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The future importance of short term markets: An analyse of intraday prices in the Nordic intraday market; Elbas

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Renewable Energy

Preface

This thesis marks the end of my master's degree in Renewable Energy at the Norwegian University of Life Science (NMBU). My five years at NMBU have been an incredible experience, and I have truly appreciated every step on the way.

The analysis in this thesis was made possible by Nord Pool. I would like to thank Jan Fredrik Foyn for granting me the access to the FTP servers, and Nord Pool´s helping desk for always answering questions along the way. I also want to thank Gaute Bremnes the section head for demand response/flexibility trading in Enfo AS for contributing with valuable knowledge along the way.

A special thanks to my supervisor Aleksandra Roos for excellent feedback and advice during this process. I also want to thank my co-supervisor, Professor Torjus Folsland Bolkesjø for contributing with great and helpful advice close to the finish line.

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Abstract

The intraday market allows market participants to trade energy nearer to the period of delivery, and will play an essential role in enabling the expected increase of renewable energy in the European energy mix. This thesis analyses the trading behaviour and the price determinants in the Nordic intraday market. Trading behaviour was analysed by examining the trading pattern, the number of trades and volume. The results concluded that the high trading activity was connected with a high level of intermittent energy. Additionally, the tests showed that the imbalance costs and the amount of generated power were other significant factors in trading behaviour (see figure 9). Furthermore, most of the trades were settled nearer the gate closure. In the regression analysis, the spot price and the regulating power price were used as price determinants, and an intraday price model was developed. Both price determinants could be used to explain the intraday price, and the impact they had on the intraday price varied between seasons, time periods within a market session, and the Norwegian price areas. Furthermore, the intraday price model had an overall good prediction ability, but struggled when extreme low or high prices occurred (see figure 13).

Samandrag

Intradagmarknaden tilet marknadsaktørar å handle nærare leveringsperioden, og vil derfor spele ei viktig rolle for å mogleggjere den forventa aukinga av fornybar energi i det europeiske energisystemet. Denne studien analyserte handelsåtferd og prisdeterminantar i den nordiske intradagmarknaden. Handelsåtferda vart analysert ved å undersøkje handelsmønster, tal på transaksjonar og volum. Resultatet viste ein samanheng mellom høg mengde ny fornybar energi og høg aktivitet på intradagmarknaden, men også høge ubalanse kostander og stor mengde generert kraft spelte ei rolle (sjå figur 9). De fleste handlane vart utført nært marknad slutt. I regresjonanalysen vart prisane i spot- og regulerkraftmarkanden brukt som prisdeterminantar, og ein prismodell for intradagmaknaden vart utvikla. Begge prisdeterminantane var signifikante og kunne nyttas til å forklare intradagprisen. Korleis spot og regulerkraftprisen påverka intradagprisen varierte mellom sesongar, tidsrammer innan ein handelsperiode og dei norske prisområda. Intradagmodellen viste seg å ha gode prognoseeigenskapar, men var svak når det gjaldt å forutsjå dei ekstreme prisverdiane (sjå figur 13).

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1 Introduction

The European Union's long-term climate target is to reduce the greenhouse gasses from the 1990 levels with 80 to 95% by 2050 (European Commission 2017). In 2009, the European Parliament and Council made the EU Renewable Energy Directive 2009/28/EC. This directive requires that 20% of the share in the European energy consumption should come from renewable energy and compels each of the members of the EU to set a plan to reach their individual goals. Norway formed a National Renewable Energy Action Plan (NREAP) in 2012 to meet the terms set in the EU Renewable Energy Directive 2009/28/EC. Norway's aim was to increase the renewable share in energy consumption from 60.1% to 67.5% (Ministry of Petroleum and Energy 2013). This has resulted in an increasing penetration of renewable energy sources for electricity (RES-E) in Europe (figure 1).

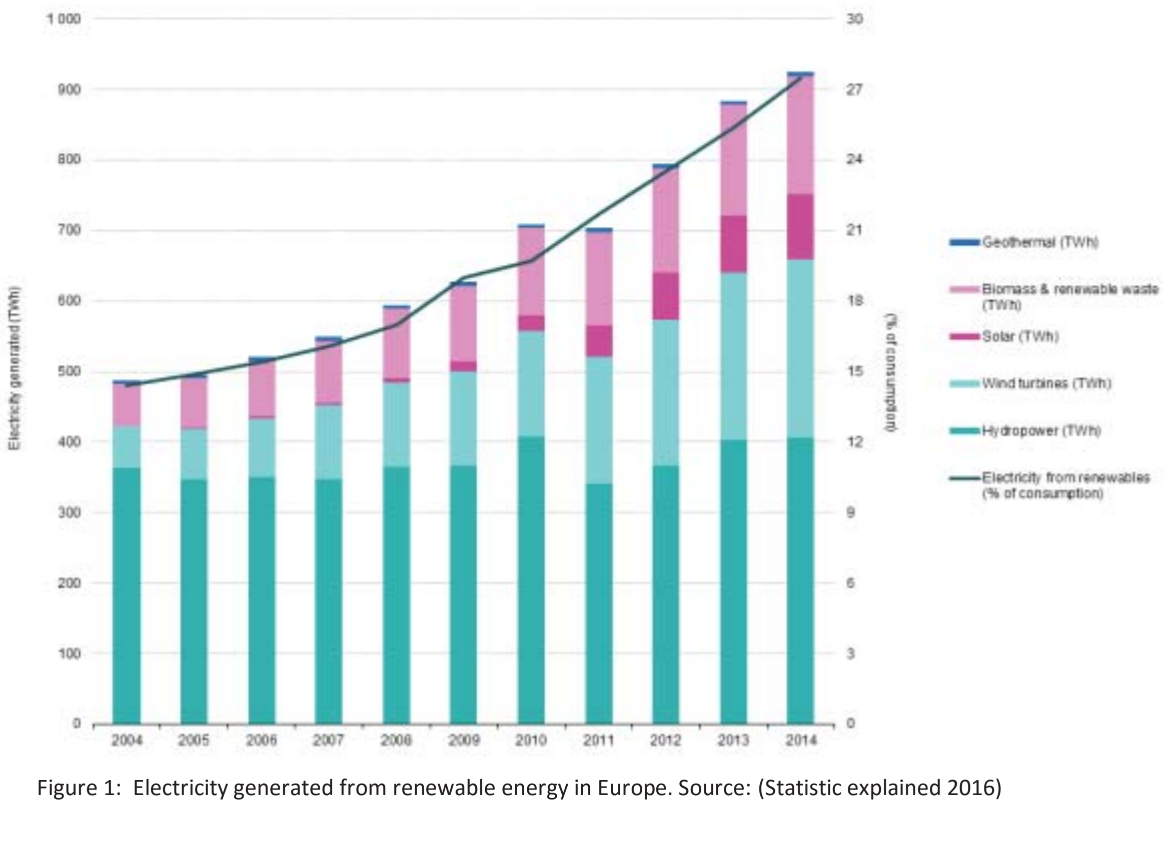

Figure 1: Electricity generated from renewable energy in Europe. Source: (Statistic explained 2016)

As shown in figure 1, the share of renewable energy has increased from 19% in 2009 to around 28 % in 2014. The highest increase has been in wind turbines, followed by solar and biomass and renewable waste. Although hydropower is the main renewable source in generating electricity, there has not been a significant change in the last 10 years. Both wind and solar power is characterized by their unpredictability, as they produce power when the resource is available. Therefore, they are hard to manage within the power market due to large, short-term variations in their generation profile. The Nordic Energy Technology Perspectives 2016 (NETP) suggests that 31 % of the total energy consumption for the Nordic countries will be covered by wind power (2016). This may lead to a more challenging task in keeping the system in balance. Today physical markets and reserve capacities together carry out the work of balancing the energy system. Thus, understanding the mechanisms that regulate this system is key in order to meet these challenges and is consequently one of the main motivations of this thesis.

In the Nordic countries and in other nations in Europe the main power trading market is the physical day-ahead market. In this market, the demand and supply of power is settled a day in advance. The buyer provides information on the volume they need and their willingness to pay for the power and the seller gives information about the amount they can produce and to which costs. Consequently, the amount of production and consumption is balanced between seller and buyer (Nord Pool). Within this market, the system will be fragile when there is an unexpected surplus in production or a halt in production of unregulated renewable power such as wind power or an unexpected issue with a generator.

A way to secure the balance in the system is to introduce a capacity reserve to deal with unexpected changes in the system frequency. The transmission operator (TSO) has the responsibility to keep the system in balance and this is solved with capacity reserves. The different services are designed to activate at different stages of imbalance. In Norway, the TSO Statnett have three services to handle frequency deviation: Frequency Containment Load, Load Frequency Control, and regulating power.

Frequency Containment Reserve (FCR) is designed to handle imbalance that occurs instantly and is activated automatically (SF Statnett 2013a). If FCR can´t handle the deviation, the Frequency Containment Load is activated to take over and manage the disturbance. The third service is the regulating power and is activated after 15 minutes (SF Statnett 2013b). To regulate the bottlenecks in the grid a common Nordic balancing market is needed.

A balancing market is used to produce balancing services and it is an established market to manage the function of system balancing within the framework of a liberalised electricity market (MacDonald 2013). The participants of this market announce how much it will cost them to change the production or the consumption and the different orders are added to a merit order list. The merit order list registers the cheapest order first, followed by the next cheapest and so on (SF Statnett 2014).

Many European countries such as Spain, Germany, France, the Nordic countries and several others, have introduced an intraday market to deal with spontaneous changes after the day-ahead market is closed. Intraday markets have a power trading advantage by adjusting accordingly to the market status.

The intraday market and the regulating power market are good options to handle any kind of disturbances in the system. These two market options can become a solution to the increasing levels of RES-E penetration in the power market and the volatile energy production. Thus, both intraday markets and the regulating markets will play a more important role when the share of variable renewable energy increases.

Elbas is the Nordic intraday market, and Norway entered the market as late as 2009. Scharff and Amelin (2016) stated that Norway only traded 350 GWh from the 2^{nd} of March 2012 to the 28^{th} of February 2013, and 2 % were within the country. Norway has a high share of flexible hydropower which is fit to handle imbalance as it occurs (Statistic Norway 2016), and a low share of intermittent renewable energy (Nordic Energy Research and IEA 2016). In addition, Norway has a well-integrated regulating power market to balance the system after delivery. The incentives for intraday trading is not strong enough, and the market liquidity is low. Chapter 2 will further deliberate the liquidity in the whole market.

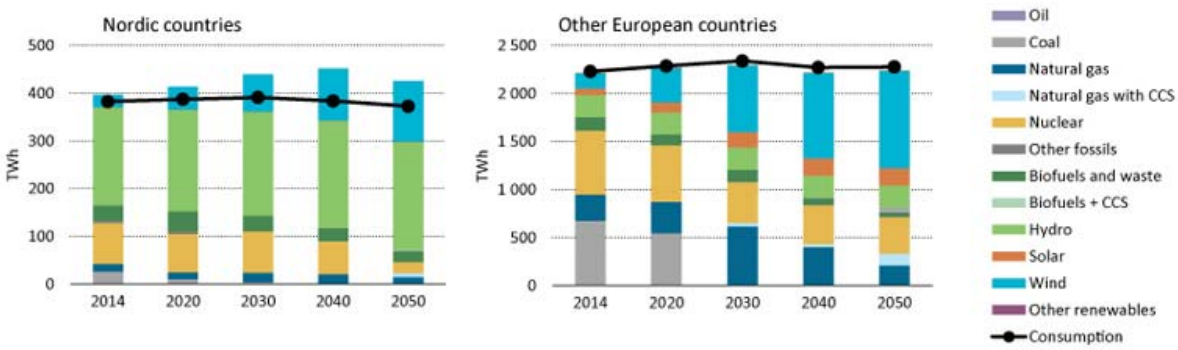

Figure 2: The generation of electricity in the overall power system in the Nordic countries and other European countries. Source: Nordic Energy Research and IEA (2016)

Norway is committed through international agreements, such as the EU renewable directive and the common electricity certificate market with Sweden. The power market will become more integrated in Europe with the expansion of interconnectors and trading between the Nordic region and the continental Europe will increase (Haaland 2015). Figure 2 depicts a scenario from the NETP report; a potential mix of electricity generation in Europe. In the Nordic countries, the mix will consist largely of hydro and wind power, while in the other European countries[1] the mix consists mostly of wind power, solar power, natural gas and hydro power. The Nordic countries, particularly Norway, will contribute with their flexible hydro power as a base load in position to the variable renewable powers that will have a fluctuated production in an integrated European market. Together, these points suggest that trading on the intraday market will increase. With the EU directive's long-term goal of creating a sustainable Europe with a high share of intermittent energy, a better understanding of the mechanisms of the intraday market is important. With a focus on Nord Pool's intraday market, this thesis purports to participate in the work of gaining more insight into the system of the intraday market.

