the price will be the best approach for predicting future values of the price.

Both hypotheses are plausible and could be combined for further research. A combination of the two hypotheses could make use of the ARMAX framework, which is ARMA with covariates. However, this combination will not be explored in this thesis. In the following, we choose to investigate the first hypothesis further. Our belief is that all data that affects the Nordic system price should be included, and thus standard multivariate machine learning algorithms for prediction will be investigated. Time dynamics will be included in the form of seasonal dummies, otherwise the observations are treated independently. The aim is to investigate whether the standard machine learning algorithms can be applied to the more complex nature of power prices. In that sense, the prediction can be thought of as an experimental case, investigating whether machine learning can contribute in price prediction used for hedging policies. Univariate ARIMA and NNAR models are also briefly included in Section 4.4 to compare the two hypotheses.

## 4.2 Cross-validation

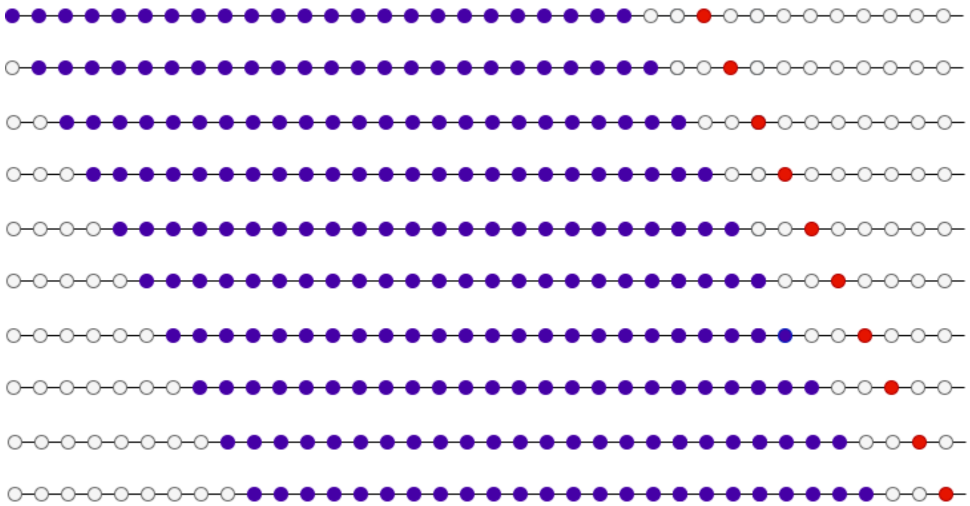
Prior to making predictions of 2018, the performance of the eight machine learning algorithms is first tested through time series cross-validation. Cross-validation is the process of estimating a model on a subset of the full data set, and then testing its performance on a separate subset, referred to as the test set. A subset of the training observations is hence held out from the fitting process. The method is applied to the held-out observations and test errors are calculated (James et al., 2013). The measure for the test errors in our use of time series cross-validation is the test MSE, shown in Equation 4.1. Through the cross-validation, both the full set of variables introduced in Chapter 3 as well as smaller subsets are used as inputs in the cross-validation. The set used for predictions in 2018 will be the one with the lowest test MSE.

$$E(y_0 - \hat{f}(x_o))^2 = Var(\hat{f}(x_0)) + [Bias(\hat{f}(x_0))]^2 + Var(\epsilon) \tag{4.1}$$

Equation 4.1 shows that the expected test MSE of a given learning method can be decomposed into the variance of $\hat{f}(x_0)$, the squared bias of $\hat{f}(x_0)$ and the variance of the error terms $\epsilon$. The first two terms constitute the reducible error and show that prediction errors will increase with a model's bias and variance. High variance entails high sensitivity to training errors (James et al., 2013). In such cases, a model can pay too close attention to the noise, and therefore cause what is referred to as overfitting. The risk of overfitting involves the estimated model performing really well within the sample, however once making predictions out of the box, the fit is usually bad. A model with high bias will usually have the opposite effect. Such models generally simplify too much, causing underfitting. By decreasing bias, variance will generally increase and vice versa. There is thus a trade-off between bias and variance when finding appropriate models, as high values of neither is desirable. In the same sense, there is a separation between flexible and restrictive methods. Restrictive methods are more intuitive to understand and interpret, while flexible methods give more complex estimates and understandings of how predictors and the response are associated. These methods usually require larger data sets and more predictors, however they can have advantages in prediction accuracy. On the other hand, restrictive methods usually have advantages in the case of overfitting. Highly complex models with low interpretability are often referred to as a black boxes. Although powerful and usually associated with high prediction accuracy, the exact process of black box models in between the inputs and outputs are not certain.

Our use of time series cross-validation is applied to replicate how the predictions will be made in practice. In this approach, a rolling window is used, where one observation is added and one observation removed, as predictions one period plus a month ahead are made. The training data is thus continuously split into training and test sets, illustrated in Figure 4.2.

**Figure 4.2:** Time series cross-validation



In practice, the test set of monthly predictions is set at the time when the prediction and the decision of whether or not to buy a futures contract is made. The test set in the cross-validation is set two months after the training set ends, to replicate the way the model will be used in practice. As discussed in Section 4.1, the training set cannot include unknown observations of the dependent variable, i.e. what the system price will be one day after the prediction is made. Following the same logic, the test set in the cross-validation with quarterly prices is set four months after the training set ends, while the test set for yearly prices is set a year and one month after the training set ends. Models are iteratively estimated on the training set (blue data), tested on the test set (red data) and test MSEs are calculated.

The rationale for using time series cross-validation is to avoid problems related to overfitting, which is especially common in the in the case of non-linearity. The rolling window is used with folds, or training sets, the size of 800 observations. With a rolling window, the model is assumed to be constant, and allows parameters to change slightly when observations are added and removed. Hence, a rolling window works well for detecting change. Rolling windows are often used in cases where there are theories of non-linearity, but these are hard to prove.

## 4.3 Algorithms

The target variable is the Nordic system price, which is continuous. Hence the used methods apply for regression and not classification. Until otherwise is stated, the material of this section is retrieved from James et al. (2013). We present the main traits and design of the different algorithms. The following models are estimated and tested on the training set: Linear regression with backwards selection, ridge regression, lasso regression, partial least squares, regression trees, random forests, boosting and support vector regression. No single method will be best in all cases. Performance varies from case to case, however there are some advantages and disadvantages of the different methods. Traits of each method are summarized in Table 4.1. The terms will be elaborated on in the upcoming paragraphs regarding each method.

**Table 4.1:** Machine learning methods

| Methods | Linear | Interpret-ability | Flex-ibility | Variable treatment | Some applications | Advantages | Disadvantages | Specified parameters |
|---|---|---|---|---|---|---|---|---|
| **Backwards selection** | Yes | High | Low | Identify subset of variables through BIC | Truly linear relationships when $n$ is large relative to $p$ | Low bias | Higher variance than other linear methods<br>Predictive power | Maximum 60 predictors are chosen |
| **Ridge regression** | Yes | High | Low | Shrink coefficients | Linear relationships where predictors are associated with response | Decreased variance<br>Computational time<br>Handle multi-collinearity | Higher bias<br>No variable selection | $\lambda$ found through cross-validation |
| **Lasso regression** | Yes | High | Low | Shrink coefficients | Linear relationships when not all predictors are associated with response | Decreased variance<br>Computational time<br>Handle multi-collinearity | Higher bias<br>Assuming a number of coefficients should equal zero | $\lambda$ found through cross-validation |
| **PLS** | Yes | Medium | Medium | Dimension reduction | Collinear data with many variables | Decreased variance<br>Computational time<br>Handle multi-collinearity | Difficult interpreting effects of individual variables | Optimal components found by cross-validation |
| **Regression trees** | No | High | Medium | Divide predictor space into regions through recursive binary splitting | Highly non-linear and complex relationships | Easy to explain<br>Graphical display<br>Low bias | Non-robust<br>Predictive power<br>High variance | |
| **Random forests** | No | Low | High | Random sample of $m$ predictors considered at each split of each tree | No particular assumption of data distribution and noisy data with missing values | Decreased variance<br>Calculation of variable importance<br>Robust | Computational time<br>Black box | $m$ is $\sqrt{p}$ |
| **Boosting** | No | Low | High | Few splits of each tree is usually sufficient | Complex relationships and non-linear data not being fully understood by weak learning algorithms | Decreased variance<br>Calculation of variable importance | Computational time<br>Black box<br>Sensitive to over-fitting | 5000 trees are built<br><br>Maximum number of splits considered set to four |
| **SVR** | No | Low | High | The cost determines the number of data points used as support vectors | Non-linear data with flexible distributions of underlying variables and relationships | Generalization capability<br>Robust | Computational time<br>Black box | Radial kernel<br>$\epsilon$ is 0.1<br>Optimal cost and $\gamma$ found through cross-validation |

The first four methods of Table 4.1 are all linear. The standard linear model by least squares is given in Equation 4.2:

$$Y = \beta_0 + \beta_1 X_1 + ... + \beta_p X_p + \epsilon \tag{4.2}$$

where the estimates of $\beta_0, \beta_1, ..., \beta_p$ are chosen through minimizing the residual sum of squares (RSS):

$$RSS = \sum_{i=1}^{n}(y_i - \beta_0 - \sum_{j=1}^{p}\beta_j x_i j)^2 \tag{4.3}$$

These estimates will have low bias if the true relationship between $Y$ and its predictors is approximately linear. If the number of observations are high relative to the number of predictors, the least squares estimates also tend to have low variance. This implies a high performance on test data. At the beginning, all predictors are included in the model, but if they prove to be unhelpful or not show a particular association with the response, they are removed or given different weight through a constraint or shrinkage of the estimated coefficients. In that case, the variance can get significantly reduced at the cost of a small increase in bias. Through backwards selection, a subset of the predictors believed to be related to $Y$ is identified in a standard least squares model. The method is called *backwards* selection, because all predictors are included at the start, and then removed one at a time if they are not useful. We use the Bayesian information criterion (BIC) to find the best model. The BIC is calculated by $\frac{1}{n\hat{\sigma}^2}(RSS + log(n)d\hat{\sigma}^2)$, where $n$ is the number of observations, $d$ is the predictors and $\hat{\sigma}^2$ is the estimated variance of the error $\epsilon$. The BIC usually holds small values for models with low test errors.

Lasso and ridge regression are shrinkage methods, where all predictors are standardized and included in the model, while coefficients are thereafter shrunk towards zero. In lasso regression, coefficients can be set to equal zero, making the algorithm perform a form of subset selection. Ridge and lasso regression are similar to least squares, however, the shrinkage is performed through introducing a penalty term into Equation 4.3, so that:

$$Ridge : RSS + \lambda \sum_{j=1}^{p} \beta_j^2 \tag{4.4}$$

$$Lasso : RSS + \lambda \sum_{j=1}^{p} |\beta_j| \tag{4.5}$$

$\lambda \geq 0$ is a tuning parameter chosen by cross-validation that chooses the impact of the penalty term. The higher $\lambda$, the more coefficients are penalized.

The fourth linear method, partial least squares, does not include the original predictors themselves, but rather transformations of these. The model is found through dimension reduction, where the predictors $p$ are projected into a $M$-dimensional subspace. $M<p$ projections are included as predictors in a least squares model in the form of $Z_1, Z_2, ..., Z_M$, where

$$Z_m = \sum_{j=1}^{p} \phi_{jm} X_j \tag{4.6}$$

The set of features $Z_m$ are identified in a supervised way, as they are related to the response. The $p$ predictors are first standardized, then the first direction $Z_1$ is found by setting $\phi_{j1}$ equal to the coefficient from regressing $Y$ onto $X_j$ through linear regression. The highest weight will be placed on the variables that are strongest related to $Y$. $Z_2$ is further found by regressing each variable on $Z_1$ and finding the remaining information that was not explained by the first PLS direction. This remaining information can be thought of as residuals. $Z_2$ is computed using the orthogonalized data in the same way as $Z_1$ was computed on the original data. The process is repeated $M$ times to find the components up until $Z_m$.

The three next methods in Table 4.1 are tree-based. A regression tree is a decision tree, where each split is an internal node eventually leading to a terminal node, or the leaf of a tree. The nodes are connected through branches. Regression trees are built through dividing the possible values of $X_1, X_2, ..., X_p$ into $J$ distinct, non-overlapping regions $R_1, R_2, ..., R_J$. The regions are constructed as boxes, seeking to minimize the RSS:

$$\sum_{j=1}^{J} \sum_{i \in R_j} (y_i - \hat{y}_{R_j})^2 \tag{4.7}$$

The mean of the response values, $\hat{y}_{R_j}$, for training observations in box $j$ is set as the prediction for every observation in the region of $R_j$. Trees are grown using recursive binary splitting. Recursive binary splitting begins at the top of the tree, where all observations are in the same region, and then moves down, splitting the tree in branches. At each split, the best split at that point is made and best trees further down the branches are not considered. The first split of predictor $X_j$ at cutpoint $s$ occurs where $\{X|X_j < s\}$ and $\{X|X_j \geq s\}$ leads to the greatest possible reduction in RSS. The process is repeated, finding the best predictor and cutpoint to minimize RSS within each new region. The splitting continues until terminal nodes are too small or too few to be split.

Random forests and boosting build on regression trees to construct more powerful prediction models. Random forests build a number of decision trees on bootstrapped training samples. The bootstrap is an approach to quantify the uncertainty related to a given estimator or statistical learning method and can be applied in this case to improve the decision tree. As decision trees suffer from high variance, bootstrapping can be used to obtain data sets with minimized variance. The data sets are obtained by repeatedly sampling observations from the original data set with replacement. Finally, $B$ different bootstrapped training data sets are generated, and $B$ regression trees are constructed on these. In the construction of each tree, a random sample of $m$, equal to $\sqrt{p}$, predictors is chosen as split candidates, and of these, only one is used at the split. The split candidates are restricted to $m$. The rationale is that in the case of strong predictors that will be used at the top splits every time, the trees will become too similar. By using $m$ random split candidates, predictions from each tree will be less correlated, or in other words the trees are decorrelated.