[1] Includes all the European countries except Russia and Ireland

1.1 Scope and structure

Accordingly, this thesis will examine Nord Pool's intraday market, a market which has not yet been thoroughly researched. Nevertheless, a few studies have been conducted the last years: Scharff and Amelin (2016) and Mauritzen (2013) have analysed the trading behaviour on the Elbas market. Weber (2010) has analysed the liquidity in several intraday markets in Europe. Hageman (2013) and Pape et al. (2016) have studied prices and price determinants in the German intraday market. These studies have been helpful in my own research and will be described in more detail in the literature review section. Still, when it comes to the Nordic intraday market the research is scarce. Thus, the objective of this study is twofold:

The first objective is to analyse the trading behaviour in the intraday market by examining the trading pattern, volume and number of trades between the price areas in the market using operational data. I will deploy a larger data set containing all the price areas to conduct this research.

The second objective is to develop an intraday price model to examining how the prices in the spot and regulating power market impact the intraday prices. The aim is to make a model that can explain a large share of the price development in the intraday market, by using the prices in the spot and regulating power market. The data will be limited to the Norwegian price areas and the Nordic areas in trade with the Norwegian ones. The analysis will be conducted by making a multiple linear regression model using RStudio to conduct the statistical analyses.

The structure for the thesis will be as follows: The first chapter will be a general presentation of the topic and the objective of the thesis. Additionally, a section with relevant literature will be presented to provide context for the analysis. Chapter two will focus on theory, and will go further in detail regarding the Elbas design and market system including its development from start up to recent years. Chapter three will describe the methods that have been employed throughout the project starting with a description of data collection and followed by an overview of the statistical methods used in the analysis and their function. Chapter four will present the results from the descriptive analysis and the model analyses. The outcome will be discussed in this chapter. Chapter five will present the overall conclusion.

1.2 Literature review

In this section, relevant literature will be described and discussed. This will give a context to the analysis conducted for this thesis. Firstly, two papers that focus on the regulating power market will be presented. These papers develop an econometric model, or in other words, a linear model similar to the linear model of this thesis. Next, papers that have focused on trading behaviour will also be viewed. Finally, papers that have carried out price analyses on the day-ahead and intraday market in Germany will be presented.

1.3.1 Econometric analyses

Skytte (1999) did an econometric analysis of the regulation power market operating in Nord Pool. In this paper, Skytte wanted to examine the patterns between spot prices and the regulating power market prices, since this would be useful for those with a volatile production. He established a hypothetical model;

$$\begin{aligned} PR\,(P_t, S_t, D_t) = {} & \varphi \bullet P_t \\ & + 1_{St<Dt} \bullet [\,\lambda * P_t + \mu \bullet (S_t - D_t) + \eta]. \\ & + 1_{St>Dt} \bullet [\,\alpha * P_t + \gamma \bullet (S_t - D_t) + \beta]. \end{aligned}$$

where PR is the price of regulating power, P_t is the spot price, S_t is the amount announced at the spot market and D_t is the actual delivery. $S_t > D_t$ is excessive demand and $S_t < D_t$ is excessive supply. The result of the analysis revealed a substantial correlation between the spot price and regulating price. Further, Skytte identified that down regulating[2] is more sensitive then up regulating[3]. The premium of readiness[4] on down regulating is strongly influenced by the

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[2] Skytte (1999) explains how "If an amount is supplied more or used less than that agreed upon on the spot market (excess supply), then down-regulating power is implemented to keep the balance in the market" (Skytte 1999).

[3] Skytte (1999) explain how "If a power supplier delivers less or a buyer uses more than the amount agreed upon on the spot market (excess demand), then the supplier has to pay for up-regulating power in order to be able to fulfil his agreement on the spot market"

[4] Skytte (1999) explain that premium of readiness can be defined as the price given to the suppliers of regulating service.

spot price, while the premium on up regulating is less correlated with the spot price. Thus, the cost of using the regulating power market is a quadratic function of the amount of regulation. Skytte concluded that the bidder should be more aggressive on the spot market, since the extra cost of regulating volatile production would be limited.

Ilieva and Bolkesjø (2014), also conducted an econometric analysis of the regulating power market. Their objective was to analyse how the spot price and the volume of the bid influenced the regulating power price. The paper also discussed how the seasonal variations and generation mix in separate countries would affect the result. Their research was influenced by Skyttes research and the authors developed this equation:

$$P_r = \sigma_0 + 1_{v>0}(\alpha P_s + \beta V + \eta) + 1_{v<0}(\gamma P_s + \delta V + \mu)$$

where P_r is the regulating price, P_s is the spot price and V is the volume of the regulating bids. The observed trend was divergent to the one Skytte found; here the amount of regulation affected the down regulating more than the up regulating. In addition to this, the analysis showed that the spot price differs between season and price areas.

In both studies, the authors concluded that the regulating prices will be influenced by the amount of variable renewable energy that comes in to the system and also by how much flexibility the system will have in the future. In context to this paper these studies are a good starting point for the planned model which will be made for the intraday market. The model is a linear model and the model includes variables such as the Elspot prices which will be included in the price model for the intraday market.

1.3.2 Trading behaviour

Mauritzen (2013) examines if error forecasts in wind power relates positively to the volume trading in Elbas. An econometric analysis was carried out with data from the Danish price areas. Their results showed that when the wind generation is overestimated, the volume traded is increased, and the opposite effect occurs when the wind generation is underestimated.

Scharff and Amelin (2016) conducted the first analysis of trading behaviour on the intraday market Elbas. The objective of this paper was to give a detailed presentation of the trading activity on the market and price development, and in this way, give a better understanding of Elbas. Their results showed a substantial difference between the volume of trading between the price areas. An explanation is that trading on Elbas is affected by a country's share of RES-E; a higher share of RES-E equals more volume traded on Elbas. Furthermore, trading might be influenced by how much is traded on the regulating power market. The price development could vary significantly irrespective of the system's need for up or down regulation.

Mauritzen and Scharff and Amelin (2013, 2016) are two papers that complement each other. Mauritzen started with conducting a simple analysis of Elbas in the Danish Eastern price area, and Scharff and Amelin conducted a larger analyse of the entire market. Even though they have different objectives, they are both looking at trading behaviour, and are some of the first to study Elbas. The Scharff et al. study is able to give a good overall analysis on the trading behaviour for different price areas and the reason for this outcome. The research conducted in their papers will be of great value in my own research, and similar methods will be used as descriptive analyses as well.

1.3.3 Price analyses on other intraday markets

Hagemann (2013) carried out an empirical analysis to explain the price determinants in the German Intraday Market for Electricity (GIME). In this analysis, the errors in wind forecast and solar forecast were tested to see if they affect the price, as well as plant outages and foreign trading. The result showed that the price was significantly influenced by errors in solar and wind forecasts. When there was a shortage of wind power production or unexpected plant outages, the price increased, and if there was an overload of wind and solar power production, the price decreased. Foreign trading did not have any substantial influence on the price. The analysis also concluded that the level of influence the determinants had also varied during a whole day.

In Pape et al. (2016), a fundamental supply-stack model was developed to explain the price variation in the German day-ahead and intraday market. With the results from the model, they used a linear regression model to examine if there are any difference between the modelled prices and the prices observed in the market. The regression analysis tested if the prices were influenced by start-up costs, different markets states and trading behaviour. The fundamental model could explain a large share of the price variance in both markets, and the intraday market prices could be explained by the prices on the day-ahead market. The linear regression model showed a significant impact on the prices from start-up costs, market states and trading behaviour. This indicates that the fundamental model, despite the fact that it could explain much of the variance, is a simplification of the reality.

In Hagemann (2013) the method used is a simple regression model, while Pape et al. (2016) employs a more intricate model. Hagemann (2013) examines which parameters determines the price, with the conclusion that a regression model is adequate, and a more complex model would be unnecessary. Pape et al. (2016) requires a more complex model to examine why there are price variations in two markets, thus, they have more complex interactions in their model. In relation with this research, Hagemann's method will be more similar to my own, consequently, the parameters he has employed in his model are of great interest. Both papers give a good insight into which parameters to use and provide a better understanding in an intraday market that has similarities to Elbas.

2 Theory - The Nordic intraday market

This chapter will present the Electricity Balance Adjustment Service (Elbas) in more detail: its design, its purpose and the current status of trading in the Nordic intraday market will be displayed. The first section will introduce Nord Pool and its markets, while the second will discuss the future development of Elbas.

2.1 Motivation: Elbas – status quo

2.1.1 Nord Pool – three markets

Nord Pool is the physical wholesale marketplace for the Nordic countries and the Baltic states. It is the largest power market in Europe, and 84 % of the consumption for the region were traded in the electricity market in 2013. Within the Nord Pool region, there are no individual national electricity markets. However, since the region has grid bottlenecks, the region is divided up in several price areas with individual pricing. Nord Pool consist of three markets: Elspot, Elbas and N2EX (Mäntysaari 2015).

N2EX is the physical market for the United Kingdom. Elspot is the day-ahead market, where physical electricity contracts are settled hourly for the next day. The market region includes Norway, Sweden, Finland, Denmark, Latvia, Lithuania and Estonia. Elbas is the intraday market, which is a physical balance adjustment service. The intraday market also includes Germany, the Netherlands and Belgium (Mäntysaari 2015). Elbas is a complement of the Elspot market, and is a service to manage imbalance after the Elspot market is closed.

Another option to manage imbalance is through the regulating power market. Even though the trading is exchanged in the common Nordic market, the settlement in the regulating power market is being carried out by the TSO within each country. Figure 3 depicts the operation procedure for the markets.

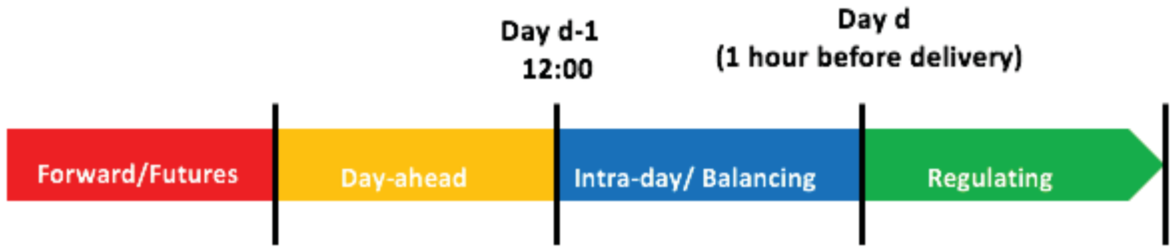


Figure 3: The operational procedures for Nord Pool markets. The figure is inspired by the work done in the NETP report (2016).