Similar to random forests, boosting also creates many different decision trees $\hat{f}^1, ..., \hat{f}^B$. However, instead of bootstrap sampling, each tree is fit on a modified version of the data set. When constructing a tree $\hat{f}^b$ with $d$ splits, information from previously grown trees is used, so that the trees are grown sequentially. The boosting approach thus learns slowly, and fits a decision tree using current residuals as the response, instead of $Y$. Each new decision tree in a shrunken version is added into the fitted function $\hat{f}$, and residuals are updated. The shrinkage is determined by the parameter $\lambda$, controlling the rate at which boosting learns. We use a $\lambda$ of 0.1. In contrast to random forests, smaller trees with a lower number of splits are often sufficient for boosting, as growing trees take the other trees into account. The number of splits is referred to as the interaction depth.

The last machine learning algorithm introduced in Table 4.1 is support vector regression (SVR). The method extends upon the more familiar support vector machine (SVM), however it differs from SVM as it allows for continuous responses, and hence regression (Boehmke and Greenwell, 2019). Before introducing the nature of SVR, we first introduce the terms *kernel* and *hyperplane*. A kernel is used to map low dimensional data into higher dimensional data and allows non-linear boundaries by enlarging the feature-space. In the SVR, a radial kernel is used to capture non-linear relationships, and takes the form $exp(-\gamma \sum_{j=1}^{p}(x_{ij} - x_{i'j})^2)$, where $\gamma$ is a positive constant. A hyperplane divides a $p$-dimensional space into a ($p$-1)-dimensional flat subspace. The aim of SVR is to find a hyperplane in a kernel-induced feature space. The hyperplane should have good generalization performance using the original features.

A problem with least squares is that residuals *r(x,y)* are squared which gives outliers more influence on the regression function presented in Equation 4.2. SVR models are more robust to outliers, using a loss metric called $\epsilon$-insensitive loss ($L_\epsilon$), where $\epsilon$ is given by $max(0, |r(x,y)| - \epsilon)$. $\epsilon$ is set to 0.1, and represents the width of the margin around the regression curve. The aim is to have as many data points as possible within the margin, with a minimal number of violations. A cost argument is introduced to specify the cost of violating the margin. The residuals of data points satisfying $r(x,y) \pm \epsilon$ in the kernel-induced feature space, form what is referred to as support vectors. Support vectors are the points defining the margin. An $\epsilon$-insensitive model implies that data points within the margin has no influence on the fitted regression line. Ten-fold cross-validation is performed to find the optimal cost parameter and $\gamma$ for the radial basis kernel.

### 4.3.1 Performance

By cross-validating each of the eight methods for the monthly, quarterly and yearly prediction models using the approach presented in Section 4.2, the best-performing models were those estimated on the full set of variables. The three best-performing methods for each period are summarized in Table 4.2. Test MSEs are in parenthesis.

**Table 4.2:** Most accurate methods

| | *Best method* | *Second best* | *Third best* |
|---|---|---|---|
| *Year* | Random forests (43.40) | Boosting (48.37) | Regression trees (49.41) |
| *Quarter* | Ridge regression (29.77) | SVR (36.19) | Lasso regression (36.69) |
| *Month* | SVR (41.07) | Ridge regression (46.47) | Boosting (55.53) |

As stated, the best-performing algorithms are the ones with the lowest test MSE. By taking the root of the MSE, we end up with the Root Mean Square Error (RMSE). The RMSE is interpreted as the standard deviation of the residuals, i.e. prediction errors. The measure thus indicates how spread the residuals are and is given in the same unit as the response. The interpretation of Table 4.2 is thus that the spread of the residuals in the best yearly model is 6.59 euros, while the spread in the best quarterly model is 5.45 euros and that of the best monthly model is 6.41 euros.

The methods of Table 4.2 will compute the predictions of 2018. Hence the yearly Nordic system price of 2018 is predicted using random forests, boosting and a regression tree. The quarterly Nordic system prices of 2018 are predicted using ridge regression, SVR and lasso regression. Finally, the monthly predictions are made using SVR, ridge regression and boosting. Quarterly and monthly predictions are generated iteratively in 2018. The results of each prediction will be elaborated on in Section 5.1.

## 4.4 ARIMA and NNAR

In addition to machine learning predictions, forecasts are introduced briefly as an alternative approach, following our second hypothesis. In the following, the procedure for developing forecasts of 2018 by ARIMA and NNAR models is introduced. For this purpose, monthly observations of the Nordic system price is used as $Y$ and the data goes back to January 1999. The points in time of decision follow the same pattern as for the machine learning predictions, so the first prediction is made on December 1st, 2017. These models will only be analyzed superficially, and built-in functions in R are used to determine the optimal models.

For monthly forecasts, the models are re-estimated each month from December 2017 to November 2018, along with optimal model parameters and lambdas for Box-Cox-transformations. The model for forecasting January uses values up until November 2017 and makes forecasts two steps ahead. The second forecast is used as the monthly forecast for January. For quarterly forecasts, models and the respective parameters are re-estimated every third month from December 2017 to September 2018. Forecasts four periods ahead are computed, and the average of the three last forecasts are used as the quarterly prediction. The yearly forecasts are only made at one instance. Using data until November 2017, the model parameters are estimated, and forecasts 13 steps ahead are made. The average of the last 12 forecasts constitute the forecast of 2018. When forecasting one step ahead, available historical inputs are used. Forecasting two steps ahead however, historical inputs as well as the one-step ahead forecasts are used. The process continues until all required forecasts are computed. Results of the forecasts are presented in Section 5.3.2.

ARIMA models are among the most widely used time series forecasting methods (Hyndman and Athanasopoulos, 2018). Data is required to be stationary, which implies that properties should not change over time, i.e. $E(Y_t) = \mu, Var(Y_t) = \sigma^2$ and $Cov(Y_t, Y_{t-k}) = \gamma_k$. The dependent variables of our series are not stationary, and thus have to be differenced. Differencing is the process of computing differences between consecutive observations. ARIMA models aim to describe autocorrelations in the data and combine the three techniques of autoregressive models (AR), differencing (I) and moving average models (MA). AR models create forecasts using $p$ past values of $Y$, while MA models do the same using $q$ forecast errors instead of observations of the dependent variable itself. The number of differences taken is denoted as $d$. As such, an ARIMA model can be denoted as ARIMA($p$,$d$,$q$). ARIMA models can also be seasonal on the form of ARIMA$(p,d,q)(P,D,Q)m$, where $m$ is the number of periods within a year, here set to 12. The seasonal model thus includes values of $Y$ for the same month the past $P$ years and forecast errors of the same month the $Q$ past years. To stabilize the variance of the data, a Box-Cox transformation in the form of $y_t^p = (y_t^\lambda - 1)/\lambda$ is used. $\lambda$ is found using the method of Guerrero. The built-in function in R firstly determines $D$ and $d$ using repeated KPSS tests, testing for stationarity (Hyndman and Athanasopoulos, 2018). Thereafter, the other model parameters $p$, $P$, $q$ and $Q$ are found by minimizing the Akaike's Information Criterion ($AIC_C$). The $AIC_C$ is defined as $\mathrm{AIC_c} = \mathrm{AIC} + \frac{2(p+q+k+1)(p+q+k+2)}{T-p-q-k-2}$, where $\mathrm{AIC} = -2\log(L) + 2(p+q+k+1)$. $L$ is the likelihood of the data, and $k$=1 if the model has a constant, and 0 otherwise.

Compared to ARIMA models, artificial neural networks represent a more typical machine learning approach to forecasting. Similar to ARIMA models, NNAR make use of lagged values of $Y$, however in a more complicated manner. Lagged values are used as inputs to a neural network (Hyndman and Athanasopoulos, 2018). A neural network is a network of neurons, organized in layers. The bottom layers are the inputs, while the top layer is the forecasts, also referred to as outputs. In-between there is a hidden layer of hidden neurons, making the neural network non-linear. Each layer of nodes receives inputs from the previous layers and their outputs are inputs to the next layer. Inputs into hidden neuron $j$ are put in a weighted linear combination so that $z_j = b_j + \sum_{i=1}^{p} w_{i,j} x_i$. The combined inputs are modified using a nonlinear function such as a sigmoid $s(z) = \frac{1}{1+e^{-z}}$. The parameters $b_1, ..., b_j$ and $w_{1,1}, ..., w_{i,j}$ are learned from the data. The NNAR models used are feed-forward networks with one hidden layer, NNAR($p$,$k$), where $p$ represents the lagged values and $k$ is the number of hidden nodes. The models can also be made seasonal by including the seasonal parameters $P$ and $m$, so that NNAR($p$,$P$,$k$)$m$. Unlike ARIMA, the model does not require stationarity. The built-in function in R chooses the optimal parameters $P$=1, $k$=$(p+P+1)/2$ and $p$ is chosen from the optimal linear model that is fitted to the seasonally adjusted data.

# 5 Analysis

In this section we will present a simplified version of how the predictions made using the methodology from Chapter 4 can be used when securing future power prices, in accordance with the theory of futures contracts in Section 2.2.1. The machine learning predictions are conducted as an experiment, to discuss whether a simple approach to electricity price prediction could be of use. Hence, the analysis in this chapter is based on the experiment, as hedging strategies are discussed based on the results of the machine learning.

The analysis will start by using the machine learning predictions to decide whether a hydropower producer should purchase a futures contract at a given time. For each contract type, the predicted system prices of the three algorithms that performed best on the training set will be presented. All predicted prices, contract prices and actual prices of 2018 are included in Appendix A3. The main emphasis of our analysis will be on the best-performing method, however, the two other methods will also be reviewed. First, in Section 5.1, we present the yearly predictions and the futures contract for 2018, followed by quarterly predictions and contracts, and at last we present the equivalent for the monthly terms. We presume that hydropower producers have little negotiating power at Nasdaq. For simplicity we thus assume that they secure prices at the market price and take the contract prices as given. Further, we use the contract prices at Nasdaq as a benchmark for how well the machine learning algorithms work. The strategy of purchasing all contracts will be referred to as the benchmark strategy. In Section 5.2, we evaluate the performance of the machine learning models. Lastly, in Section 5.3.2, the predictions from the machine learning models are compared to the forecasts made by the ARIMA and NNAR models we estimated in Section 4.4, and to predictions made by analysts and market experts.

In Section 5.1, the strategy that determines whether or not a hydropower producer should purchase a futures contract is discussed. The basis of recommendation when determining whether or not to purchase a contract for a given term of 2018 is what is expected to give the highest revenue. Our recommendations are based on the machine learning method that performed best in the cross-validation. If this model predicts that the system price for a given term will be higher than the contract price of that term, the conclusion is that the hydropower producer should not purchase the contract at this time. On the contrary, if the model predicts that the system price will be lower than the contract price, the best decision is to purchase the contract. The *purchase decision* is illustrated in Equation 5.1.

$$Purchase\ decision = \begin{cases} Buy, & \text{if } \hat{Y}_t \leq CP_t \\ Not\ buy, & \text{if } \hat{Y}_t > CP_t \end{cases} \tag{5.1}$$

Where $\hat{Y}_t$ is the predicted system price and $CP_t$ is the contract price of the futures contract at time $t$.

The decision of whether the contract should be purchased or not will be made on the 1st of the month before the initiation of the contract. Hence, the first predictions and decisions are made on December 1st, 2017. The first of the month before the start of the contract is chosen as the *decision date*, as the most common practice for hydropower producers when buying a futures contracts is to secure prices for the period closest in time. At each decision date, the three best models for the respective periods are re-estimated, along with the model parameters. Decision dates are illustrated in Table 5.1.

**Table 5.1:** Decision dates

| Decision date | Year | Quarter | Month |
|---|---|---|---|
| 2017/12/01 | 2018 | Q1 | January |
| 2018/01/01 | | | February |
| 2018/02/01 | | | March |
| 2018/03/01 | | Q2 | April |
| 2018/04/01 | | | May |
| 2018/05/01 | | | June |
| 2018/06/01 | | Q3 | July |
| 2018/07/01 | | | August |
| 2018/08/01 | | | September |
| 2018/09/01 | | Q4 | October |
| 2018/10/01 | | | November |
| 2018/11/01 | | | December |

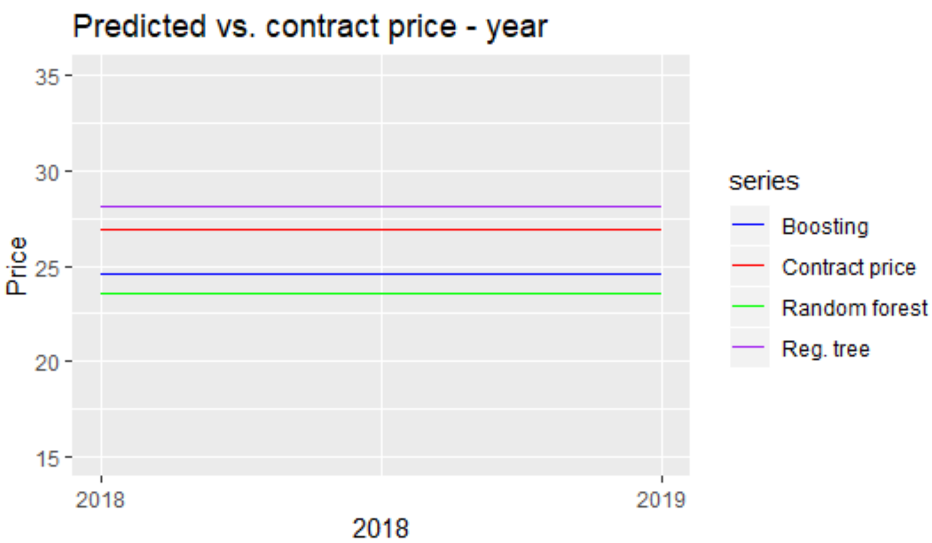
In their decision-making, other power producers and power consumers could also benefit from the strategies we present. The activity of purchasing a futures contract will be the same for other power producers as for hydropower producers, however their general risk management strategies might differ. The power consumers would enter into a contract on the opposite side of the producers. Thus, if the predictions indicate that the hydropower producer should purchase the contract, so should other producers, while the power consumer should not enter into the contract. As producers and consumers stand on opposite sides of the contract, the producer's profit is the consumer's loss.

## 5.1 Strategy based on the machine learning results

### 5.1.1 Yearly strategy

The analysis will start by presenting the yearly predictions and contract prices and find the optimal yearly strategy. When performing cross-validation on the methods predicting yearly system prices on the training set, random forests performed the best, followed by boosting and regression trees. Hence, these three methods are used to predict the yearly prices of 2018. December 1st, 2017 is the decision date, where we suggest whether or not the hydropower producer should purchase the yearly contract, as can be seen in Table 5.1. This is also the date where the average system price of 2018 is predicted.

**Figure 5.1:** Yearly predictions and the contract price

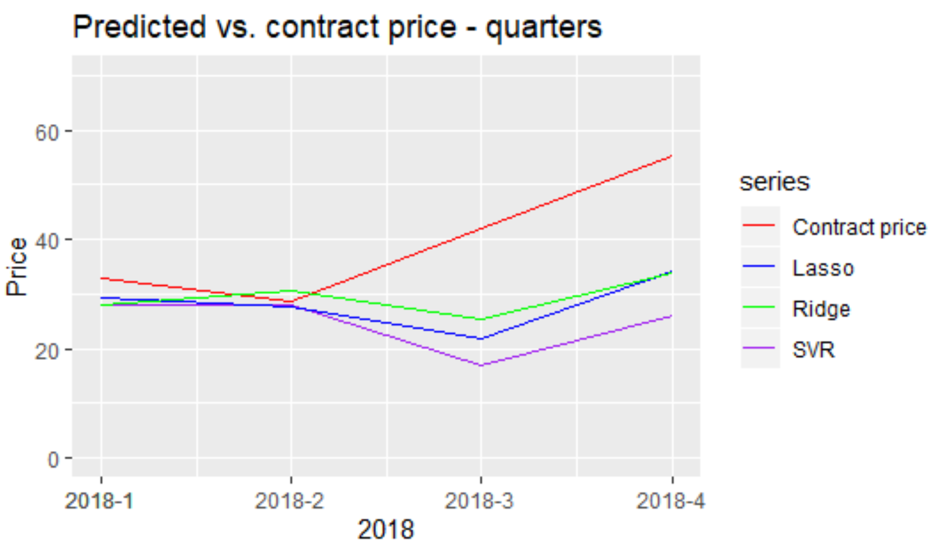



The yearly predictions and the contract price are illustrated in Figure 5.1. Random forests predict an average system price for 2018 of 23.57 euros per MWh. As the futures contract for the year has a price of 26.90 euros per MWh, the results from the prediction by random forests suggests that the contract should be purchased. Boosting also predicts a price that is below the contract price, 24.55 euros, and thus renders the same strategy. The regression tree predicts a price of 28.13 euros, and thus suggests that the best decision is to not purchase the contract. Both random forests and boosting generally give lower variance than regression trees, and with a main emphasis on the best-performing model, the recommendation is to purchase the yearly contract.

### 5.1.2 Quarterly strategy

Moving on to the quarterly predictions and prices, ridge regression was the method that performed the best in the cross-validation. SVR performed second best and lasso regression third best. Thus, we will use these three methods to predict the quarterly prices of 2018. As seen in Table 5.1, the decision of whether the contract for the first quarter in 2018 should be purchased is made on December 1st, 2017, and so this is also the date of the first prediction. On March 1st, the contract decision and prediction is made for the second quarter, and for the third and fourth quarter, the respective dates are June 1st and September 1st.

**Figure 5.2:** Quarterly predictions and contract prices

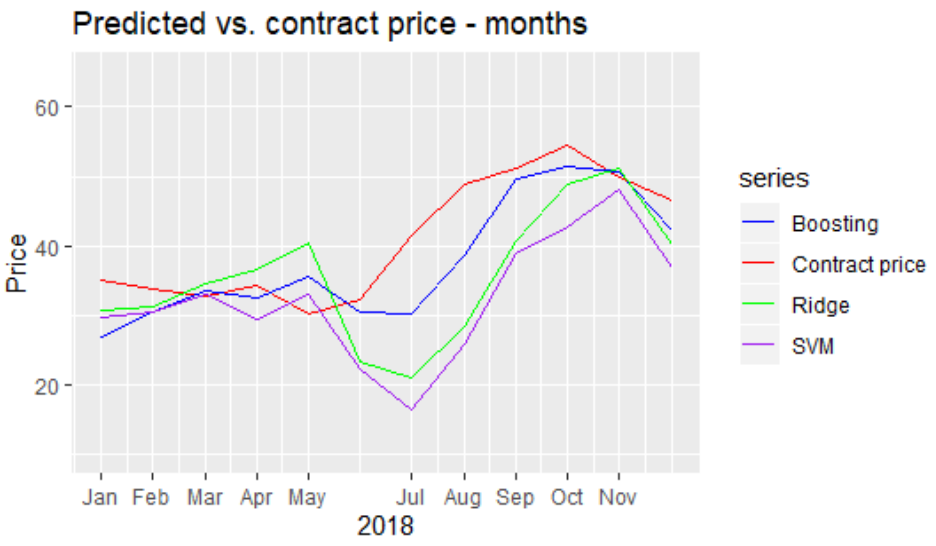



As can be seen in Figure 5.2, the results from ridge regression indicate that the best decision is to purchase the futures contract for the first, third and fourth quarter, but not for the second. SVR and lasso regression suggest that the contracts should be purchased for all quarters. Adding most weight to the ridge regression results, the hydropower producer should choose to purchase all quarterly contracts except the second.

### 5.1.3 Monthly strategy

When performing cross-validation on the methods predicting monthly system prices on the training set, SVR performed best, followed by ridge regression and then boosting. In the following, we will use these methods to predict the monthly prices of 2018. The decision dates follow the pattern illustrated in Table 5.1.

**Figure 5.3:** Monthly predictions and contract prices




As can be seen in Figure 5.3, the predicted prices by SVR are lower than the contract price for all months except March and May. As the alternative expected to generate the highest revenue is viewed as optimal, the predictions from SVR imply that the best strategy for a hydropower producer is to purchase contracts for all months except March and May. The results from ridge regression indicate that the system price will be higher than the contract prices in March, April, May and November. Lastly, boosting predicts that the system price will be higher than the contract price in March, May and November, and lower than the contract price the remaining months.

In total, all models predict that the system price will be higher than the contract price in May and March, thus the producer should not enter into a contract these months. Strategies relying on boosting and ridge regression indicate that the contract should not be purchased for November either, while ridge regression would not suggest purchasing the contract for April. However, relying most on the strategy produced by the SVR predictions, contracts should be purchased for all months but March and May.

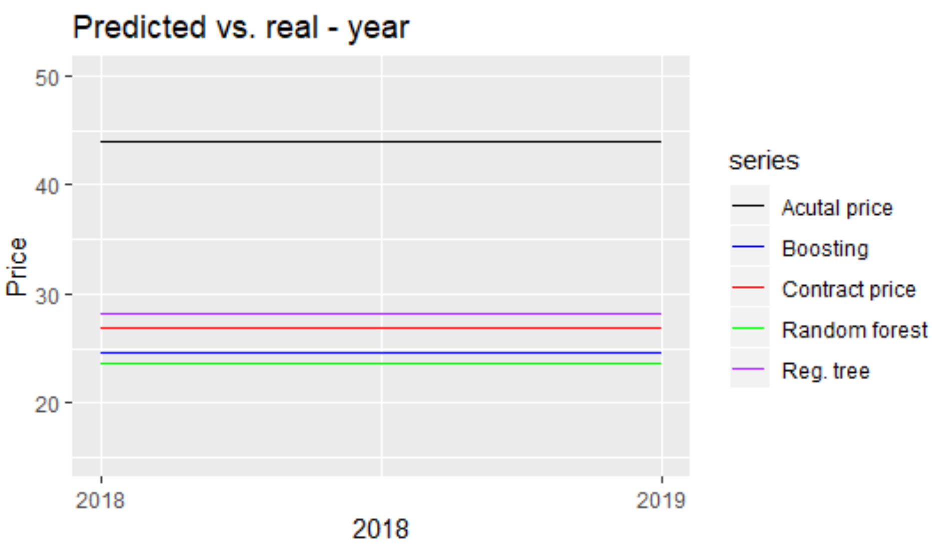
## 5.2 Performance of machine learning methods

### 5.2.1 Comparison of predicted and actual prices

So far in the analysis, we have compared the predictions to the contract prices at the set decision dates and decided which contracts should be purchased and not for 2018. In the following section, the actual periodical system prices of 2018 are shown. In hindsight, we are able to discuss the performance of the predictions and see how the imposed strategies would have worked. As we will see, the predictions of the machine learning models generally proved to be too low throughout 2018. However, the same was often true for the contract price. Discussing the hedging strategies in a profit-maximizing view, the strategies suggested by the machine learning models provided the same or a better result than the benchmark strategy. However, when comparing the predictions and contract prices with the actual prices, the ranking was opposite.

#### 5.2.1.1 Performance of yearly predictions

**Figure 5.4:** Yearly system price, the contract price and the predicted prices

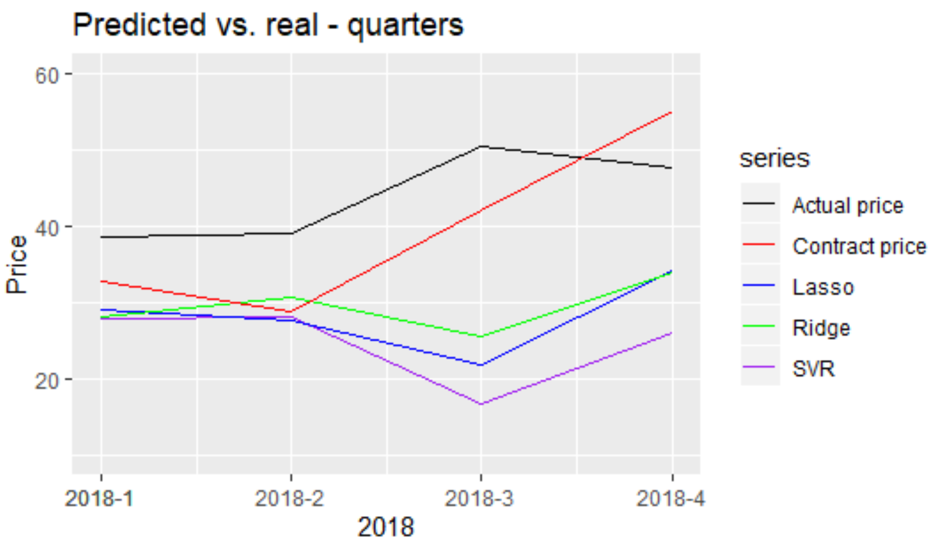



For the yearly term, random forests were presumed to give the best prediction of system prices. As can be seen in Figure 5.4, random forests predicted a system price of 23.57 euros, 3.33 euros per MWh further away from the actual system price than the contract price. The yearly system price ended up being 43.99 euros, while the contract price was 26.90. Using the recommended strategy based on random forests of buying the contract would generate a loss of 17.09 euros per MWh compared to a strategy where the price was not secured. Thus, in retrospect we see that the contract should not have been purchased. Boosting was 2.35 euros further from the system price compared to the contract price, while the regression tree was 1.24 euros closer to the system price than the contract price.

Out of the three presented models, random forests, that performed best on the training set, was the furthest away from the actual system price, followed by boosting. The regression tree, which was the third best model in the training set, was somewhat surprisingly the model that predicted prices closest to the actual system price and suggested the best strategy. In hindsight, we see that this was the machine learning model we should have used. Even though the predicted price by the regression tree was closest to the actual price, it was still far from the actual system price of 43.99 euros. Nevertheless, the regression tree was the only model that suggested a better strategy than the benchmark.

#### 5.2.1.2 Performance of quarterly predictions

**Figure 5.5:** Quarterly system prices, contract prices and predicted prices

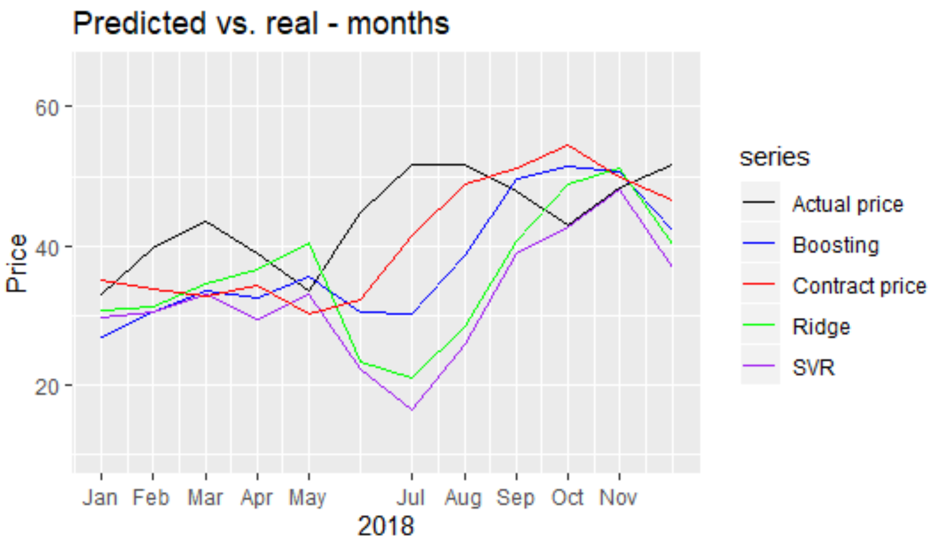



Out of the estimated machine learning models on the quarterly basis, ridge regression was assumed to give the best prediction of system prices. Figure 5.5 shows an illustration of the actual quarterly system prices, contract prices, and predicted prices. The figure shows that the predictions were lower than the actual prices in all quarters. The predictions made by the machine learning models for the third quarter were particularly poor. In reality, prices increased from 39.02 to 50.50 euros, while all models predicted a decrease. The contract price also increased, and targeted the system price better. In the first and last quarter, the contract price was also closer to the actual prices. Hence for all periods, all machine learning models predicted prices further away from the system price than the contract price, except for ridge regression in the second quarter. The average quarterly deviation of the contract price from the system price was 8.03 euros in 2018. Likewise, the average deviation of predictions using ridge regression, i.e. the mean absolute error (MAE), was 14.40 euros, 19.21 euros using SVR and 15.68 euros using lasso regression.