2.1.2 Design and procedure

The design of the intraday markets varies throughout Europe, as shown in table 1; some markets are continuous, some have discrete auctions, and some have a combination of the two. (Furió 2011; Scharff & Amelin 2016). Raviv et al. (2015) define a discrete auctions market by restricting trading to pre-established times. In the Spanish intra-day market the trading is restricted to six auctions sessions. Whereas, in the continuous market "bids are matched one by one as soon as they match" (Raviv et al. 2015).

Table 1: List over different intraday markets and their design in European countries. Source: (Scharff & Amelin 2016)

European Countries	Intra-day market	Design
Nordic, Baltic, UK and Germany	Elbas	Continuous trading
Poland	TGE	A mix*
Czech Republic	OTE	Continuous trading
France, Germany/Austria and Switzerland	EPEX SPOT	Continuous trading
Spain and Portugal	OMIE	Discrete auctions
UK	APX	A mix*
Italy	GME	Discrete auctions

*Mix = a combination between continuous and discrete auctions.

Elbas is a continuous market and was first launched in 1999 for Sweden and Finland as separate market for balance adjustments. Throughout the years, the market has been launched in several countries, and market significance has increased with higher share of renewable energy and the downscaling of thermal energy (Nord Pool).

Elbas opens at 14:00 CET (figure 4), on the same day as the Elspot prices are set for the Nordic and the Baltic countries, the Netherlands, and Belgium. Germany can start trading as early as 08:00 within the German price zones the same day. In the Belgian and the Dutch price areas, domestic trades can be settled as late as 5 min before delivery, and for Germany it is 30 min earlier (Mäntysaari 2015; Scharff & Amelin 2016). Scharff & Amelin explain that the hourly period of delivery of Elbas is called *powerhours* (2016). The first power hour is 0:00 to 00:59, and the last one is 23:00 to 23:59. The longest lead time is 33 hours when the trading takes place at 14:00 for hour 23:00-23:59 the following day. The lead time for the first powerhour is 10 hours. In Germany, the longest lead time is respectively 39 hours and 16 hours.

The prices in Elbas are settled by matching the lowest seller price with the highest bid price. Elbas offers several order types; hourly and block contracts, 'Immediate or Cancel'[5], 'Fill or Kill'[6] and 'Iceberg'[7]. The currency is Euro and the minimum amount is 0,1 Euro and the lowest volume allowed is 0,1MWh (Nord Pool 2015).

Figure 4: Operation time on the Elbas market.

The original Elbas system was replaced in 2014. The new and upgraded system made trading across different markets possible. This enhanced the trading opportunity for all ten countries, especially for Germany. The market is separated into several price areas to deal with the

[5] "Immediate-or-Cancel means an Order that shall be immediately matched for as much of the order volume as possible and then cancelled" (Nord Pool 2014).

[6] "Fill-or-Kill Order means an Order that shall be immediately matched for the whole order volume or cancelled" (Nord Pool 2014).

[7] "Iceberg Order means an Order in the Elbas Market that has a partly hidden overall volume. Each part of the Iceberg Order is called a Clip. When the Order has been submitted, other Participants will only see the first Clip as a part of the total volume when the Order is submitted. When the first Clip is matched, the next Clip receives a new order number and time stamp". (Nord Pool 2014).

bottlenecks: Norway is divided into five areas; Sweden and Germany into four; Denmark into two; while Finland, Belgium, Netherlands, Latvia, Lithuanian and Estonia have one price area each (see figure 5).

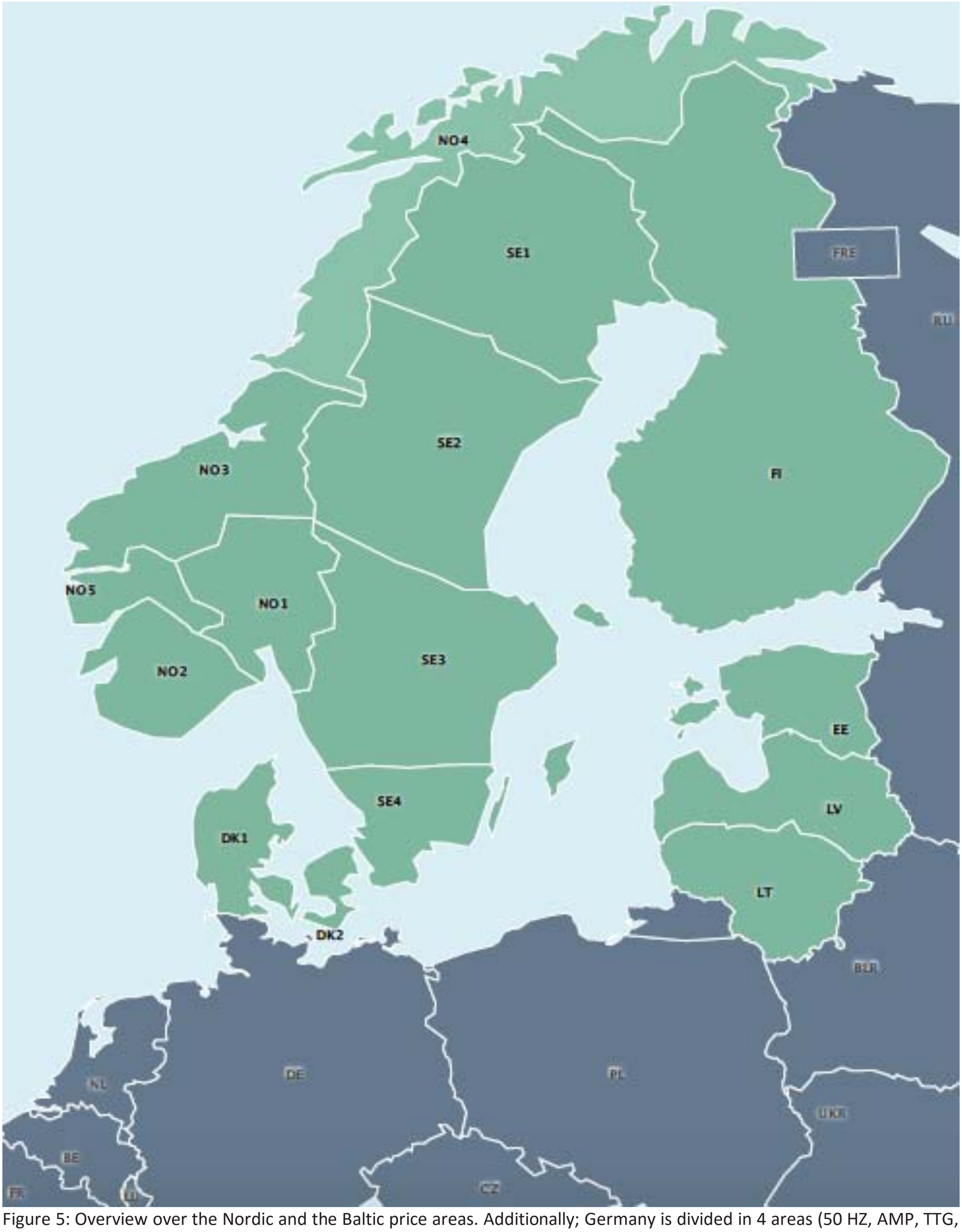


Figure 5: Overview over the Nordic and the Baltic price areas. Additionally; Germany is divided in 4 areas (50 HZ, AMP, TTG, TBW), and Netherlands and Belgium have on area each.

2.1.3 Trading activity

The amount of power traded in Elbas has increased since it first launched in 1999, as depicted in figure 6. This is a natural development, since more countries have implemented the market and the demand for a balancing service increased with the higher share of RES-E. The liquidity of the new intraday markets has been discussed in several papers; Scharff and Amelin (2016) Weber (2010) and Borggrefe and Neuhoff (2011) to mention a few.

Borggrefe and Neuhoff (2011) define a market as liquid "...if the number of bids and the amount of trading activity is high enough to create transparent prices and ensure that individual actors only have small impacts on the price formation ". Weber (2010) analysed the liquidity for the intraday markets in Germany, Scandinavia, France, Spain and the UK, and used traded volume as an indicator of liquidity. His research concluded that the liquidity was low in most of the markets. For example, Germany traded 1,7 TWh in 2007 on EEX´s intraday market[8] and this indicates that the market was not sufficiently liquid. Sweden, Finland and Denmark East had the same outcome with a low amount of traded volume in Elbas.

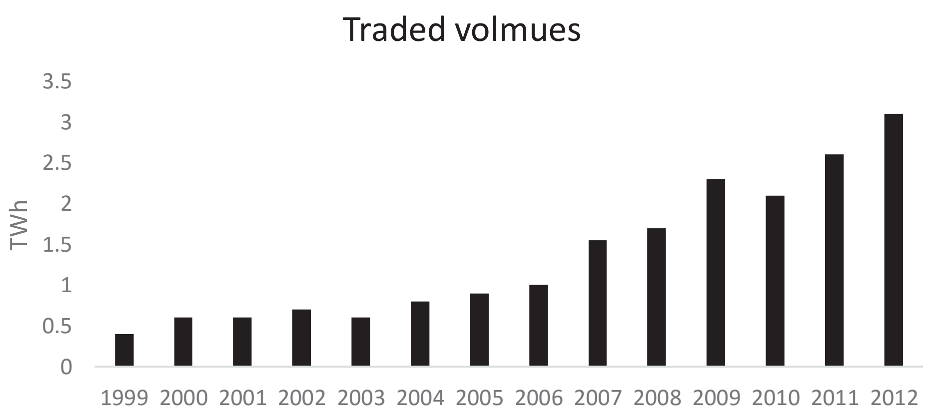


Figure 6: Historical traded volumes in Elbas. Source: Nord Pool

[8] Germany implemented Elbas in 2006

However, in the report from Pöyry Management Consulting (Norway) AS (2011) the Elbas market liquidity was evaluated to be quite high in comparison to the APX[9] intraday market in the Netherlands. From 2007 to 2012 the intraday volume has more than doubled in Elbas, and this indicates an increase in market liquidity. According to the paper from Scharff et al., the volume traded on the Elbas market from 2nd of March 2012 to the 28th of February in 2013 was 3624 GWh. However, there is a large difference in the amount of traded volume between areas and countries. Norway traded around 350 GWh of power in this period. Since the total generated power in Norway was 145 018 GWh, the trading on Elbas accounts for only 0.24 %. Referring to Weber (2010), this would strongly indicate a low market liquidity.

From the period Scharff and Amelin conducted the study, only 37% of the volume was traded within the same country. This implies that Elbas is to a large extent used for cross-boarding trading. Another important observation is that the price areas with a high share of traded volumes, often had a high share of intermittent energy. An example of this is Denmark, which has a high share of variable renewable energy, and also has a high share of traded volume in Elbas in relation to its generated energy (Scharff & Amelin 2016). A likely reason for this is Denmark's high share of wind power which increases the need to regain balance after Elspot closes (Mauritzen 2013). In total, there were 190 533 transactions from March 2012 to February 2013. The Finnish price area (FI) had the most transactions, both as an importer and an exporter. SE3, Swedish price area, follows up with the second highest number of transactions as a seller and buyer.

In the first quarter in 2018 the Cross-Border Intraday Initiative (XBID) is scheduled to be activated. This is a joint project between EPEX spot, GME, Nord Pool and OMIE and TSO´s from 11 European countries. The plan is to make intraday cross-border trading more efficient throughout Europe, and improve the market liquidity (Nord Pool 2017a). Norway is planning to construct two new interconnectors to Germany and the United Kingdom (NVE 2016), which will enhance trading across Europe. The intraday market has received more attention the last years, and improvements like creating better systems and enhancing the trading opportunities overseas is an indication of this. The intraday market will play an essential role in enabling the expected increase of renewable energy in the European energy mix.