In the strategy derived from ridge regression, the contracts should be purchased for all quarters except the second. The system price for the second quarter ended up being 10.22 euros per MWh higher than the contract price. Thus, the strategy assumed to be best would have given an additional value compared to the benchmark of 10.22 euros per MWh. The strategy implied by the predictions from SVR and lasso regression both indicated that the contracts should be purchased all months, and thus would not have generated any additional income compared to the benchmark. In hindsight, we see that out of the three models, ridge regression suggested the best strategy and predicted the price closest to the system price. Lasso regression had the second best performance and SVR the poorest performance regarding prediction accuracy.

#### 5.2.1.3 Performance of monthly predictions

**Figure 5.6:** Monthly system prices, contract prices and predicted prices




In Figure 5.6 the monthly system prices, contract prices and our predicted prices are illustrated. Throughout the period, there seems to be somewhat a 'lagged' effect of the predictions compared to the actual prices. This points to some information being incorporated into the models too late. The same applies for the contract price, however the effect is smaller. Especially from February to April and in the summer months, the system price was higher than both the models' predictions and the contract prices. In the summer months, prices rose from 33.46 euros in May to 44.80 euros in June, and further to the extreme levels of 51.70 and 51.73 euros in July and August respectively. See tables A3.1 and A3.2 in Appendix A3 for a full overview of prices. The strategy presumed to be the best for the monthly predictions was the one based on SVR, where the choice was to purchase contracts for all months except for March and May. In March, the actual system price ended up being 10.57 euros above the contract price, and the corresponding figure was 3.26 euros in May. In total, purchasing these two contracts would have generated an excess income of 13.83 euros per MWh compared to the benchmark where all contracts were purchased.

Using ridge regression, the strategy derived was to not purchase contracts for March, April, May and November. In March, April and May, the actual system price ended up being respectively 10.57, 4.80 and 3.26 euros higher than the contract prices. In November, the system price was 1.63 euros lower than the contract price. In total, using the results from ridge regression would have resulted in an income 17.00 euros higher than the benchmark, and also a higher income than using the strategy derived from SVR. Finally, based on the predictions by boosting, the recommendation would be to purchase the contracts for all other months than May and November. The results of May and November imply that the strategy proposed by boosting would have generated a revenue of 12.20 euros per MWh more than the benchmark. These results are subordinate to the results of SVR and ridge regression.

In total, following the predictions of each of the machine learning models provided a better strategy than the benchmark strategy of purchasing contracts for all months. However, the predictions were all further away from the actual system price than the contract price was. The monthly average deviation of the contract price from the system price in 2018 was 6.15 euros. In comparison, the MAE of SVR was 11.70 euros, while the MAE for ridge regression and boosting was respectively 10.95 and 8.70 euros.

In retrospect, we see that out of the presented models, ridge regression suggested the best hedging strategy, followed by SVR and lastly boosting. However, the predictions using boosting ware overall closer to the actual system price than the two other models. Thus, one can discuss which model really performed best. Although ridge regression did present the best strategy, boosting was the model that gave the best prediction of future power prices. Such outcomes will be further discussed in Section 6.2.

### 5.2.2 Summary of performance

The results of this analysis show that using machine learning to decide whether or not a contract should be purchased for 2018 produced the same or better result than a strategy where every contract was purchased. For the yearly predictions, the two models that performed best in the training set suggested that the contracts should be bought, while the third best model suggested that the contract should not be purchased. As the system price ended up being substantially higher than the contract price, random forests and boosting would give no additional value, while using the regression tree would have been valuable. For the quarterly predictions, ridge regression, the model with the best results in the training set, was also the model that presented the best strategy. Using the two other machine learning models for the quarterly predictions would not have added any extra value over the benchmark. Lastly, the strategies based on the monthly predictions were all better than a strategy where all contracts were purchased. Out of the presented models, ridge regression, which was the second best on the training set, had the best performance in predicting monthly prices of 2018. The runner-up was SVR, which performed best on the training set.

As discussed in Section 2.4, the actual prices in 2018 were quite extreme and far from what was anticipated at the start of the year. Moreover, the prices were extreme compared to the other prices of our data set, which begins in 2013. The average system price for 2018 was higher than all years included, and the last two quarters of 2018 were substantially higher than all other quarters. Likewise, the average monthly system prices in July, August, September, November and December were higher than all other observed months, and June and October were higher than the corresponding months all previous years. Thus, the prediction accuracy of our models must be viewed in light of other predictions.

## 5.3 Comparison with other predictions

The particular situation of 2018 has to be taken into account considering that our price predictions were generally lower than the actual prices. Both contract prices and our model predictions hit relatively poorly. Especially the yearly price predictions and the monthly and quarterly predictions for the summer months were far off. The contract prices were far from the system price some of these months. However, these were still far closer to the actual system price than the model predictions. In the following, we will look at whether other sources performed better in predicting the prices for 2018. First we will briefly mention what other analysts expected that system prices would be in 2018. Thereafter, bringing back the second hypothesis mentioned in Section 4.1.1 of how to best predict Nordic system prices, we will introduce the forecasts made by the ARIMA and NNAR model. The expectations and forecasts will be used to evaluate the performance of the machine learning predictions.

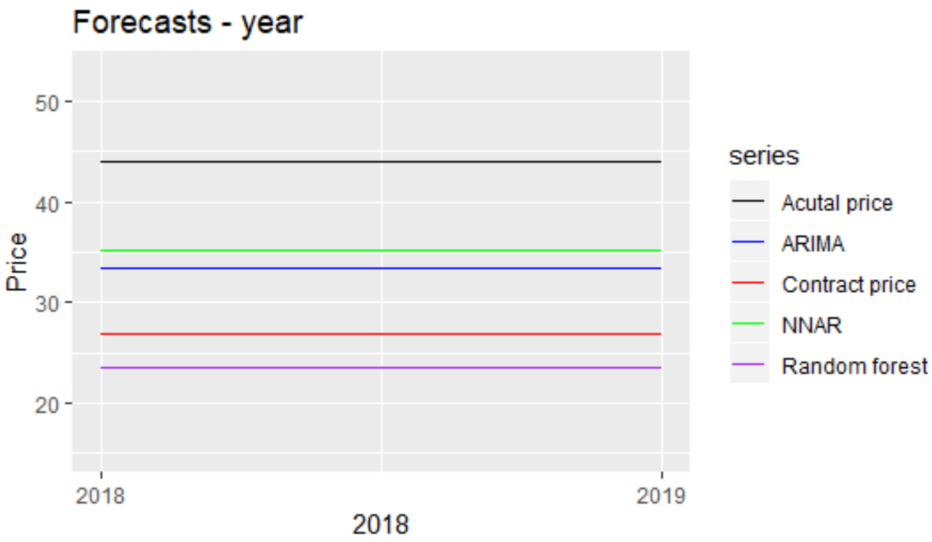
### 5.3.1 Market expectations of 2018

On December 1st, 2017, the price of the yearly contract for 2018 was of 26.90 euros per MWh, reflecting the market's expectations. In hindsight, this price turned out to be far too low. On January 23rd, the energy trading group Energi Salg Norge (2018a) stated that due to the strong hydrological situation in the Nordic countries, there was no pressure on the supply situation in the forthcoming months. However, on March 26th, the same source noted that the Nordic hydro balance had turned to a deficit, pointing towards high spot prices during the spring (Energi Salg Norge, 2018b). Power distributor Kraftriket stated on April 6th that even though the expected price development for spring and summer were somewhat higher prices than the previous year, the expectation was still declining prices (Kraftriket, 2018). However, because of the warm and dry summer, prices became record high and July 2018 had the highest registered July price of all times (Hovland, 2018a). Power analyst John Brottemsmo of Kinect Energy group predicted that if the fall turned dry, Nordic prices could end up at 60-70 euros per MWh. By September, storms and heavy rainfall followed the dry summer (Hovland, 2018b). As such, hydro reservoirs started filling up. Brottemsmo then stated that with current outlooks, prices were expected to continue falling, though there was much uncertainty as reservoir levels were still low. To summarize, the uncertainty related to the development of prices in 2018 was high, and several predictions proved wrong.

### 5.3.2 Forecasts made by ARIMA and NNAR

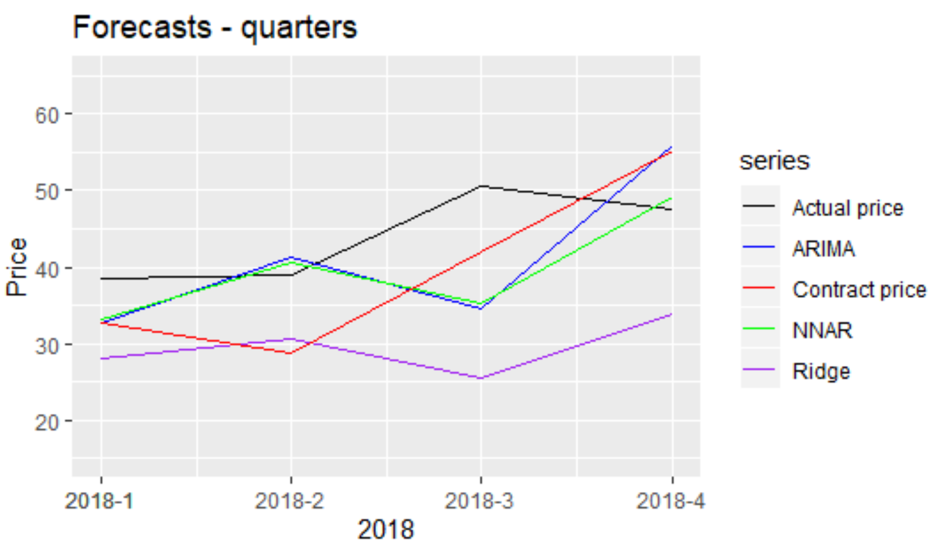
In the following, we compare the results of the ARIMA and NNAR models with the predictions introduced in Section 5.1. A complete overview of the predicted prices for each period are included in Table A3.1 and A3.2 in Appendix A3. Estimating the models on data up until December 2017, ARIMA$(1, 1, 0)(2, 0, 0)_{12}$ and NNAR$(1, 1, 2)_{12}$ models were chosen. The ARIMA model thus generated the forecast using one lagged value of the price and two seasonally lagged values. In addition, the series was differenced once to assure stationarity. The NNAR model made use of one lagged value of the system price, one seasonally lagged value and two hidden nodes to predict future values of the system price.

**Figure 5.7:** Yearly system price, contract price, predicted price and forecasted prices



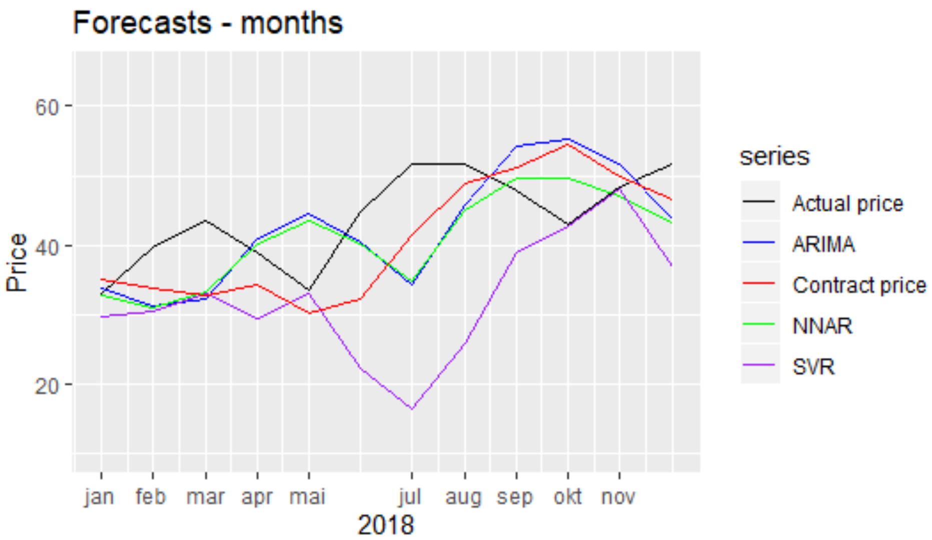

In the yearly prediction of 2018 ARIMA forecasted an average power price of 33.32 euros per MWh, and NNAR 35.17 euros per MWh. These prices are illustrated along with the actual system price, the contract price and the prediction made by random forests in Figure 5.7 As can be seen in the plot, NNAR was the forecast closest to the system price. Nevertheless, forecasts by both ARIMA and NNAR were quite far from the system price of 43.99 euros, however, they were still closer to the actual system price than all machine learning predictions and the contract price were. Using the forecasts on the decision date would thus have rendered the optimal strategy of not purchasing the futures contract.

**Figure 5.8:** Quarterly system prices, contract prices, predicted prices and forecasted prices



In Figure 5.8 the quarterly forecasts based on ARIMA and NNAR are illustrated against the system price, contract price and the predicted price from ridge regression. Out of the two forecasts, NNAR was once again closest to the system price, and like the yearly term, both forecasts were closer to the actual prices than the ridge regression prediction. The NNAR forecast was also more accurate than the contract price in all quarters but the third. It would also have led to a better strategy than ridge regression did, by purchasing futures contracts only for the third and fourth quarter. Still, both the ARIMA and NNAR forecasts were quite far from the system price. Moreover, these forecasts followed the same pattern as the predictions, as the price decreased towards the third quarter instead of increasing as the system price did. The forecasted prices increased again towards the last quarter.

**Figure 5.9:** Monthly system prices, contract prices, predicted prices and forecasted prices




In Figure 5.9, the monthly forecasts from ARIMA and NNAR are plotted against the monthly system prices and SVR predictions. The same lagged effect that was seen for the predictions also occurred for the forecasts, as if information is conceived too late. In general, the ARIMA and NNAR forecasts followed each other quite closely and were on a higher price level than the SVR predictions. Although both forecast models predicted too low prices in the summer months, the predicted prices were not as low as those made by the machine learning models. Altogether, NNAR was closest to the actual system prices, however contract prices were on average marginally closer. A hedging strategy based on the NNAR forecasts would be to purchase futures contracts all months apart from March until June. Such a strategy would have been superior to those imposed by SVR, ridge regression and boosting.