[9] In 2015, APX intraday market were integrated in EPEX Spot (EPEX Spot 2015)

3 Materials and methods

The chapter will begin with a description of the data used in the analysis, and end with an overview of the statistical methods used in the model building process and in the analysis.

3.1 Data collection

The data material used in the analysis was gathered from Nord Pool´s FTP server through a special authorisation from Nord Pool.

3.1.1 Elbas ticker data

The Elbas ticker data is the core of the data set in the analysis. The most important information collected from this data was trade time, product code, price, and quantity, buyer area (BArea) and seller area (SArea). The file format was CVS, and each ticker data file included information for one day (24 hours), and the total amount of 365 files were used from 01.01.2015 to 31.12.2015. Table 2, depicts the layout of the ticker data after being transformed from text format to table format in excel. The trade time is the date and the time of the trade. Product code is the date and time for when the product is used. Price is in Euro/MWh and the quantity is MWh/h. BArea = buyer area and SArea = seller area. There were no cancellations in the ticker data used in this thesis.

Table 2: An example of the layout for the Elbas ticker data after being handled in excel. (Source: Nord Pool)

Trade Time	Product Code	Currency	Price	QTY	BArea	SArea	Cancelled
2015/05/19:09:30:43	PH-20150519-19	EUR	21,6	1	NO4	SE3	0
2015/05/19:12:58:27	PH-20150519-17	EUR	27	13,5	EE	NO3	0

3.1.2 Elspot and the Regulating power market data

The data used from the Elspot market was hourly price data from 01.01.2015 to 31.12.2015. It contained 8760 entries divided for different price areas. Similarly, the regulating power market data contained individual prices for the different price areas, however in this case the prices were separated in up and down regulating prices. They were both downloaded from the Nord Pool´s web page (Nord Pool 2017b).

3.2 Data processing

All the data from Nord Pool was downloaded into an Excel document where it was transformed from text format to a table format. The 365 data ticker files were merged into one file and contained 285349 trades for the year 2015. Accordingly, two main data sets were created; the intraday market data set and the Norwegian intraday data set. The intraday market data set contained all the price areas that were employed in order to do a simplified analysis on the general position of the market. The Norwegian data set was limited to the Norwegian areas (NO1, NO2, NO3, NO4 and NO5) and the other Nordic areas. The other Nordic areas were then in trade with a Norwegian price area. The data set ended up containing 21780 trades.

Since the intraday market consists of different prices for each trade there are many transactions with their respectively individual prices within an hour. The hourly price data from Elspot and the regulating power market needed to be manually added to the corresponding hour in the Elbas data. Since the Elbas data consists of a buyer area and a seller area, the Elspot and regulating prices were added for each of these. As a result, the data set contained two columns with Elspot prices, one for the prices in the buyer areas and one for the prices in the seller areas. Since the regulating prices are divided in up and down prices, they consisted of 4 columns; up and down prices for the buyer areas, and up and down prices for the seller areas.

Afterwards, the Norwegian data set was loaded into the open source statistics program RStudio (RStudio). The model building, the statistical analysis and the graphical visualization were all done in RStudio. In RStudio, several statistical packages were installed to make the programming and data handling easier. The packages were:

- *tidyverse*. Which is a collection of R packages; ggplot2, tibble, tidyr, readr, purrr, and dplyr. These are helpful in making the data frame easier to handle and in improving the graphic visualizing (Wickha 2017).
- *mixlm*. Mixed Model ANOVA and Statistics for Education (Liland & Sæbø 2016).
- *faraway*. A helpful tool to identify sign of multicollinearity (Faraway 2016).
- *ggfortify*. Data Visualization Tools for Statistical Analysis Results (Horikoshi & Tang 2017).
- *car*. (Fox & Weisberg 2011)

3.3 Statistical methods

3.3.1 Multiple regression model

The analysis was based upon multiple regression statistic. A multiple regression model is the most common form of linear regression. It is used to explain the relationship between a dependent variable and two or more independent variables (Mendenhall & Sincich 2014). In equation 1 a general form of a multiple regression model is depicted. In this study, the response variable (y) will be the intraday price, and the explanatory variables (x_n) will be the Elspot price and the up and down regulating power price. The method to estimates the independent variables is called standard least square.

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n + \varepsilon \quad (1)$$

ε is the random error term, which is unexplained variation. To verify that a model is adequately sufficient to fulfil its purpose, the assumption for the error term should be satisfied. The assumptions are:

- ε has a normal probability distribution with mean equal to zero and the variance equal to σ^2 ($\varepsilon \sim N(0, \sigma^2)$).
- The random errors are independent and identically distributed.

The methods used to determine if the terms are satisfied will be presented in the residual analysis section.

3.3.2 Assessing the variables and the fitted model

Two sampled paired t-test

This test was used to test the mean difference between the response variable (intraday price) and explanatory variables. Since the variables in the model are dependent on each other, a paired t-test is a valid option. A paired t-test can discover if the explanatory variables are insignificant to the response and can therefore be removed. The hypothesis for the test is the following:

$$H_0: \mu_0 = 0 \quad (2)$$
$$H_1: \mu_0 \neq 0$$

Where H_0 is the null-hypothesis and state that the population mean of difference equals zero, and H_1 is where the difference is not equal to zero. H_0 is rejected if the paired t-test statistic is lower than the stated significance value; $|t| > t_{\alpha/2}$ (McDonald 2009; Mendenhall & Sincich 2014). The significance value; $\alpha = 0.05$ was applied throughout the analyse.

Stepwise regression and all-possible-regression selection procedure

To further test if the selected variables were significant for the model two variable screening methods were used; stepwise regression and all-possible regression selection procedure. Stepwise regression is one of the most common selection method, and is divided into forward and backward selection. In the forward selection, the procedure starts with zero variables and then adds one and tests it using t-test to check its significance. Then a new variable is added till the model is no longer significant. Backward selection starts with a full model, and removes one by one till the model is significant (Mendenhall & Sincich 2014). A combination of both procedure was used to test the variables in this study.

The all-possible-regression selection procedure is used to select the best subset of variables. The criterion used for this type of test varies, and several criteria's can be included. For this test, C_p, R^s, and $R^2_{adjusted}$ were set as criteria. They are described and presented in the following sections.

The analysis of variance F-test

To test the overall utility of the model, a Global F-test was performed on the fitted model. In contrast to testing one variable at the time, all the β`s are tested to check if they are suitable for prediction (Mendenhall & Sincich 2014). The hypothesis for this test is:

$$H_0: \beta_1 = \beta_2 = \beta_3 = \cdots = \beta_k = 0 \qquad (3)$$

$$H_1: At\ least\ on\ of\ the\ \beta_k\ is\ not\ equal\ to\ zero$$

If the H_0 hypothesis is not rejected, all the variables are unsuitable for prediction, and if it is rejected at least one of the variables will be useful for prediction. The equation used is depicted below.

$$F = \frac{\frac{SS_{yy} - SSE}{k}}{SSE/[n-(k+19]} = \frac{\frac{R^2}{k}}{\frac{1-R^2}{[n-(k+1)]}} \tag{4}$$

Multiple coefficient of determination – R^2 and R_a^2

To determine the fit of the model, how well the model fit with the data set, the adjusted and the multiple coefficient of determination ($R_a^2\ and\ R^2$) are effective criteria. Their value ranges from 0 to 1 (R_a^2can be negative), and the closer to 1, the better the fit. They are also useful to determine the model's suitability for prediction of the response variable (y). R^2 and R_a^2 gives the same insight. However, the adjusted multiple coefficient of determination is not affected by the number variables added to the model. R^2 could be "forced" to 1 by having a large number of variables in the model. By taking this into account, the R_a^2 will always have a lower value than R^2, but is possibly a better criterion to use when having multiple variables (Mendenhall & Sincich 2014).

$$R^2 = 1 - \frac{SSE}{SS_{yy}} \tag{5.1}$$

$$R_a^2 = 1 - \left[\frac{(n-1)}{n-(k+1)}\right]\left(\frac{SSE}{SS_{yy}}\right) = 1 - \left[\frac{(n-1)}{n-(k+1)}\right](1 - R^2) \tag{5.2}$$

3.3.3 Cross Validation

Mallows´s C_p

This criterion focuses on minimizing total mean square error (MSE_k) and the bias in the regression model. The model with the lowest C_p is the best choice. Firstly, a low C_p means a low MSE_k. Secondly, if the value is close to p+1 (p is the number of independent variables in the model) it indicates hardly or no bias in the model (Mendenhall & Sincich 2014). This was used in combination with all-possible regression and stepwise regression methods.

$$C_p = \frac{SSE_p}{MSE_k} + 2(p+1) - n \qquad (6)$$

Prediction sum of square – PRESS / Root mean squared error of prediction – RMSEP

PRESS calculates the sum of response value (y_i) minus the predicted value of the response ($\hat{y}_{(i)}$). The goal is to have a PRESS value as low as possible, since this implies a small difference in y_i - $\hat{y}_{(i)}$. In other words, this suggests that the prediction conducted by the model has a low error and the model is suitable to predict (Frost 2013).

$$PRESS = \sum_{i=1}^{n} [y_i - \hat{y}_{(i)}]^2 \qquad (7)$$

RMSEP calculates the mean square root of the PRESS value, and here the goal is to find a model with a low value of RMSEP. Similar to the PRESS criterion, a low value indicates a higher prediction ability for the model (Mendenhall & Sincich 2014).

$$RMSEP = \sqrt{\frac{PRESS}{n}} \qquad (8)$$

Jackknife R² - $R^2_{prediction}$

This method expresses how well the fitted model can predict the response variable for new observations, together with PRESS and RMSEP it is an important criterion in order to evaluate the prediction ability. The criterion is calculated by taking out a sample from the data each time, and then estimate the model, and see how well the model can predict the removed sample. It is favourable that the $R^2_{prediction}$ is close to the R^2 (Mendenhall & Sincich 2014). Additionally, if the model is over-fitted (too many variables) and there is noise in the prediction, the $R^2_{prediction}$ will be able to indicate this by having a considerable lower value than R^2 (Frost 2013).

$$R^2_{prediction} = 1 - \frac{PRESS}{SSyy} \quad (9)$$

3.3.4 Residual Analyse

In residual analysis, the assumption for the error term are tested to check if the model has satisfied these expectations. This will give a good indication whether or not the model is suitable for its purpose. These assumptions have been specified in the multiple regression model section, while this section will present the graphical tools and statistic tests that have been employed throughout the project. In this project, six residual plots will be used to evaluate whether or not the assumptions for the error term were fulfilled:

- Residual vs. fitted
- Normal probability plot of the Residual
- Scale – Location
- Cook's distance
- Residual vs. Leverage
- Cook's distance vs Leverage

The plots were created in R by the *ggplot2* and the *ggfority* packages, by using the code "autoplot".

Residual vs fitted

For detecting non-linearity, outliers and, most importantly, deviation from constant variance the Residual vs Fitted plot was used. There should be no sign of a heteroscedastic pattern. In other words, the points should be randomly distributed to show sign of homoscedasticity (Mendenhall & Sincich 2014).

Histogram of Residual / Normal probability plot of the Residual

The goal is to check if the error term is normally distributed with mean equal to zero and the variance equal to σ^2. This can be accomplished by creating a "Normal probability plot of the residual". Any skewness in the plot should be traced and if detected, and the response variable should be transformed in order to remove the skewness (Mendenhall & Sincich 2014).

Scale – Location

To check the assumption of equal variance (homoscedastic) the Scale- Location plot was used. There should not be sign of possible patterns in the plot (Bommae 2015).