## 5.4 Conclusion of machine learning performance

Altogether, predictions made by the machine learning models performed poorly in many cases. The time series forecasts were on average a lot closer to the actual prices. However, these forecasts, along with expert opinions, market expectations and external forecasts of the price were also flawed. A time series model with important covariates could prove to improve the results in later studies. As 2018 proved to be such an extreme year, several of the predictions came short in grasping the decisive developments. One of the most significant contributing factors to why prices were extreme and difficult to predict was the weather. In essence, the weather is extremely difficult to predict, and the longer the predicted horizon, the more difficult it is to make an accurate prediction. As such, poor performance of different predictions is understandable, but the performance can also be improved. In the following chapter, discussions of why the machine learning algorithms in many cases performed particularly bad, and possible adjustments to improve accuracy will follow.

# 6 Discussion

Based on the analysis of the machine learning predictions and proposed hedging strategies, we will in the following chapter discuss the results and their implications. To begin with, we discuss how machine learning in general can contribute to hydropower producers, and what value our proposed models add. We thus include modifications and recommendations for applying machine learning in practice. Thereafter, the chapter continues with a discussion of hedging strategies, what information should be considered in the decision making and what type of futures contracts should be purchased. Further, we move on to a general risk assessment. Development of risk in the power market in general is introduced, before the risk associated with the results of our analysis is discussed. Firstly, we introduce algorithmic risk as a concept before assessing the algorithmic risk of our models. Thereafter, we analyze regulatory risk of machine learning, and the future trends that could impact hydropower producers. The discussion ends with a conclusion of how hydropower producers can benefit from our analysis when assessing and handling price risk. Finally, we include a robustness check of our conclusions, by applying the same methods as in Chapter 5 to generate predictions in 2017, and recommendations for future research.

## 6.1 Discussion of machine learning results

As was seen in the analysis of the predicted monthly, quarterly and yearly prices of 2018, the point predictions were usually significantly lower than the actual prices. In the following, a discussion of why the predictions were not more accurate will follow. We begin with a general discussion of advantages and disadvantages of using machine learning for prediction purposes, both in general and for electricity prices specifically. Thereafter, we evaluate the performance of our predictions and discuss alternative approaches and recommendations.

### 6.1.1 General discussion of machine learning

Machine learning is growing in importance across organizations and businesses as its potential in business operations and decision making is being revealed (Boehmke and Greenwell, 2019). Machine learning has a wide range of applications for businesses, also for hydropower producers. This thesis has focused on price prediction through supervised learning. The machine learning methods introduced all aim to learn from data provided to them in order to make the most accurate prediction of the Nordic system price. With a reasonable understanding of the application of the different models in addition to data capabilities, machine learning can be applied in many operational and financial decisions across divisions.

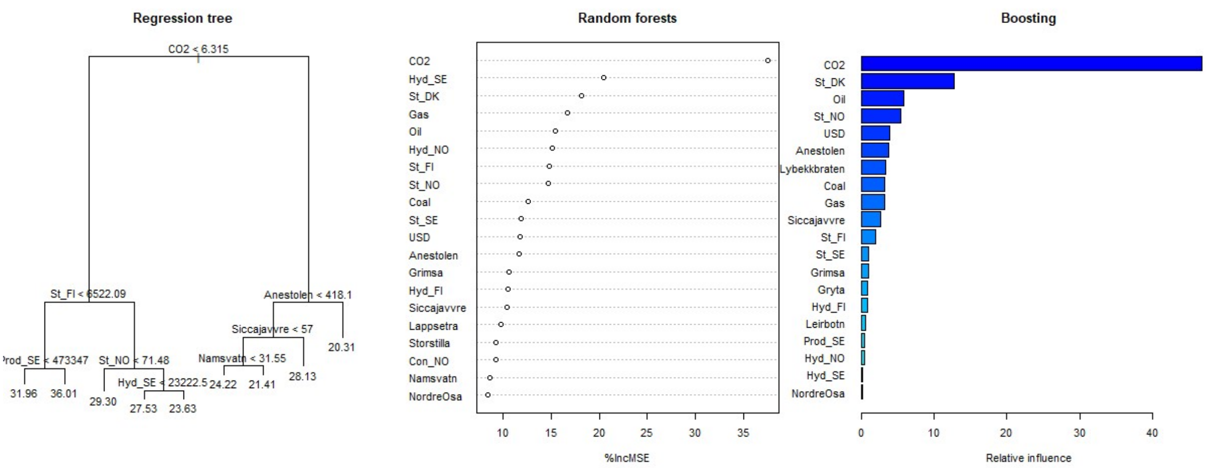
Complicated machine learning algorithms usually require large data sets (Datatilsynet, 2018). These data sets are often impossible for humans to manually analyze. By letting machines learn from the data, the process is automated and ultimately, the machines find patterns and outcomes on their own. A downside is the resources required for managing the data sets used for analyses. Hydropower producers hence need large data sets that the algorithms can be trained on. This makes standardized routines for data collection and storing more important, which are time-demanding processes. On the other hand, the importance of businesses becoming more data driven is increasing. Hydropower producers generally register and retrieve large volumes of data that can be applied for prediction purposes. In addition to time-consuming data routines, computational time in itself can often constitute a downside of machine learning. Furthermore, the interpretability of certain algorithms is not optimal. Section 6.3 will further elaborate on the risks associated with the machine learning methods.

Altogether, with a clear understanding of the limitations and risks associated with machine learning for prediction purposes, the potential still exceeds the downsides. Predictions through machine learning can easily be implemented through programs free of charge, and much data is open for retrieval online, which we have exploited in this thesis. The data cleaning, predictions and analysis of this thesis has been made in R. R is a programming language and system widely used for statistical purposes and analyses. For applying statistical methodologies and for analyzing data, R has been a consistent leader. R is freely available, used by academics and professionals, and powerful enough to use all packages required in this thesis (James et al., 2013). However, other software packages such as Python could be applied for the same purpose. Applying machine learning using R or different software, provides great automation benefits.

### 6.1.2 Yearly predictions

Yearly predictions were made by random forests, boosting and regression trees. Even though boosting and random forests performed best on the training set, they were outperformed by the regression tree as the actual system price was record high. All three methods are tree-based, implying that non-parametric methods are more suitable for yearly predictions. Given that the system prices are affected by many different factors that in themselves are difficult to predict, the longer the prediction horizon, the more difficult an accurate prediction is. Compared to the contract price and expert opinions, the predicted prices were actually not too far off.

**Figure 6.1:** Output of the yearly prediction models




The regression tree provided the most accurate prediction of the actual price. The estimated regression tree is shown in Figure 6.1 As can be seen, the CO2 price is the first split point, representing the greatest possible reduction in RSS. Based on the CO2 price, the stock exchange index of Finland and water equivalent of surface snow at Anestølen represents the next two splits. At December 1st, the CO2-price was 7.68 euros. The prediction therefore followed the right branch of the regression tree. Water equivalent of surface snow at Anestølen was 236.6 mm, therefore the left branch was followed. The correspondent figure at Siccajavvre was 73 mm, and thus the predicted price was 28.13 euros.

One of the downsides of regression trees is that they are often too simple. Typically, they are not competitive with the best supervised learning approaches (James et al., 2013). The trees have high variance, as results can get very different depending on the sample. A small change in the data can cause large changes in the final estimated tree. Still, the regression tree was the best performing model on the test set. However, boosting and random forests performed better on the training data, and deal with the problem of high variance by generating many trees. Their downside is that they are more difficult to interpret, however they do calculate variable importance, which can be seen in Figure 6.1.

The variable importance plot for random forests shows the average amount that the test MSE would increase by if the predictor variable was permuted. For boosting, the plot shows the reduction of the squared error attributed to each predictor. Both identified the CO2 price as the most important variable, as was also the case for the regression tree. As was seen in Figure 2.2, CO2 prices went from an average level of 5.94 euros from 2013 to 2017 to a maximum of 25.25 euros at the end of 2018. As the variable was given such high importance in all models, this is likely one of the most important reasons why the predictions turned out too low. None on the three models valued weather-related variables, consumption or production high, except for production in Sweden and consumption in Norway which was given some importance in boosting and random forests respectively. This makes sense, as the variables are believed to give more effect instantaneously, and not impact prices a year ahead. Many of these instantaneous factors will likely be incorporated into the price already. The rationale of relying on yearly machine learning predictions that make use of much event-based data is thus less clear than for quarterly and monthly predictions, as the uncertainty of how associated variables will develop is very high. To investigate the accuracy for other terms, the performance of the three models in predicting the price for 2017 is briefly contemplated in Section 6.4

### 6.1.3 Quarterly predictions

The three best-performing models on the training data for quarterly predictions were ridge regression, SVR and lasso regression. Throughout 2018 all predictions turned out to be too low. The predictions of the two first quarters followed the contract price quite closely. However, the last two quarters the contract price targeted the high levels of the actual price much better. The trends were the same for all three predictions. It is thus clear that the market, through the contract price, conceived something that our models did not.

The price of the third quarter was predicted on June 1st, 2018. On June 1st, 2018 there was (nearly) no precipitation at any station in the data set, except for at Aura. In addition, average temperatures were generally high, with the exception of Tromsø. From March 1st, the CO2 price increased from 10.12 to 15.26 euros, coal prices increased from 65.03 to 81.71 euros, the dollar exchange rate from 0.8152 to 0.8576 euros and the gas price from 2.67 to 2.91 dollars. A brief look at the coefficients of the ridge regression model estimated for predicting the third quarter, shows negative coefficients of the CO2 price, gas prices and the stock exchange index of Sweden, among others. This contradicts our expectations of the predictors. In addition, temperature and precipitation amounts show a mix of negative and positive coefficients.

In this case, removing the instantaneous variables discussed in the yearly predictions could have made sense, as they seem to contribute to much noise. However, cross-validating models without these variables did not yield better results, and neither in the predictions of 2018 did the models catch the upwards trend of the two last quarters. In addition, several of the predictors not considered instantaneous also show strange coefficients. The overall performance of the lasso and ridge regression points to that the models are too simple to predict such a volatile price. As the models consider all the noisy data observed daily, the exact predictions vary highly based on what is observed that day. Being linear models assuming linear relationships, the models fail to find true causal relationships between predictors and the response. Thus, the predictions are not very accurate.

The third and fourth quarter of 2018 had the highest quarterly prices of the entire data set. A plausible explanation for why predictions proved too low might therefore be that the data set does not stretch long enough back in time. The same reasoning could apply to the yearly predictions. Another question is why SVR performed worse than both ridge and lasso regression. Since SVR is considered a black box, there is no exact answer to how the algorithm considers the different variables in making the prediction. However, the explanation of a too short time span of observations and the extreme situation of the two last quarters of 2018 seem plausible.

### 6.1.4 Monthly predictions

The monthly predictions were conducted using SVR, ridge regression and boosting. The three algorithms are very different in their nature, so it is somewhat surprising that these were the three best-performing models. On the other hand, the test MSEs of the different models had a large spread. SVR had the best performance on the training set, followed by ridge regression and boosting. However, when making actual predictions of the months of 2018, the ranking was opposite.

Especially in the summer months of June to August, all predictions performed particularly bad. While the actual price increased towards July, the predicted prices instead decreased. As discussed in Section 2.4, the summer was especially warm, and precipitation and stock of hydro reservoirs were low. In addition, CO2- and coal prices increased. The models did not seem to make use of this information when predicting prices. Considering boosting, which in hindsight performed the best in predicting the monthly prices, coal prices, USD exchange rates, water equivalent of surface snow at Lybekkbråten and Storstilla, the hydro reservoir in Finland and oil prices were considered the most important predictors both in June and July.

In the test set for predicting the average price of June, Lybekkbråten registered the water equivalent of surface snow at 0, as the only station in the data set. In July, both NVE stations had a value of 0. Coal, and oil prices increased consistently from April 1st to June 1st, as was also the case for the dollar exchange rate and hydro reservoirs in Finland. All these developments, apart from the hydro reservoirs in Finland, would isolatedly indicate an increase of the system price. When the predicted system prices nevertheless decreased, the estimated models must have made different ponderations. The general historical pattern is that power prices decrease in the summer months along with consumption. In 2018, the seasonal effect was opposite. The high monthly prices mid 2018 were the highest monthly prices of the data set throughout the period. Historical behavior of the system price is important to consider. However, there is a fine line in whether to weigh the historical patterns or the instantaneous factors. Also in the case of these predictions, there could be problems related to the data set not going far enough back in time.

The predictions showed somewhat of a lagged effect over the whole period. The same, applied for the time series forecasts as well. This points to there being an effect that could be possible to make use of and integrate into further models. The lagged effect could as an alternative be exploited by training against weather forecasts instead of the observed weather. Hydropower producers receive different forecasts every day that they use in their production planning. In this analysis, these forecasts have not been accessed. Other forecasts could also be incorporated into the model instead for the direct observations. In this case, hydropower producers could make use of their existing data, and feed this into the machine learning models instead of, or in addition to, the data used for this thesis.

### 6.1.5 Conclusion of all models

To sum up, the system price predictions presented were generally too low in all periods. As 2018 was an extreme year in the data set, this result could have been anticipated. For further analyses making use of machine learning to predict power prices, a longer time horizon of the data set can be recommended. In addition, training on forecasts instead of the instantaneous variables could prove a better alternative. As there seemed to be a lagged effect, especially in the monthly predictions, there appears to be information that could be fed into the model to generate better predictions. None of the analyzed models put much weight on the precipitation and temperature data collected. Hence, as we know power prices are highly weather-dependent, other versions of the weather data could prove a better fit.

Our transformation of the Nordic system price could also have caused problems for the assumed relationships between predictors and the response. Variables associated with the system price at a given date might not be associated in the same obvious way to the average future price. Therefore, for further analysis, we recommend exploring different versions of the response. In addition, the data collection and analysis has had a particular focus on Norway. Since the price is joint for the Nordic countries, and impacted by other European countries, there might be much information missed because of this focus. Summed up, this suggests that the time horizon, instantaneous variables, access to data, the transformed response and a narrowed focus might have posed problems for the predictions. Nevertheless, machine learning in itself as a means of predicting power prices could still prove useful.

## 6.2 Discussion of hedging strategies

As presented in the analysis in Section 5.2, the yearly predictions using random forests, boosting and the regression tree were quite far from the actual system price. The evaluation of whether the yearly contract should be purchased was only made at one point in time, on December 1st, and thus each model only made one prediction. Out of the three presented models, the regression tree was the only model that predicted a price closer to the actual system price than the contract price. As such, only following this prediction the strategy would have been to not purchase the contract.

For the quarterly contracts, using the predictions of ridge regression led to a better strategy than the benchmark strategy where all contracts were bought. However, we also saw that contract prices on average were closer to the actual system price than these predictions. The reliability of the predictions can therefore be questioned, and it is possible that ridge regression could suggest a strategy that performs worse than the benchmark in other periods. In retrospect, we see that the best strategy would be to only purchase the contract for the fourth quarter, which none of our models were able to predict. Also a strategy where no contracts were purchased would give a higher revenue than the suggestions presented by our predictions.

Moreover, as presented in the analysis, all monthly predictions by the three machine learning models suggested strategies that were better than the benchmark where all contracts were purchased. Thus, using the machine learning models as a supplementary tool for deciding which monthly contracts to buy in 2018, would have given considerably higher revenues compared to the benchmark. This indicates that using machine learning as a supplement for deciding which contracts to purchase in 2018 was a good strategy in a profit maximizing view.

### 6.2.1 Comparison of durations

Following the discussion of which machine learning models led to the best hedging strategies for the yearly, quarterly and monthly terms of 2018, we will evaluate the advantages and disadvantages of the three durations of the futures contracts. The evaluation will be based on predictions by the machine learning methods that performed best on each period in the training set, and a discussion of uncertainty related to securing prices for different terms.

Random forests predicted an average yearly system price in 2018 of 23.57 euros per MWh. This implied a deviation from the actual system price of 20.42 euros per MWh. The quarterly predictions using ridge regression led to an average deviation of 14.40 euros per MWh from the actual system price. From the monthly prediction using SVR, the average monthly deviation was 11.70 euros from the actual price. These results show that the predictions made from the monthly model were on average closest to the actual system price. The result seem logical, as there is more available information when predicting the near future.

Securing for periods closer in time has the benefit that more relevant information is available than when securing for periods further away. However, there are also disadvantages connected to only securing for the near future. When hedging prices only for the upcoming month, a hydropower producer is secured against declining prices for that month. However, they are not secured against declining prices in periods further ahead. If market participants expect prices to fall, the monthly contract prices are likely to fall as well, and such fluctuations could be secured against by initiating a yearly contract. On the other hand, if prices are expected to rise, hedging using monthly contracts could provide benefits, while the yearly contract will not unless the price increase happens before the yearly contract is purchased.

Overall, using the quarterly and monthly predictions to decide the hedging strategy would have generated a higher income than the benchmark of purchasing contracts for all periods. Thus, in a profit maximizing view, our strategy using machine learning renders a better alternative than the benchmark strategy. However, whether a prediction is above the contract price at one time and below at another time could be coincidental and based on small margins. The system price was quite far above both the yearly contract price, the contract price for three out of four quarters, and for most months in 2018, more so than for all other years in the data set. For most terms, predictions of a system price higher than the contract price would therefore generate an excess revenue.

We also see that on average, contract prices were closer to the system price than the model predictions were. This suggests that the machine learning models conceive less vital information than the futures prices. Thus, one can discuss whether the strategies presented above were indeed better than the strategy where all contracts were purchased, or if it was due to luck as the actual prices in 2018 tended to exceed the contract price. If prices on the contrary had declined to a level below the contract prices in the quarter and months we did not purchase a contract, there would be a loss rather than a gain. In that case, the strategies had not been better. With the volatility of the system price and the extreme case of 2018, such developments could occur other years. Thus, initiating the yearly contract could still be the best alternative in a risk minimizing view, even though contracts for shorter periods could generate higher earnings. Overall, we argue that a model that predicts prices as close to the actual system price as possible is preferred over a model providing the best strategy in one year. The recommendations of Section 6.1.5 should therefore be given focus.

## 6.3 Risk analysis

The goal of this thesis has been to figure out whether using machine learning can give hydropower producers a better decision basis when hedging power prices. The main purpose when estimating machine learning models has been to provide a tool that can help hydropower producers in their risk management. As the model aims to help reduce risk, it is important to also assess risk the model could introduce, and the risk connected to machine learning in general. There are several relevant risk factors, and this section will discuss some of the most important ones. The topics that will be elaborated are risk in the power market, model selection and model weaknesses, and regulatory risk. First, we present the development of risk in the power market.

### 6.3.1 Risk in the power market

As introduced in Section 2.1, the electricity market differs from standard commodity markets, primarily as electricity is not a storable commodity. Moreover, spot prices are very volatile due to inelastic demand, shortages in generation and capacity restrictions. As a result, most hydropower producers adopt hedging policies. The future market is uncertain, as political regulations will impact the pricing and mix of energy sources. Hence, active risk management could prove to be even more important for hydropower producers.

With the adopted climate goals of the EU, the production of solar and wind power will likely increase largely towards 2030 and 2040, as these energy sources are emission-free (Bøhnsdalen et al., 2016). With a larger share of solar and wind power in the Nordic energy mix, power prices are thus expected to become more volatile. Other factors that cause uncertainty of future power prices relate to how the prices of fossil fuels and CO2-emissions will be set in the future. As the EU have expressed a wish to increase the share of renewables, the uncertainty of how these prices will develop is evident. In addition, capacity expansions and margins will impact prices. As the Nordic market gets further integrated with the European market, the Nordic prices get more closely linked to continental prices. Also developments within energy storage and flexibility on the demand side increase uncertainty of future prices.

The declining liquidity at Nasdaq Commodities in recent years could pose an extra risk for hydropower producers. As the supply side increases relative to the demand side, producers could in the future risk not attracting buyers for their contracts. The market development points to hydropower producers transitioning towards purchasing less contracts through Nasdaq Commodities. Without the presence of an exchange, the advantages of clearing, which ensures the financial settlement of contracts, could be mitigated. The low liquidity, in addition to future system prices becoming even more volatile, points towards an increased price risk of the power market in the future.

In order to make an informed decision of how much should be hedged, the taxes and transmission costs of hydropower producers should be considered. When the producers develop a hedging strategy, they should not secure income that must be paid in transmission costs. This would not be hedging, in reality it would be pure speculation. For a given volume of electricity, it is possible to hedge against the tax variations. When securing the price this way, spot prices that are higher than the contract price will result in higher taxes. However, it will also give the producer a higher income for the production they did not initiate a contract for. On the other side, if the actual spot prices are lower than the contract prices, both taxes and the income from unsecured production will be lower. In both cases, the increase (decrease) in taxes will be the same as the decrease (increase) in production revenues, so the bottom line will be the same, regardless of the price change. By adjusting for transmission costs and taxes, producers can secure a relatively stable bottom line, regardless of what the spot price ends up being. It is thus possible to calculate the amount that should be secured to eliminate the risk of variations in the bottom line. This process of securing prices does not take variations in volume into account.

### 6.3.2 Model selection and weaknesses

Section 6.1 elaborated on the strengths and weaknesses of the machine learning models in terms of prediction accuracy. However, a discussion of the models from a risk perspective is also required. By making use of machine learning, the hydropower producers should also consider an algorithmic risk management strategy. This strategy should involve a continuous monitoring of algorithms, which specify processes and approaches for the machine learning work, from data collection to testing and implementation. The algorithmic risk factors discussed in this section are based on the publication of Krishna et al. (2017).

Before estimating and testing models, data has to be collected and prepared. The algorithmic risk analysis thus starts at this point. Through the data collection in Chapter 3, variables assumed to be associated with the response was collected. The simplicity of collecting data and loading it into software like R however increases risk. Therefore, considerations of the data collection to avoid errors become more important. Using data from open sources involves the risk of errors and missing values, and many sources state disclaimers for these occurrences. In addition, biases in the training data often occur, as was discussed in Section 3.2.14. The data collection of this thesis has aimed to provide complete and relevant data and avoid biases, although risks of the opposite has been discussed.

Further, there is risk related to the algorithms themselves. Algorithms are generally thought to be objective, however they can often exhibit biases and errors. The potential bias that followed the data collection also poses a risk in applying the models. In addition, there is always a risk of coding errors and bugs. Through the time series cross-validation, the models including all variables had the highest accuracy. In hindsight, when evaluating how the models interpreted the relationships, the expectations were not always as initially assessed. There is therefore a risk that the initial associations were flawed. With ridge regression, outcomes are not unbiased as there is a trade-off of variance by bias. Without variable selection, we also saw that assumed relationships between the response and predictors seemed strange in several of the estimated models. Moreover, with increasing complexity of the algorithms applied, the decision making becomes further based on black boxes. The main risks of SVR is related to its complexity. As several model parameters need to be estimated, the risk also increases of underlying assumptions and parameters being wrong or suboptimal. In the case of random forests, as well as the other tree-based methods, the outcomes will always be within the range of observed values in the historical data set. Thus, when predicting rare outcomes, such as the case of 2018, the methods perform worse. Further, random forests have risks related to complexity as well.

There is thus an overall risk posed by human biases, e.g. in the data collection, a risk of technical flaws in the development, training, testing and validation of algorithms and a risk of usage flaws in implementing and using algorithms. In addition, for large businesses relying on machine learning, there is a risk connected to internal or external threat actors, such as hackers. These actors can gain access to the systems or the data used as inputs and manipulate them in their favor. The most likely implication of all these risk factors is the financial risk. As such, the resulting outcome could be financial losses.

### 6.3.3 Regulatory risk

The Norwegian Ministry of Local Government and Modernisation (2019) describes artificial intelligence, such as machine learning, as a technology that could have a large impact on the development of society. Machine learning could provide new ways of solving challenges, improve public services and contribute to a higher value creation in the business sector. However, although the area could encourage improvements and development, there are regulations that need to be considered when using machine learning. In this thesis, we look at whether using machine learning can create extra value for hydropower companies through providing an additional basis for decision making. Thus, it is important to consider how regulations could affect their use of the machine learning algorithms. There is no universal regulation, however, attempts to enforce such regulations regionally have been made by the EU and the Norwegian government are currently working on a strategy for artificial intelligence in Norway.

There is a lack of consistent business controls for developing, implementing and using algorithms today (Krishna et al., 2017). Developers often use of their own theoretical knowledge and experience when making decisions, without oversight from management. As a result, there are variations in processes, and an increased probability of errors. Current regulations are still evolving, and only apply to a limited set of algorithms. Although there have been attempts to regulate the use of algorithms, it is still unclear how the regulations will be implemented. The lack of regulations and standards make it difficult to ensure an accountable and fair use of algorithms.

Although there is a lack of universal regulations, the Norwegian government are currently working on a strategy for artificial intelligence in Norway. Artificial intelligence poses some challenges, especially in connection to protection of personal data, ethics and privacy (Norwegian Ministry of Local Government and Modernisation, 2019). The proposed strategy for artificial intelligence should be ready within 2019, and include guidelines on artificial intelligence. These guidelines could pose problems for using machine learning for predicting future power prices if they introduce restrictions on variables in such a model. Predictions of power prices might not require the use of sensitive information or other factors that might be regulated by the guidelines. However, there is still a possibility that the models could contravene the new Norwegian regulations. Thus, although we have concluded that machine learning could provide an additional decision basis for hydropower producers, the matter of whether the new guidelines could pose implications for its usage has to be reviewed before models are implemented.

### 6.3.4 Summary of the risk analysis

As we have seen in this Section, there are several risk factors that have to be assessed, both regarding risk in the power market in general, risk related to the machine learning models and regulatory risk. Although Chapter 5 showed that the hedging strategies derived from using the predictions of the machine learning models led to the same or a better strategy than securing all prices, there is considerable risk related to such strategies that must be taken into account. As was seen by the RMSEs in Section 4.3.1 and the MAE in Section 5.2, the predictions are not perfect, and exhibit errors. Even if models are adjusted by our suggestions to improve accuracy, there will always be irreducible errors in the models. Hydropower producers therefore need to be aware of this risk, and the risk related to the models in general. A combination of predictions should thus be relied on, and an algorithmic risk management strategy should be considered. In addition, the future risks of the power market must be addressed in risk management strategies. The practices should be continuously updated with new information, such as the publication of the Norwegian AI regulations.

## 6.4 Robustness of predictions

The data set introduced in Chapter 3 includes data from January 1st, 2013 up until December 31st, 2018. Observations of the Nordic system price are available from January 1999, and other variables can also be retrieved prior to the start of the applied data set. However, in order to have a complete data set with all variables assumed to be associated with the Nordic system price, the open-source data is retrieved from 2013, as multiple variables start being registered on the open sources this year. As discussed in Section 2.4, several of the applied machine learning methods require large amounts of data. To make use of the retrieved data, 2018 is hence chosen as the test set for how well the models work, despite the potential downsides. To see how peculiar prices in 2018 really were, we therefore test the performance of the same models of Chapter 5 on 2017 prices instead. For this purpose, the models have not been cross-validated, and the predictions are only included as a reference and robustness check for the conclusions of 2018. To conclude on which models are optimal for predicting prices of 2017 and other years, more thorough examinations should be performed.

The predictions of 2017-prices are conducted by estimating the three best-performing methods for each period, as was done in Chapter 5. The same dates only one year prior are used as the training set for each model. Thus, for yearly predictions, random forests, boosting and regression trees. For the quarterly predictions, the applied methods are ridge regression, SVR and lasso regression, and for monthly predictions the corresponding are SVR, ridge regression and boosting. All predictions, along with actual system prices and contract prices are shown in Figure 6.2, 6.3 and 6.4. The exact quarterly and monthly numbers are included in Appendix A4, in Tables A4.1 and A4.2.