Cook's distance

Cook's distance measures the influence an observation has on the estimated β – coefficient, and is used to detect outliers. A thumb of rule is to consider a unit as influential when $D_i > 1$.

$$D_i = \frac{(y_i - \hat{y}_{(i)})^2}{(k+1)MSE}\left[\frac{h_i}{(1 - h_i)^2}\right] \tag{10}$$

Residual vs. Leverage

The plot was used to detect data that has a great influence on the analysis, and can therefore, have a negative impact in the regression analysis.

Cook`s distance vs. Leverage

Identifies any of the numbers in the variables that have a big impact on the regression analysis.

3.3.5 Identify potential underlying problems

Multicollinearity

"Multicollinearity exists when two or more of the independent variables used in regression are moderately or highly correlated" (Mendenhall & Sincich 2014). This can induce the chances of rounding errors in the estimation calculation of the parameters and standard errors, and complicate or mislead the regression result. To summarize, the estimated parameters can be inaccurate and not dependable. According to Mendenhall & Sincich (2014), there are four signs to look for in order to detect multicollinearity:

1. *Moderate or high correlation between two or more variables*
2. *The t-test for each parameter is nonsignificant, but the overall adequacy of the model is significant (F-test)*
3. *The estimated parameters have other signs than its expected*
4. *A variance inflation factor (VIF) for a variable is below 10*

$$(VIF)_i = \frac{1}{1 - R_i^2} > 10 \tag{11}$$

Autocorrelation: Durbin-Watson test and the Autocorrelation function

Mendenhall and Sincich (2014) define autocorrelation as the "…correlation between time series residuals at different points in time". Further they state that a "…special case in which neighbouring residuals one time period apart (at times t and t+1) are correlated is called first-order autocorrelation". Studies that have focused on the hourly prices in the day-ahead market have established that autocorrelation is one if the characteristic for the electricity prices (Huisman et al. 2007; Levin 2011; Raviv et al. 2015). Testing intraday prices for autocorrelation is necessary to a get a better understanding behind the qualities. Two tests were used to detect autocorrelation: Durbin-Watson test and the autocorrelation function (ACF).

The Durbin – Watson test was used to detect residual correlation, and is calculated as follows:

$$d = \frac{\sum_{t=2}^{n} (\hat{\varepsilon}_t - \hat{\varepsilon}_{t-1})^2}{\sum_{t=2}^{n} \hat{\varepsilon}_t^2} \tag{12}$$

The hypothesis which was tested is:

$$\begin{gathered} H_o: No\ residual\ correlation \\ H_1: Positive\ residual\ correlation \end{gathered} \tag{13}$$

If the null-hypothesis is rejected the regression model have residual correlation. The Durbin – Watson test was calculated using the *car* package in RStudio, and the code *durbinWatsonTest*. Furthermore, the model was tested by using an autocorrelation function (ACF) to detect if it was strongly and/or positively correlated, and if there were any visible seasonal pattern.

4 Results and discussion

This chapter will present the results of the analysis and my discussion. Firstly, the results of the descriptive statistics conducted on the entire data set will be explained and discussed. Accordingly, the first section will contain all the price areas in the market, and a more thorough presentation of the Norwegian price areas. The second part of the chapter will address the results of the multiple regression analysis.

4.1 Descriptive market analysis

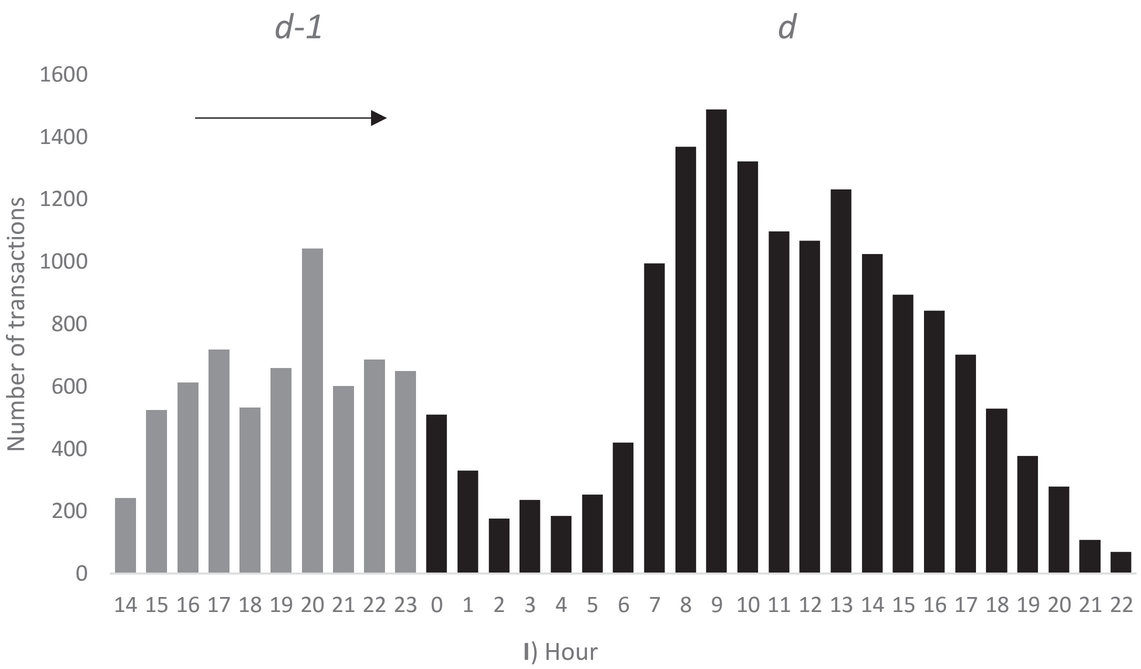
4.1.1 Trading time

Figure 7 consists of two graphs, the first one illustrates how the trades are hourly allocated from the market opens till the last possible trading hour. The main trading time is 20:00 for day *d-1*, and around 08:00 – 09:00 for day *d*. Overall, most of the trades takes place around 08:00 in the intraday period. Larger parts of the trades are settled in day d.

While, in graph II, the trading that occurs in *d-1*, is transferred to *d*, to display in which powerhour the need to restore the balance mainly occurs. The frequency of trading starts to pick up around 07:00 and reaches a peak at 08:00. It is stable during the day before it reaches a new peak in the afternoon. Except from an increase around 20:00, the amount of trades decreases from the afternoon until the next day. The number of trades seems to correspond to typical daily load variations, with two peak loads - in the morning and in the afternoon.

In this study, the trading time was limited to the Norwegian price areas, while in Scharff and Amelin the analysis was conducted for the entire market. Both studies showed the same trend in trading time. Scharff and Amelin suggest that since the trading happens manually in Elbas, the trend follows a work-day pattern. The number of trades picks up when the office hours starts, and even decreases during lunch hour.

Errors in forecasting can explain why the re-established balance increases further into the powerhours. The early powerhours are closer to the updated day-ahead and consumption forecast, while the later powerhours will be further away. This leads to higher probability for forecast errors for the later powerhours (Scharff and Amelin 2016). An additional explanation for the morning peak can be that the latest updated weather prognosis[10] is available at 08:30. The weather forecast updates twice a day, first at 08:30, and then at 20:30. Considering that the market participants get a chance to revise their demand/supply according to the latest forecast, the two updated weather prognoses could explain the peaks in the morning and the evening.



[10] The weather prognosis comes from the European Centre for Medium-Range Weather Forecasts (ECMWF) located in Reading, UK. "ECMWF produce ensemble-based analyses and predictions that describe the range of possible scenarios and their likelihood of occurrence"(ECMWF). The member states have access to these, and all the countries in Elbas is a member or a co-member. The weather prognosis for Europe is ready at 08.30 (07.30 during winter time) and 20:30 (19:30 during winter time) every day (ECMWF).

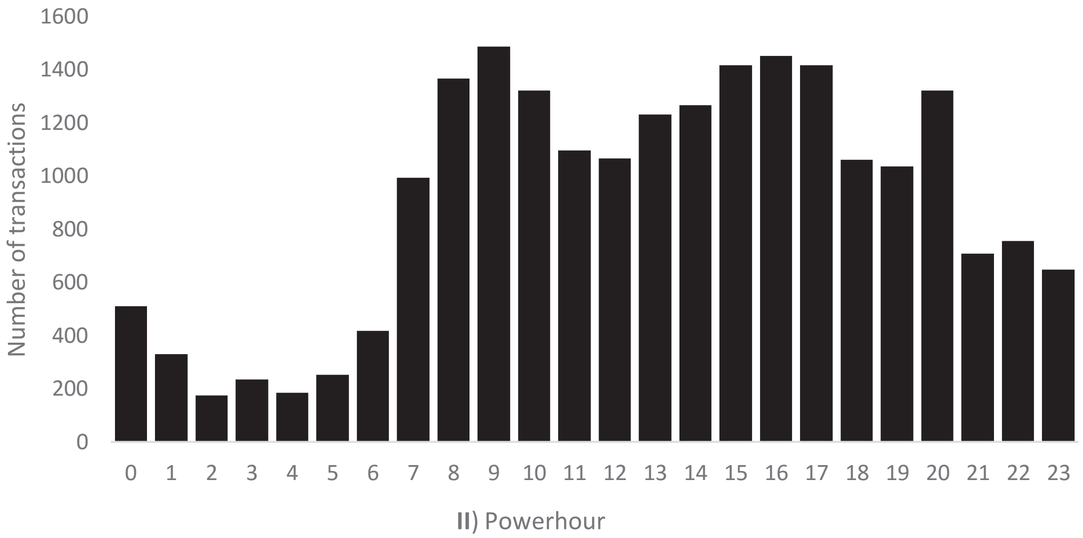


Figure 7: Number of trades per hour for the Norwegian price areas from 01.01.2015 to 31.12.2015. Graph I show how the trades are hourly allocated from the market opens till the last possible trading hour. Graph II describe the number of transactions for each powerhour. The trades that occur in d-1, are transferred to d.

4.1.2 Number of trades and volume on Elbas

The total number of transactions from 01.01.2015 – 31.12.2015 was 285 385. In table I in appendix A, an overview of the number of trades between areas is presented. Finland is the price area with the highest number of trades for both the import and export side with respectively, 67934 and 65249 trades. The second highest is SE3 with 38591 trades as an exporter, and 46105 transactions as an importer. Key results:

- AMP, BE, DK1, DK2, FI, NL, SE2 and SE3 had the largest amount of trades.
- Lowest number of trades; 50HZ, LV, TBW and the Norwegian areas
- Finland had the highest number of domestic trades.
- BE and NL trades primarily between each other.

Figure 8 shows that NO2 and NO5 are the areas that have the highest number of trades. They trade frequently between each other, while NO3 regularly trades with NO4 and SE3. NO4 often trades with NO4, and NO1 regularly trades with NO5. Overall, 63 % of the total 24816 transactions are with areas abroad, and 36 % are within Norway.

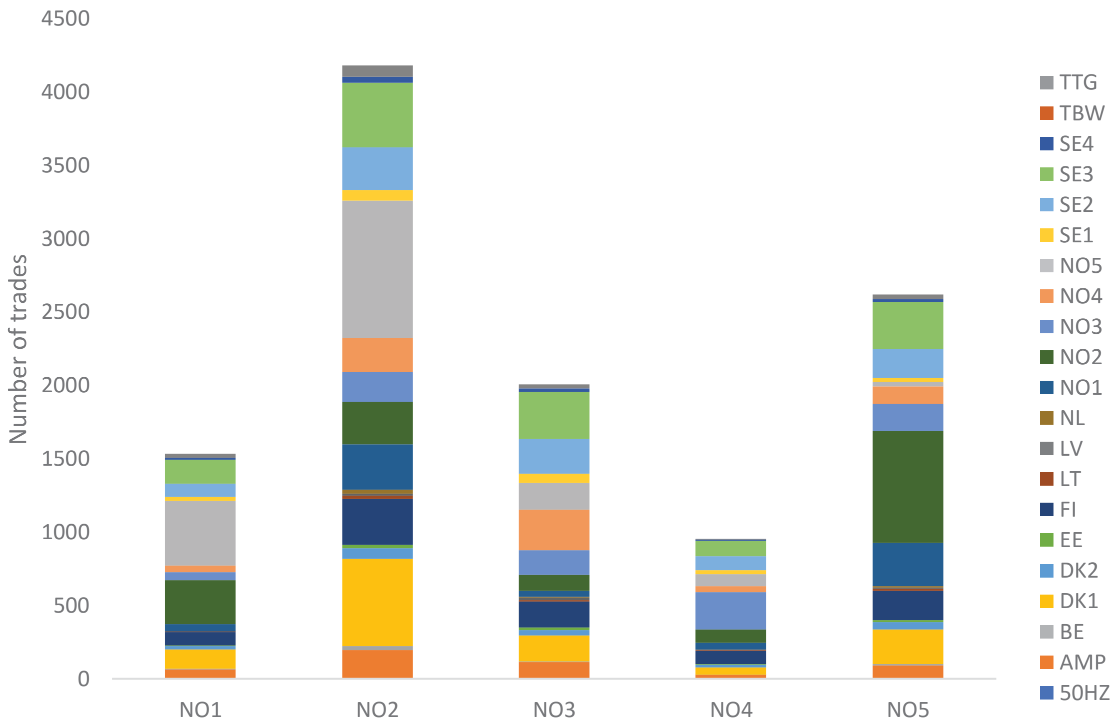


Figure 8: Shows the number of trades the price areas NO1, NO2, NO3, NO4 and NO5 conduct within the area and with others. For example, NO2 have the highest number of trades with NO5 [ ]

The total volume for 2015 was 5759,92 GWh and figure 9 depicts the distribution of power traded in that period. The Swedish price areas have the largest variations among each other, and SE3 is the area with the highest amount of traded volumes in total. SE3 produced 77 397 GWh which makes up for 50 % of the total production among the Swedish areas in 2015 (Friberg 2016; Svenska Kraftnät 2017). In SE3 nuclear power stands for 50 % of the production, while in the other Swedish price areas the main power is hydro power and wind power (Svenska Kraftnät 2017). Table I in appendix A shows that SE3 has a high number of trades with areas that has a large share of intermittent energy (Danish, Swedish and German price areas).

DK1 and DK2 produced a total of 27 704 GWh in 2015, and 34 % of the electricity consumption was traded in the intraday market (Friberg 2016). This is the largest share of volume in Elbas in relation to the generation of power. Scharff and Amelin (2013) indicate that Denmark's high share of wind power is the reason for the large volumes in Elbas. In 2015 wind power covered 42 % of the total electricity consumption (Friberg 2016). The incentives for intraday trading in Denmark is strong, because of the high share of unstable wind production.

Finland has the second largest volumes on the intraday market, but in contrast to Denmark, Finland´s share of intermittent energy is low. Wind and solar power covered only 2388 GWh out of the total electricity production of 66 155 GWh in 2015 (Niininen & Hautakangas 2016). The up and down regulating prices are higher in Finland than for the Norwegian and Swedish price areas and therefore trading in the intraday market may prevent high imbalance costs for the market participants (Scharff and Amelin 2013).

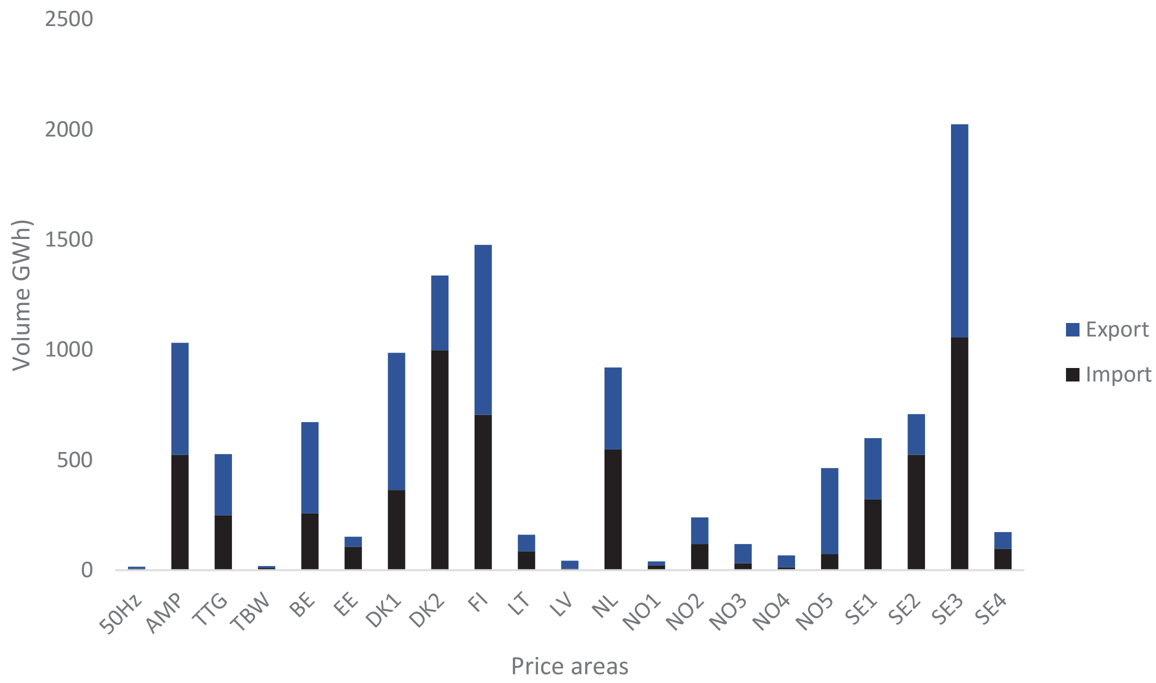


Figure 9: The amount of volumes traded in the intraday market for each price area from 01.01.2015 to 12.31.2015.

Even though NO2 has the highest number of transactions, NO5 trades a considerable larger amount of power than any of the other areas (figure 10) in the intraday marked. NO5 exported 84 % of the traded power. In total NO5 produced 35132 GWh in 2015 and had the second highest production among the Norwegian price areas (Nord Pool 2017b). The overall production for all the Norwegian price areas was historically high in 2015, because of high water inflow. This resulted in a lower spot price for the Norwegian price areas, in comparison to the Nordic price areas and the Netherlands (Statistic Norway 2016). The market participants had free capacity that could be used to cross-border trading to increase the profit, and overall, Norway exported 22000 GWh (Statistic Norway 2016).

In the Norwegian price areas only 25% of the volume is traded within the country. 75% of the trades are cross-border trades. This further implies that Norway has such a flexible energy system and a robust regulating power market, that domestic trading becomes unnecessary.

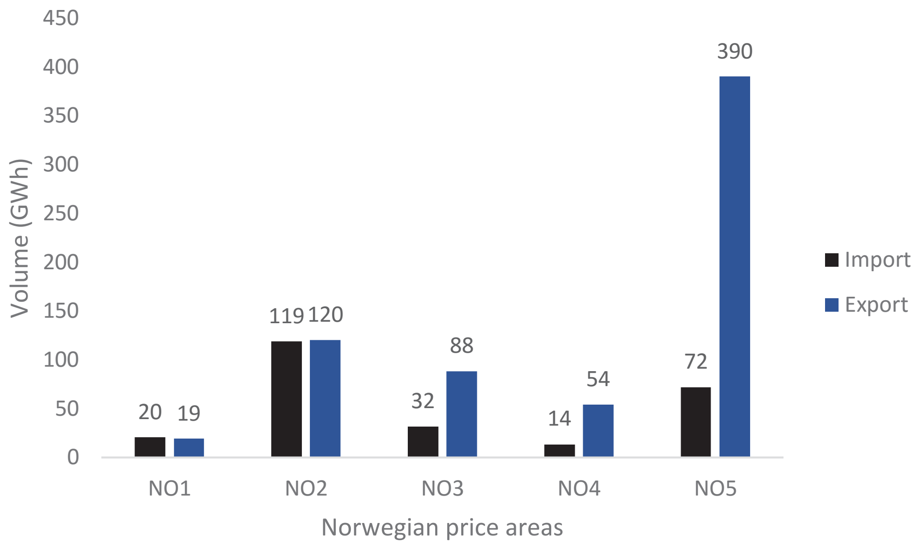


Figure 10: The amount of volume traded in the Norwegian price areas from 01.01.2015.

The descriptive market analyses identified an increase in the intraday trading activity between the years 2012/2013 and 2015. The number of trades was 285 385 and the traded volume was 5759 GWh within the period of the analysis. In Scharff and Amelin (2016) the results were, respectively, 190 533 trades and 3624 GWh from March 2012 to February 2013.

There could be several reasons for the increased activity. In 2013, Elbas was launched in Latvia and Lithuania, which would naturally lead to an increase (Johansen 2013). Elbas 4 replaced the old trading platform in 2014 to enhance the opportunity for cross-border trading. In addition, the renewable energy share has increased in several European countries from 2012 to 2015; Denmark: 25.7 – 30.8%, Germany: 12.1-14.6%, Sweden: 51.1 – 53.9%, Finland: 34.4 – 39.3% and Norway: 65.6 – 69.4% (Statistic explained 2017). With a growing renewable energy share Elbas' role in balancing the power system becomes more important.

The Norwegian price areas also had an overall increase of market activity in comparison to the findings in Scharff and Amelin (2016). The observed tendency shows a higher share of cross-border trading, resonating with the results of Scharff and Amelin (2016). The Norwegian electricity prices do not differ much between the domestic areas (Bleskestad et al. 2015), therefore the market participants prefer cross-border trading which gives the opportunity to trade with price areas with higher or lower prices. In addition, Norway has a flexible energy system which can be used to re-establish the system balance, in contrast to countries with a high share of intermitted renewable energy, such as Denmark and Germany, where large price variations occur. When the wind production is high in Denmark, the prices decrease and in some cases negative, consequently it is favourable to buy cheap power from Denmark and save the hydropower for later (NVE 2016).

Despite an overall increase in Norwegian trading, the intraday volume is still low compared to other countries. In 2015 Norwegian electricity production consisted of 95,6 % hydropower, and wind power cover as little as 1.7 % (Statistic Norway 2016). These characteristics would explain the low intraday volume. Another reason could be that the regulating power prices do not deviate much from the spot price. The market participants undertake a low risk in choosing to trade in the regulating power market, thus trading in the regulating power market is beneficial.

Additionally, Scharff and Amelin (2016) discuss that trading with Norway is less attractive because of the earlier gate closure (120 min) and the capacity limitations of the overseas cables makes it disadvantageous trading with continental Europe. In 2013, Statnett changed the gate closure time to one hour before delivery to prevent being excluded from as much as 30 % of the trades in Elbas (Nord Pool 2013). The capacity of the interconnectors to Europe are allocated primarily in the day-ahead market, and the remaining capacity is given to the intraday market (Energy Authority 2015). This implies that little or no capacity remains for the intraday market, when it is fully utilised in the day-ahead market.

4.2 Regression analyses

4.2.1 Variable selection

Skytte (1999) and Illieva and Bolkesjø (2014) explicitly point out that the relationship between spot prices and regulating prices is “of particular interest” for market participants with a volatile supply and demand, like intermittent energy. Therefore, the authors aimed to analyse this relationship in their studies. The findings of Pape et al. (2016) concluded that the fit of the regression intraday model improved when the intraday prices is determined based on the day-ahead price. This gives a strong indication that the spot price is a suitable variable for explaining the intraday prices.