**Figure 6.2:** Yearly system price, the contract price and the predicted prices in 2017

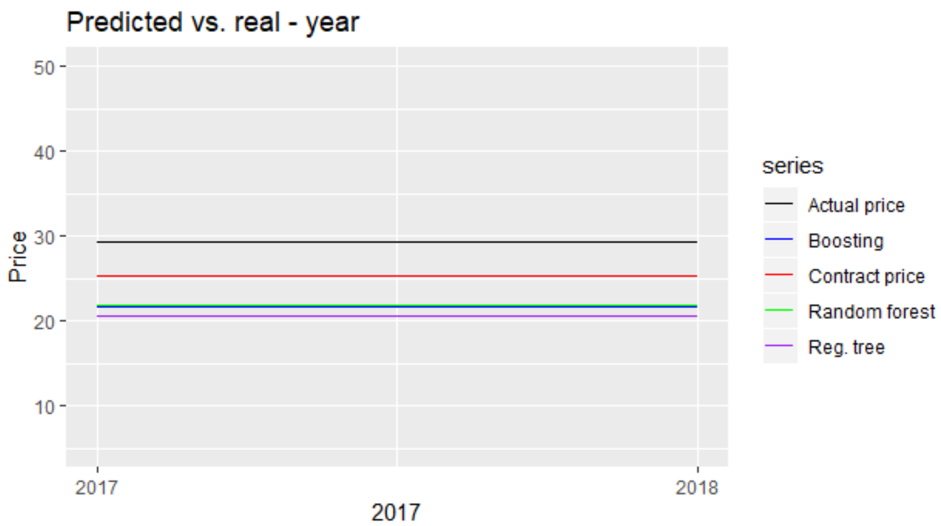



**Figure 6.3:** Quarterly system prices, contract prices and predicted prices in 2017

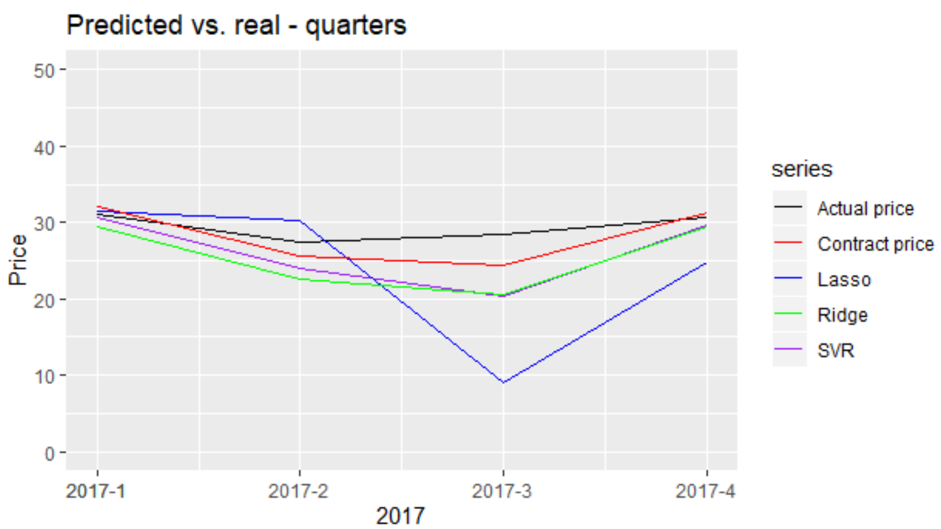
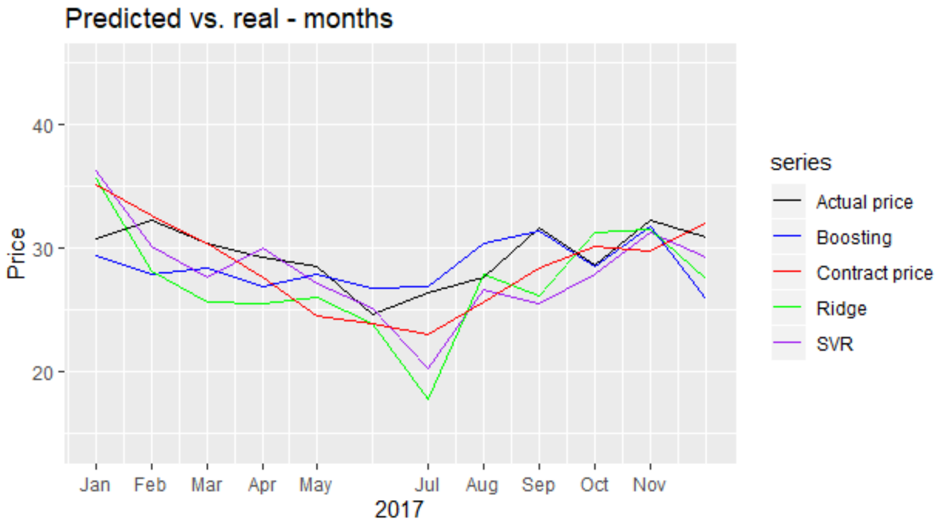


**Figure 6.4:** Monthly system prices, contract prices and the predicted prices




As can be seen in Figure 6.2, the yearly predictions are lower than the system price and contract price in 2017, similar to the results of 2018. Random forests predicts a price of 21.90 euros, boosting of 21.60 and regression trees of 20.55. The contract price was 25.35 euros, while the actual price turned out to be 29.41 euros. That being said, on a yearly basis the average prices do not vary too much, while the day-to-day changes can be large. Thus, all variables added to the yearly model could prove to increase the noise and confusion of a model with a response that is already uncertain, being far away in time. One can therefore discuss the rationale of using these kinds of event-based models for yearly predictions. On the other hand, the predictions are significantly closer to actual prices than in 2018.

In the quarterly predictions of 2017, shown in Figure 6.3, the predictions, apart from lasso regression, follow the actual price as well as the contract price much more closely than in the case of 2018. The predicted prices are in general still lower than the two other prices, however the deviation from actual prices is much smaller. The MAE of the SVR prediction is 3.30 euros, the corresponding figure for the lasso regression and ridge regression is respectively 7.12 and 3,93 euros, while the contract price on average deviates by 1.87 euros.

Similar to the yearly and quarterly predictions, the monthly predictions are also much closer to the actual price in 2017 than in 2018. Ridge regression and SVR still predicts a sharp decline towards July, which was also the case of 2018. This effect should be investigated further for other attempts to predict the Nordic system price. Altogether however, the MAEs are quite low. The contract price on average deviates by 2.05 euros, while the predictions by boosting, SVR and ridge regression deviates by 1.86, 2.47 and 3.48 euros respectively. Accordingly, predictions made by boosting is on average closer to the actual monthly prices in 2017 than the contract prices.

In total, when applying the models in 2017, the results are better than when applied to 2018. With more thorough testing and validation, the results have a potential of becoming even better. As such, the conclusion is that machine learning methods have great potential in predicting Nordic system prices in 2017. Although the prediction accuracy of the applied models in 2018 were lower than desired, we still concluded that the discipline has potential for predicting the system price. This conclusion is substantiated with the performances of the prediction models in 2017.

## 6.5 Recommendations for future research

Through this thesis we have found that machine learning methods have good potential in their applications to enhance decision support in price risk management. The prediction accuracies of the machine learning models were mixed depending on the time period the prediction targeted. In general, most of our machine learning models, when compared to other sources, predicted too low prices. For further research, a more thorough analysis of why this was the case should be performed. Moreover, when testing the three most accurate prediction models from 2013-2017 iteratively in 2018, the performance ranking of the models often turned. Building on the findings of this thesis, the same models could be tested for other time horizons.

Especially extending the short time horizon of the data set could prove to increase model performance. To address this limitation of the thesis, the data set could make use of observations from further back in time. As a result, more high observations of the dependent variable would be included, and the models would learn how to predict these values, in the case that 2018 prices would not stand out as much. Moreover, the appropriate models could be applied in other years than 2018 to get a more thorough discussion of the general performance of the models.

In addition to expanding the time horizon of the data set, other variants of the independent variables could also be used as inputs by the machine learning methods. The variables retrieved from the data collection were all assumed to be associated with the response. However, other forms of these variables could prove more useful. Hydropower producers possess a great deal of data for operational and financial purposes that are not open to external actors. By replacing some of the open data used in this thesis with licensed or proprietary data, e.g. using forecasts instead of instantaneous variables, the inputs could prove to be more precise.

The analysis has been made in the context of hydropower producers in the Norwegian market. However, the research question could be applied in other contexts as well. By replacing Norwegian hydropower producers and futures contracts with other market actors and financial instruments, the analysis could be transferred to other markets and market actors. Thus, future research could analyze markets where price risk management is important and explore the potential value generated by applying machine learning for prediction purposes with the same methodology used in this thesis.

The theory of the methodology could correspondingly also be expanded. The focus for price prediction methods has been standard machine learning algorithms. Nevertheless, more advanced algorithms could be applied. For instance, neural networks were applied to the training set, but due to computational limitations, the final validation and analysis did not become thorough enough to include in this thesis. In addition, time series forecasting could have been given a greater emphasis, prioritizing the second hypothesis explored in Chapter 4 over the first. As such, multivariate forecasts could also be applied.

# 7 Conclusion

The research question that has been discussed in this thesis is:

*How can predictions of the Nordic system price using machine learning methods enhance decision support for hydropower producers when trading medium-term power derivatives?*

In order to answer this question, we have trained eight machine learning models to predict the future Nordic system price on an annual, quarterly and monthly basis. The three best performing models were estimated to predict prices for the different periods in 2018. Based on these predictions, we assessed which futures contracts a hydropower producer should have purchased, providing a form of a hedging strategy. Further, we evaluated how well the imposed hedging strategies performed compared to a strategy of securing all prices with the contract price, which we used as a benchmark. For evaluating the prediction accuracy in 2018, the performance of the machine learning models were reviewed by a comparison with the actual system prices. The predictions were also compared to forecasts made by ARIMA and NNAR models and to analysts' expectations of the system prices in different terms of 2018. Finally, we discussed how machine learning models can be applied by hydropower producers when hedging future power prices, and discussed potential risks associated with the models and machine learning in general.

Through our analysis, we found that the actual system prices in most terms of 2018 were far higher than both our predictions and the contract prices. The yearly, quarterly and monthly strategies implied by the machine learning models were either better or equivalent to a strategy where contracts were purchased for all terms. However, we also found that on average, the contract price was closer to the system price than our predictions. To improve the prediction accuracy of the models, we have proposed several suggestions for future research. The most relevant suggestions include expanding the theory and addressing the limitations introduced by a short time horizon of the data set and suboptimal variables.

The aim of this thesis has been to introduce the use of artificial intelligence for prediction of power prices and apply the results to the risk management of hydropower producers, as an additional basis for managing their hedging strategies. As the imposed hedging strategies led to higher or equal profits as the benchmark, the introduction has proved beneficial in a profit-maximizing view. However, as the aim is to contribute in the risk management, the risks associated with the models and their predictions must be taken into account. When predicting the future Nordic system price, hydropower producers should first review the risks of the data collection, the algorithms themselves and the implementation of these. After generating predictions, these should be viewed in combination with other information, such as expert views and other available predictions, both of the system price itself and associated variables. When all information is used to determine which contracts should be purchased, the potential gain of the futures contracts has to be seen in light of taxes and transmission costs. As a final risk factor, the machine learning models need to be in accordance with the new Norwegian AI regulations.

Following the strategy of the previous paragraph, we set a path for how predictions of the Nordic system price using machine learning methods can enhance decision support for hydropower producers when trading medium-term power derivatives. Based on the predictions we have introduced, we see a greater potential for predictions of monthly and quarterly prices, as the uncertainty of the variables used in the machine learning models increases with the length of the term predictions are generated for. Yearly predictions could still prove useful, but hydropower producers must have an awareness of the high risk.

Altogether, we recommend hydropower producers to make use of machine learning methods for predictions of the system price when trading medium-term futures contracts. Hydropower producers or other market actors benefiting from a mix of open-source and proprietary data can estimate the specific models, and by modifying these as we suggest, we consider the market potential to be large. For risk management applications, the risks must be thoroughly considered and evaluated. As such, the machine learning predictions should be used in combination with existing price prediction models.

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# Appendix

## A1 Negative prices

In electricity markets where a significant share of production capacity is intermittent, fluctuations of power prices are typically larger. A special case is when production exceeds demand, or the capacity of transmission lines is not large enough to transfer the produced power, and as a result power prices become negative. Especially in Germany, hourly prices often move into negative territory when the intermittent wind power generation meets low demand (Buli, 2019). The result is power suppliers who have to pay wholesale customers to buy electric energy. As an example, the lowest daily price of 2017 was registered of minus 52 euros per MWh at October 29th (Amelang and Appunn, 2018). The reason was strong wind power output combined with low demand.

The fundamental question is why a power producer still would choose to produce even as they have to pay for their production. The answer is subsidies. The German day-ahead market functions in a similar way as the Nordic day-ahead market. Producers and buyers submit bids of how much they wish to supply or purchase at specified prices (Amelang and Appunn, 2018). When the high inflexible production meets the correspondingly low demand, the market clearing price can be set below zero. By being intermittent, production is difficult to plan. Wind turbines can be shut down, but this involves a cost as well. And as renewable energy producers receive subsidies for every KWh they produce, prices could reach very low levels before production becomes unprofitable. With an increase of power production by renewable energy sources with intermittent capacity, there is likely to be a moderate increase of negative prices the coming years from 2019 (Buli, 2019). However, they are expected to be rarer by 2030 as more of the production moves away from subsidy schemes.

The Nordic market, by being connected with the European, and thus the German, market is impacted by the negative prices. Denmark is also a wind power producing nation, and Danish hourly power prices have oftentimes been negative as well. However, although continental and Danish prices might be negative and drive Nordic prices downwards, the Nordic system price has never been below zero.