Mauritzen (2013) explains that the market participants’ decision whether or not to trade in Elbas is complex, and involves prices in both the spot and the balancing market. If a market participant need to re-establish the balance after Elspot is closed, there are three alternatives: to trade in Elbas, to wait and trade in the regulating power market or to stay imbalanced. The profit and the possibility of high imbalance costs in the regulating market are factors that need to be considered when deciding upon an alternative (Mauritzen 2013). Therefore, the study aims to analyse in what degree the Elspot and the regulating power price can explain the intraday price. Three variable selection tests were conducted to the Elspot and the regulating power variables, to screen out possible insignificant variables.

The two-sampled paired t-test concluded that all the selected variables were significant with a significance level at 0.05 (table 3). This indicates that the null-hypothesis was rejected for all of them, and that the mean difference in population is not equal to zero.

Table 3: The result from the two-sampled paired t-test conducted on the Elspot prices and the regulated power market for up and down prices. The significance level; $\alpha = 0.05$

Two-sample paired t – test

	Mean diff.	95% CI Lower limit	95% CI Upper limit	p-value
Difference between Elspot price (import) and Intraday price	0.117	0.0508	0.184	0.0005
Difference between Elspot price (export) and Intraday price	-1.06	-1.130	-0.990	< 2.2e-16
Difference between up reg. prices (import) and Intraday price	2.804	2.669	2.939	< 2.2e-16
Difference between down reg. prices (import) and Intraday price	-2.433	-2.512	-2.353	< 2.2e-16
Difference between up reg. prices (export) and Intraday price	0.805	0.7125	0.892	< 2.2e-16
Difference between down reg. prices (import) and Intraday price	-3.428	-3.505	-3.350	< 2.2e-16

A stepwise regression and an all-possible regression selection test were conducted with all the variables that were tested in the paired t-test to check which variables would be significant together. The stepwise regression result showed that a model that included all the variables would be the best choice. A full model had the highest R^2_a; 0.7795 and the lowest C_p; 7, and a significant p-value of 4.227e-07. The best subset test had the same outcome with the highest R^2; 0.7798 and R^2_a; 0.7797 and lowest C_p; 7. The results of both tests are presented and highlighted in Appendix B in table II and table III. These tests indicate, conclusively, that all the variables should be included in a model.

4.2.2 Intraday price model

The price model, as presented in Equation 14, with all the variables tested in the previous section was fitted and the final result is presented in table 4. As shown, all the variables are statistically significant (α = 0.05) and also the overall model has a significant p-value. The R^2 and R^2_a is 0.779, which implies that 77.9 % of the response variable can be explained by the model.

$$\begin{aligned}\hat{y}\ (Intraday\ price)\\ = \hat{\beta}_0 + \hat{\beta}_1 x\ Elspot\ price\ (buyer) + \hat{\beta}_2\ x\ Elspot\ price\ (seller)\\ + \hat{\beta}_3\ x\ Up\ regulating\ price\ (buyer) + \hat{\beta}_4\ x\ Down\ regulating\ price\ (buyer)\\ + \hat{\beta}_5\ x\ Up\ regulating\ price\ (seller) + \hat{\beta}_6\ x\ Down\ regulating\ price\ (seller)\end{aligned} \tag{14}$$

Noticeably, the model has a $R^2_{prediction}$ value close to the multiple coefficient of determinations (R^2 and R^2_a), and this suggests that the fitted model is suitable for prediction. Additionally, the variables had VIF values below 10, which indicates that the model does not have any signs of multicollinearity. However, the variables are highly correlated with each other (appendix C, table IV) and this suggests that, despite the VIF <10, multicollinearity is present in the model.

The estimated variables were all positive, which suggests that if one of the variables increases with one unit (Euro/MWh), and the other variables are frozen, the intraday price will increase. The Elspot coefficients are significantly larger than the regulating coefficients, which indicate that the intraday prices are more influenced by the spot prices. Skytte (1999) states that the regulating power price follows the spot price. Both Skytte (1999) and Illieva and Bolkesjø (2014) find that the spot price influences the regulating price. The positive impact of spot and regulated prices which is confirmed in the model above was expected prior to the estimations.

Table 4: Estimated coefficients for the intraday price model. Significance value is set to α = 0.05. Number of observation: 21766

Coefficients	Beta	$\hat{\beta}$- Estimate	Std. Error	t- value	p-value	VIF
Intercept	$\hat{\beta}_0$	1.444	0.080	18.04	< 2e-16	
Elspot price (import)	$\hat{\beta}_1$	0.415	0.006	62.68	< 2e-16	4.7
Elspot price (export)	$\hat{\beta}_2$	0.274	0.008	33.44	< 2e-16	5.7
Up reg. price (import)	$\hat{\beta}_3$	0.043	0.003	12.28	< 2e-16	2.7
Down reg. price (import)	$\hat{\beta}_4$	0.066	0.007	8.82	< 2e-16	5.8
Up reg. price (export)	$\hat{\beta}_5$	0.0317	0.006	5.06	<4.23e-07	4.3
Down reg. price (export)	$\hat{\beta}_6$	0.1346	0.008	15.60	< 2e-16	6.2

Residual standard error: 4.101 on 21759 degrees of freedom, p – value: < 2.2e-16

F – statistics: 1.285e+04 on 6 and 21759 degrees of freedom.

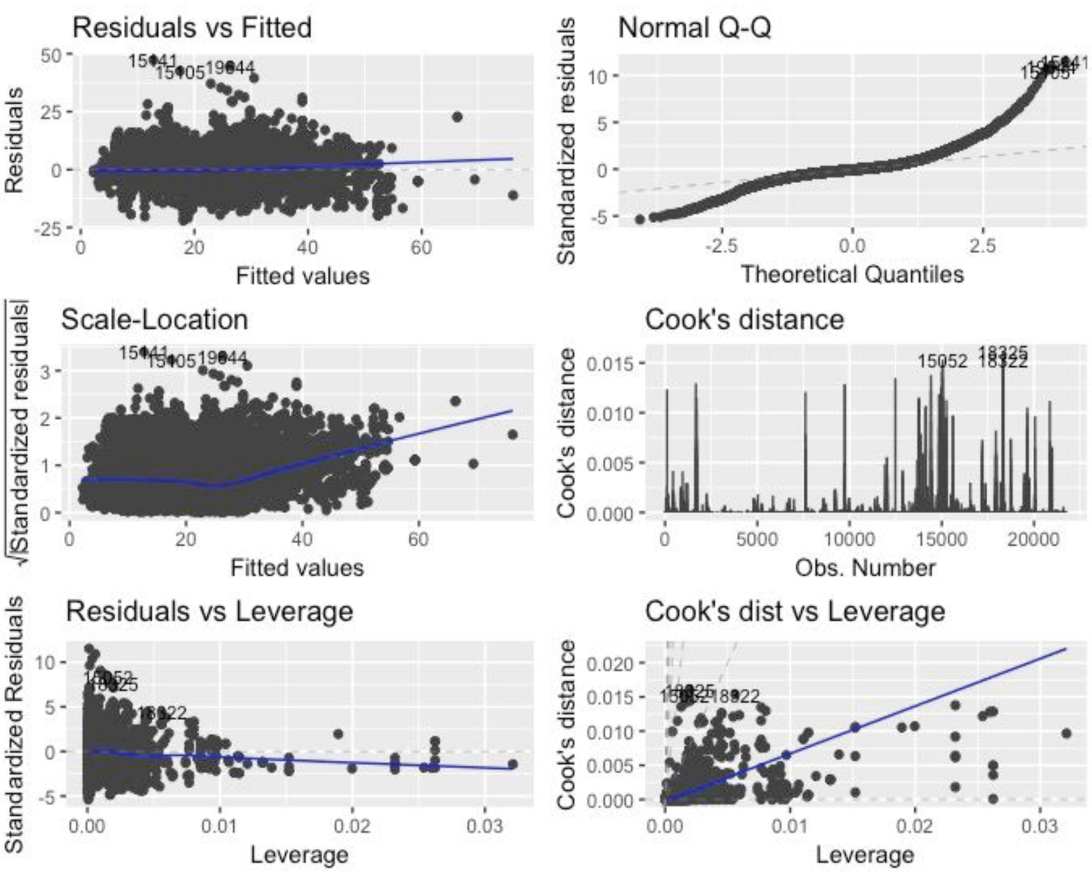
R^2 = 0.7798 and $R^2_{adj.}$= 0.7798

PRESS = 366501 RMSEP = 4.1 $R^2_{prediction}$ = 0.7794

22 outliers were removed due to extreme leverage or cook´s distance

4.2.3 Residual and autocorrelation analyse

The residual analysis was conducted by making different plots to detect if the assumption for the error term is satisfied. The plots are presented in figure 11, and the Residual vs. Fitted plots show an acceptably random distribution. Preferably, the blue line should be in line with the stippled line all the way. The result shows that the line initially follows the stippled line, then separates from the middle and outwards. However, the Residual vs. Fitted and Scale-Location plots both indicate that the points show signs of patterns and heteroscedasticity. The plots used to detect outliers, Cook´s distance, Residual vs. Leverage and Cook´s distance vs. Leverage, do not present any signs of extreme values, and are therefore considered valid. The Normal Q-Q plot shows signs of great skewness, which indicates abnormally distributed points. A way to manage skewness is to transform the response variable, an attempt that was undertaken with a “square root” and a “logarithmic” transformation, but the skewness was still present.



As a result of the existing skewness, the response variable was tested for autocorrelation by using the Durbin – Watson test and the autocorrelation function (ACF). The Durbin – Watson test rejected the null-hypothesis with a significant p-value < 0.00, and this strongly suggest that the residual is correlated. In figure 12, the ACF graph shows that the data is strongly positive correlated with lagged values of itself. The skewness in the normal probability plot (Q-Q) is most likely caused by the autocorrelation in the residuals. Autocorrelation might pose a problem for the intraday price model, and its reliability in the estimated coefficients. This will further be deliberated in the limitation section.

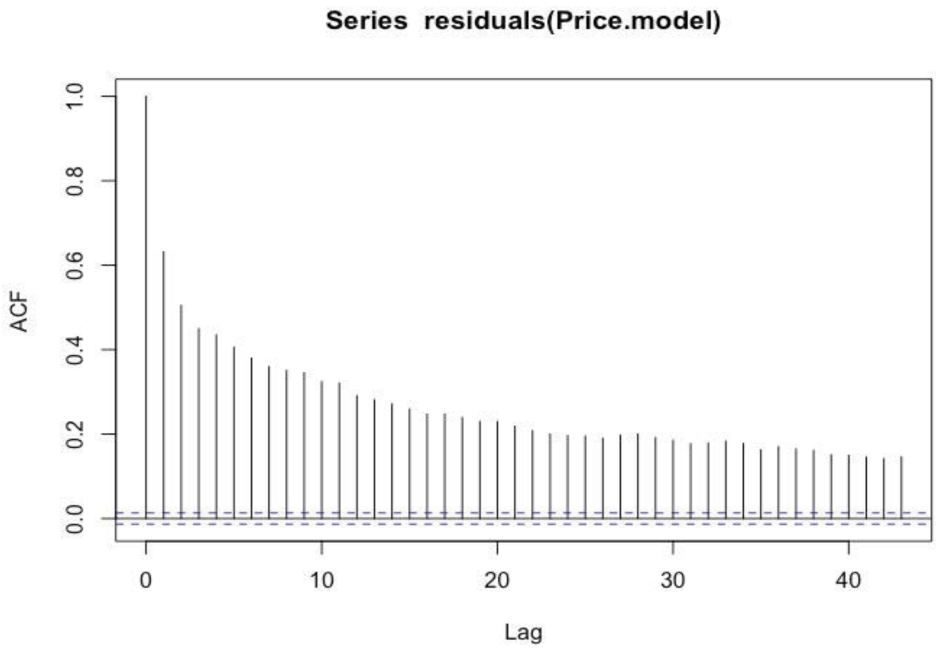


Figure 12: Autocorrelation function plot.