## A2 Descriptive statistics

**Table A2.1:** Descriptive statistics

| Statistic | N | Mean | St. Dev. | Min | Median | Max |
|---|---|---|---|---|---|---|
| Daily system price | 2,191 | 31.497 | 9.848 | 3.880 | 30.280 | 80.990 |
| Monthly system price (Y) | 2,191 | 31.717 | 9.315 | 8.699 | 30.625 | 54.468 |
| Quarterly system price (Y) | 2,191 | 31.723 | 8.812 | 12.286 | 30.723 | 51.902 |
| Yearly system price (Y) | 2,056 | 31.068 | 7.419 | 19.639 | 29.650 | 46.717 |
| Con_NO | 2,191 | 357,478.000 | 72,707.780 | 231,687 | 352,613 | 542,203 |
| Con_SE | 2,191 | 374,598.300 | 72,186.540 | 244,353 | 365,411 | 581,538 |
| Con_FI | 2,191 | 227,445.100 | 33,238.300 | 135,244 | 224,062 | 343,148 |
| Con_DK | 2,191 | 90,419.640 | 10,629.040 | 65,947 | 90,366 | 119,748 |
| Con_EE | 2,191 | 22,201.270 | 3,579.163 | 14,917 | 21,832 | 32,954 |
| Con_LV | 2,038 | 19,652.290 | 2,308.941 | 13,606.000 | 19,307.000 | 26,805.000 |
| Con_LT | 2,191 | 28,097.100 | 3,775.104 | 9,968 | 27,639 | 41,312 |
| Prod_NO | 2,191 | 392,979.500 | 76,952.290 | 208,800 | 377,716 | 615,493 |
| Prod_SE | 2,191 | 420,688.100 | 76,432.370 | 231,385 | 418,429 | 605,659 |
| Prod_FI | 2,191 | 178,393.900 | 31,549.160 | 107,837 | 178,075 | 261,282 |
| Prod_DK | 2,191 | 79,485.440 | 28,066.600 | 19,935 | 77,764 | 163,436 |
| Prod_EE | 2,191 | 28,691.050 | 6,883.772 | 10,870 | 28,943 | 47,008 |
| Prod_LV | 2,038 | 16,179.600 | 6,627.606 | 3,227.000 | 15,358.500 | 42,547.000 |
| Prod_LT | 2,191 | 8,295.022 | 3,167.870 | 576 | 8,267 | 18,480 |
| USD | 2,191 | 0.841 | 0.070 | 0.718 | 0.858 | 0.963 |
| Hyd_NO | 2,191 | 51,430.030 | 15,055.360 | 20,539 | 54,099 | 76,191 |
| Hyd_SE | 2,191 | 18,992.640 | 6,602.166 | 5,388 | 20,916 | 30,694 |
| Hyd_FI | 2,191 | 3,414.498 | 680.129 | 1,597 | 3,561 | 4,512 |
| Oil | 2,191 | 72.131 | 25.511 | 27.820 | 63.550 | 119.150 |
| Wind_DK | 2,191 | 4.709 | 1.876 | 1.300 | 4.400 | 12.800 |
| Wind_GE | 2,191 | 3.603 | 1.224 | 1.575 | 3.324 | 10.035 |
| WProd_EE | 2,191 | 1,536.980 | 1,236.638 | 0 | 1,173 | 5,872 |
| WProd_LV | 2,038 | 294.816 | 252.327 | 2.000 | 212.500 | 1,194.000 |
| WProd_LT | 2,191 | 2,179.028 | 1,916.559 | 1 | 1,595 | 11,064 |
| WProd_FI | 310 | 14,560.600 | 9,496.162 | 1,403.000 | 12,561.500 | 41,207.000 |
| WProd_DK | 2,191 | 35,140.060 | 23,845.000 | 754 | 30,404 | 105,257 |
| WProd_NO | 2,191 | 7,055.746 | 4,292.431 | 342.596 | 6,308.313 | 27,340.650 |
| WProd_SE | 1,330 | 43,482.060 | 24,182.380 | 2,489.000 | 39,019.000 | 127,335.000 |
| CO2 | 2,191 | 7.620 | 4.374 | 2.700 | 6.140 | 25.250 |

| | | | | | | |
|---|---|---|---|---|---|---|
| Coal | 2,191 | 62.625 | 12.666 | 38.440 | 59.650 | 88.300 |
| Gas | 2,191 | 3.227 | 0.809 | 1.490 | 3.020 | 8.150 |
| St_DK | 2,191 | 690.646 | 132.187 | 403.890 | 740.080 | 878.700 |
| St_SE | 2,191 | 52.610 | 5.254 | 39.460 | 53.020 | 62.020 |
| St_NO | 2,191 | 72.675 | 9.920 | 53.020 | 71.060 | 100.120 |
| St_FI | 2,191 | 8,313.599 | 1,174.207 | 5,769.730 | 8,384.160 | 10,433.910 |
| Rain Vamma | 2,155 | 2.857 | 6.216 | 0.000 | 0.100 | 61.200 |
| Rain Tokke | 2,191 | 2.646 | 5.512 | 0.000 | 0.000 | 52.500 |
| Rain Brokke | 2,142 | 3.031 | 6.113 | 0.000 | 0.000 | 54.100 |
| Rain Tonstad | 2,189 | 5.940 | 10.224 | 0.000 | 0.600 | 83.000 |
| Rain Kvilldal | 2,191 | 5.875 | 10.367 | 0 | 0.5 | 77 |
| Rain Sy-Sima | 2,191 | 3.496 | 6.993 | 0 | 0.1 | 68 |
| Rain Aurland | 2,190 | 2.198 | 4.703 | 0.000 | 0.000 | 50.400 |
| Rain Aura | 2,184 | 3.006 | 6.357 | 0.000 | 0.100 | 58.800 |
| Rain N. Røssåga | 2,188 | 3.947 | 7.462 | 0.000 | 0.400 | 74.300 |
| Rain Rana | 2,191 | 3.982 | 8.338 | 0 | 0.1 | 109 |
| Rain Svartisen | 2,191 | 4.466 | 7.290 | 0 | 1 | 81 |
| Temp. Fredrikstad | 2,191 | 8.542 | 7.064 | −12.800 | 8.100 | 24.600 |
| Temp. Oslo | 2,191 | 7.473 | 7.935 | −14 | 6.9 | 26 |
| Temp. Asker | 2,187 | 6.737 | 7.784 | −14.000 | 6.200 | 24.300 |
| Temp. Kristiansand | 2,191 | 8.882 | 6.017 | −10 | 8.7 | 23 |
| Temp. Stavanger | 2,191 | 8.691 | 4.823 | −8.700 | 8.400 | 23.000 |
| Temp. Bergen | 2,191 | 8.791 | 5.714 | −7.800 | 8.400 | 26.100 |
| Temp. Trondheim | 2,191 | 6.694 | 7.109 | −16.800 | 6.500 | 27.300 |
| Temp. Tromsø | 2,191 | 3.886 | 6.422 | −15.000 | 3.400 | 23.600 |
| WESS Anestolen | 2,191 | 232.998 | 280.713 | 0 | 62.8 | 1,011 |
| WESS Bakko | 2,191 | 65.152 | 92.724 | 0.000 | 2.500 | 375.900 |
| WESS Breidvatn | 2,191 | 151.527 | 178.863 | 0.000 | 40.300 | 543.900 |
| WESS Brunkollen | 2,191 | 46.231 | 87.359 | 0.000 | 0.000 | 395.700 |
| WESS Grimsa | 2,191 | 30.487 | 40.486 | 0.000 | 5.100 | 161.000 |
| WESS Groset | 2,191 | 105.551 | 133.392 | 0.000 | 34.200 | 516.600 |
| WESS Gryta | 2,191 | 90.852 | 132.284 | 0.000 | 5.300 | 568.400 |
| WESS Kvarstadseter | 2,191 | 86.560 | 112.565 | 0.000 | 16.100 | 416.200 |
| WESS Kyrkjestol | 2,191 | 86.806 | 110.134 | 0.000 | 19.500 | 379.500 |
| WESS Lappsetra | 2,191 | 276.796 | 316.279 | 0.000 | 145.700 | 1,075.700 |
| WESS Leirbotn | 2,191 | 128.753 | 151.760 | 0.000 | 65.300 | 611.600 |
| WESS Lybekkbraten | 2,191 | 19.384 | 48.748 | 0.000 | 0.000 | 259.700 |
| WESS Maurhaugen | 2,191 | 56.122 | 79.429 | 0.000 | 2.300 | 316.700 |
| WESS Namsvatn | 2,191 | 202.408 | 231.573 | 0.000 | 92.000 | 852.200 |

| | | | | | | |
|---|---|---|---|---|---|---|
| WESS NordreOsa | 2,191 | 58.267 | 82.019 | 0.000 | 0.100 | 314.700 |
| WESS Overbygd | 2,191 | 100.748 | 126.387 | 0.000 | 20.500 | 526.100 |
| WESS Siccajavvre | 2,191 | 60.658 | 68.338 | 0.000 | 26.400 | 257.300 |
| WESS Sognefjellet | 2,191 | 194.014 | 193.701 | 0.000 | 147.200 | 641.000 |
| WESS Storstilla | 2,191 | 192.363 | 229.790 | 0.000 | 88.600 | 877.500 |
| WESS Vauldalen | 2,191 | 77.849 | 100.685 | 0.000 | 14.600 | 399.300 |

Where *Con_* and *Prod_* is the consumption and production of the respective Nordic and Baltic countries, *Hyd_* is the hydro reservoir stock, *Wind_* is the wind power production, *St_* is the stock exchange indices and *WESS* is the water equivalent of surface snow.

## A3 Prices 2018

**Table A3.1:** 2018 quarterly values

| Quarter | System price | Contract price | Ridge | SVR | Lasso | ARIMA | NNAR |
|---|---|---|---|---|---|---|---|
| Q1 | 38.61 | 32.75 | 28.12 | 28.04 | 29.20 | 32.78 | 33.09 |
| Q2 | 39.02 | 28.80 | 30.69 | 28.06 | 27.74 | 41.37 | 40.70 |
| Q3 | 50.50 | 42.00 | 25.53 | 16.81 | 21.98 | 34.46 | 35.18 |
| Q4 | 47.65 | 55.20 | 33.85 | 26.02 | 34.13 | 55.91 | 49.08 |

**Table A3.2:** 2018 monthly values

| Month | System price | Contract price | SVR | Ridge | Boosting | ARIMA | NNAR |
|---|---|---|---|---|---|---|---|
| January | 32.93 | 35.05 | 29.70 | 30.63 | 26.81 | 33.81 | 32.83 |
| February | 39.58 | 33.75 | 30.61 | 31.37 | 30.55 | 31.32 | 31.08 |
| March | 43.42 | 32.85 | 33.02 | 34.67 | 33.43 | 32.21 | 33.23 |
| April | 39.00 | 34.20 | 29.52 | 36.55 | 32.48 | 40.99 | 40.28 |
| May | 33.46 | 30.20 | 32.95 | 40.53 | 35.68 | 44.48 | 43.61 |
| June | 44.80 | 32.35 | 22.19 | 23.44 | 30.53 | 40.44 | 40.19 |
| July | 51.70 | 41.48 | 16.34 | 21.04 | 30.35 | 34.42 | 34.71 |
| August | 51.73 | 48.75 | 25.90 | 28.47 | 38.61 | 45.76 | 45.10 |
| September | 47.98 | 51.25 | 39.04 | 40.75 | 49.71 | 54.20 | 49.68 |
| October | 43.04 | 54.61 | 42.86 | 48.98 | 51.36 | 55.34 | 49.73 |
| November | 48.37 | 50.00 | 48.11 | 51.08 | 50.73 | 51.68 | 47.16 |
| December | 51.56 | 46.50 | 36.92 | 40.07 | 42.15 | 43.73 | 43.23 |

## A4 Prices 2017

**Table A4.1:** 2017 quarterly values

| Period | Actual price | Contract price | SVR | Lasso | Ridge |
|---|---|---|---|---|---|
| Q1 | 31.13 | 32.15 | 30.66 | 31.46 | 29.52 |
| Q2 | 27.45 | 25.65 | 23.91 | 30.28 | 22.55 |
| Q3 | 28.48 | 24.50 | 20.29 | 8.97 | 20.48 |
| Q4 | 30.60 | 31.30 | 29.59 | 24.81 | 29.40 |

**Table A4.2:** 2017 monthly values

| Period | Actual price | Contract price | Boosting | SVR | Ridge |
|---|---|---|---|---|---|
| Jan | 30.81 | 35.20 | 29.40 | 36.27 | 35.61 |
| Feb | 32.28 | 32.68 | 27.87 | 30.12 | 28.09 |
| Mar | 30.40 | 30.40 | 28.39 | 27.62 | 25.65 |
| Apr | 29.23 | 27.68 | 26.83 | 29.97 | 25.48 |
| May | 28.46 | 24.50 | 27.87 | 27.07 | 26.02 |
| Jun | 24.61 | 23.91 | 26.78 | 25.11 | 23.86 |
| Jul | 26.37 | 23.00 | 26.89 | 20.28 | 17.73 |
| Aug | 27.58 | 25.65 | 30.41 | 26.58 | 27.83 |
| Sep | 31.59 | 28.35 | 31.38 | 25.54 | 26.16 |
| Oct | 28.66 | 30.10 | 28.50 | 27.90 | 31.25 |
| Nov | 32.27 | 29.80 | 31.76 | 31.26 | 31.46 |
| Dec | 30.92 | 32.05 | 25.81 | 29.21 | 27.55 |

## A5 Packages in R

Table A5.1 shows the R packages used in this thesis. A full referance of the packages is given below.

**Table A5.1:** R-Packages

| Package | Reference |
|---|---|
| *boot* | Canty and Ripley, 2019<br>Davidson and Hinkley, 1997 |
| *car* | Fox and Weisberg, 2019 |
| *dplyr* | Wickham et al., 2019 |
| *e1071* | Meyer et al., 2019 |
| *forecast* | Hyndman and Khandakar, 2008 |
| *fpp2* | Hyndman, 2018 |
| *gbm* | Greenwell et al., 2019 |
| ggplot2 | Wickham, 2016 |
| *glmnet* | Friedman et al., 2010 |
| *jsonlite* | Ooms, 2014 |
| *leaps* | Lumley, 2017 |
| *lmtest* | Zeileis and Hothorn, 2002 |
| *lubridate* | Grolemund and Wickham, 2011 |
| *pls* | Mevik et al., 2019 |
| *plyr* | Wickham, 2011 |
| *randomForest* | Liaw and Wiener, 2002 |
| *readxl* | Wickham and Bryan, 2019 |
| *tidyr* | Wickham and Henry, 2019 |
| *tree* | Ripley, 2019 |
| *urca* | Pfaff, 2008 |
| *xtable* | Dahl et al., 2019 |
| *zoo* | Zeileis and Grothendieck, 2005 |

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