4.2.4 Fitted vs Predicted observation

An out-of-sampled test was conducted on the model: data from December was removed and the model was re-fitted. Afterwards, the new estimations were used to predict the intraday prices for December. Figure 13 shows the actual intraday prices and the predicted prices plotted together. The highest deviation is marked by a circle and a number:

1. Date: 01.12 Time: kl 18:00 – 20:00 (Tuesday)
2. Date: 02.12 Time: 16.00 – 18.00 (Wednesday)
3. Date: 05.12 Time: 14-15 (Saturday)
4. Date:15.12 Time: 15:00 – 20:00 (Tuesday)
5. Date: 23.12 Time: 02.00 (Wednesday)
6. Date: 28.12 and 29.12 Time: 19:00 and 15:00 – 24:00 (Monday and Tuesday)

The highest deviation frequently occurs in the afternoon and during weekdays. A large number of the population will come home from work at this time of day, thus consumption increases. Furthermore, the prices are either very low or high. For number 4 the price was around 60 Euro/MWh and the model predicted around 40 Euro/MWh. This indicates that the model struggles to predict accurately when extremely low or high values occur.

Extreme prices usually occur when there is an unexpected happening, like a surplus or deficit in wind power production caused by forecasts errors, transmission limitations or a generator halt and so on. Since the model only contains price variables, the model is not able to handle unexpected events. This is a clear weakness when predicting the intraday price, because the main purpose for an intraday market is to offer a trading platform to re-establish balance if something unexpected happens after the sport market is closed. A way to manage this shortcoming, is to add variables which can help predict the unexpected.

Mauritzen (2013) looked at the probability for trading in the intraday market, and used total wind production and forecasts errors in wind prognosis as variables in the regression model. Although the aim is different in this study, variables that include forecast errors for both unexpected surplus or shortage could improve the prediction. Since these variables would most likely contain information that shows that sudden surplus or stop in wind production will give extreme low or high prices, due to unexpected shortage or abundance of wind power. The share of wind power is low in Norway, but most of the intraday trades is cross-border with price areas where wind power has a considerable share in the energy mix. This will further increase with new interconnector and a more integrated European electricity market.

Since the intraday market is intended to re-establish the balance after the spot market is closed, a variable contained the “Urgent Market Message” (UMM) could be useful to include in the model. This is a message that contains information if something unforeseen, like planned/unplanned production, consumption outages or planned/unplanned transmission outages occurs.

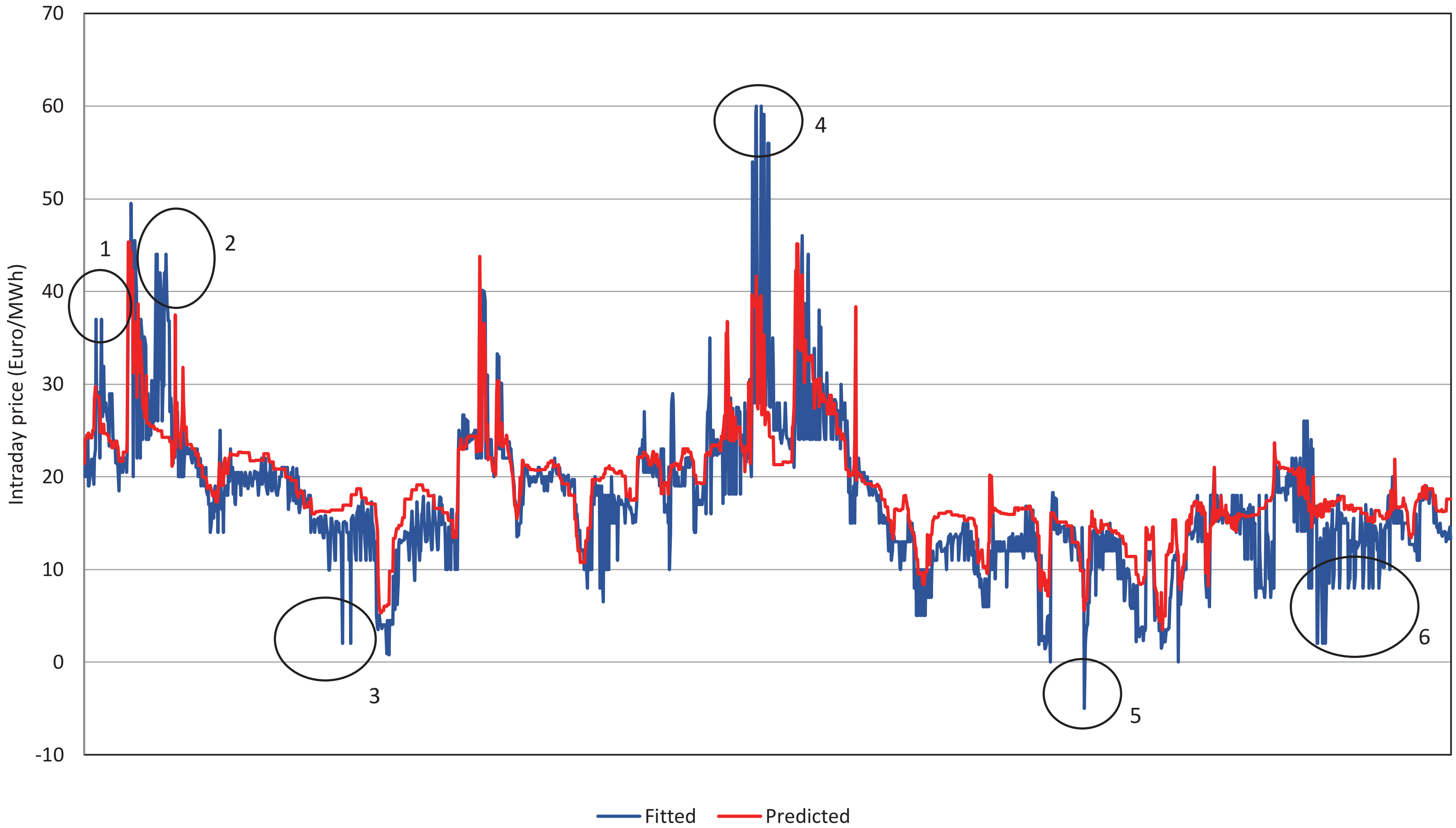


Figure 13: Fitted and predicted intraday prices for December 2015. 1795 number of observations.

4.2.5 Subset model

The autocorrelation test reviled that the variables in the intraday price model are correlated. Despite having VIF values below 10, variables with high correlation is additionally one of the signs to detect multicollinearity. This indicates that multicollinearity is present in the model. This may lead to an underestimation of the estimated coefficients. The full intraday price model was separated in two models, one with the import price variables and the other with export price variables (table 5), to see if the estimation would be higher with less variables. Table 5 shows a summary of the results which revealed that the estimated values without square brackets are significant with an 5% significant level.

Table 5: The estimated coefficients for the import and export model.
N = 21766

Coefficients	Import	Export	VIF
Intercept	3.646	3.373	
Elspot price (import)	0.629		3.2
Elspot price (export)		0.594	4.1
Up reg. price (import)	[0.003]		2.9
Down reg. price (import)	0.220		3.6
Up reg. price (export)		0.051	3,3
Down reg. price (export)		0.268	4.1
R^2_a	0.724	0.662	
PRESS	465072	570342	
RMSEP	4.62	5.11	

All the estimated coefficients have a higher estimated value in the subset models, except the insignificant up-regulating price variable (import). In the full model the values for Elspot import and Elspot export were; 0.415 and 0.274. In comparison with the best subset models the difference for Elspot were; 0.214 for import and 0.320 for export. This suggests that the coefficient estimations in the full model could be underestimated as a result of autocorrelation and multicollinearity. Both the subsets models have lower VIF values than in the full model, which only reinforces this assumption.

On the other hand, comparing the PRESS and the RMSEP values between the full and the subset models, the full model has lower values which means less errors when predicting and a higher prediction ability. The full model has a higher R^2_a which gives it a better fit to the data and has the ability to explain the intraday price in higher rate than the subset models.

Depending on the usage of the model, the result indicates that a full intraday price model is more suitable for prediction since it contains more variables which can benefit in explaining the price development and therefore have smaller errors in prediction forecast. A subset model with fewer variables has a more valid coefficients estimation, since fewer variables indicate a reduction of multicollinearity.

4.2.6 Time period modelling

The regression model was divided in the period *d-1* and *d* too see if the Elspot and regulating power price impacted differently giving the time period. The result is summarised in table 6, and all the estimated coefficient are statistically significant on a 5 % level of significance (except the ones in square brackets). In the day-ahead (*d*) period the model can explain 85% of the intraday price, while during the intraday (*d-1*) period the model can only explain 65%.

Table 6 The estimated coefficients for period *d* and *d-1*.

Coefficients	*d-1*	*d*
Intercept	1.386	2.699
Elspot price (import)	0.357	0.351
Elspot price (export)	0.395	0.178
Up reg. price (import)	[-0.000]	0.058
Down reg. price (import)	[0.109]	0.067
Up reg. price (export)	-0.020	0.064
Down reg. price (export)	0.105	0.213
R^2_a	0.852	0.651
PRESS	83927	392934
RMSEP	4.47	5.15

The high model fit in day *d -1* suggests a stronger relationship between the intraday price and the variables in the day before. Furthermore, the estimation value for the Elspot coefficients is higher in *d-1* than in *d*, which indicates that the intraday price is more sensitive to changes in the spot price during this time.

The estimated coefficients for the regulating power prices have a slightly higher value during day d, which suggest that the regulating price affects the intraday price more during this time. If market participants are imbalanced, the alternative to trade in the regulating power market becomes stronger when closing in to operating time. As a result, the intraday price has a stronger relationship with the regulating power prices closer to the market end.

The result clearly state that the model is more accurate and a better prediction tool for the intraday prices in the day before, compared to the model for the period d and the full model (table 4). A large share of the intraday prices can be explained by the Elspot and regulating prices in this period. The reason for the low explanation rate depicted in day *d*, could be that there are other important factors that contribute to the price development during these hours. Factors like wind production, errors in forecast, temperature and so on. This needs to be further researched.

4.2.7 Seasonal variations

To assess if seasonal variations had an impact, the model was run with data from four months from the different seasons. As depicted in table 7, the fit of the model varies between the months and season ranging from an 80% fit in October to a 53% fit in July. The low fit in July could be explained by the low electricity consumption during the summer months, in addition to the influence of other factors such as temperature and forecast errors upon the intraday prices.

Table 7: Estimated coefficient for January, April, July and October. All coefficients are significant with a 5 % significance level, except the ones with square brackets.

Coefficients	January	April	July	October
Intercept	[1.2502]	[1.3331]	[-0.0468]	[-0.6954]
Elspot price (import)	0.4286	0.2612	0.1320	0.5844
Elspot price (export)	0.4304	0.5921	0.5828	0.1431
Up reg. price (import)	[-0.0030]	-0.0564	0.0909	0.2010
Down reg. price (import)	[0.0324]	[0.0688]	[-0.0414]	-0.1202
Up reg. price (export)	[-0.0646]	[0.0712]	[0.0488]	-0.1587
Down reg. price (export)	0.1877	[0.0127]	0.2488	0.3911
R^2_a	0.7016	0.6077	0.5354	0.8006
PRESS	25208	10261	14261	30497
RMSEP	4.10	2.48	3.05	4.31
R^2_{pred}	0.69	0.59	0.51	0.79

The result indicates that the impact the spot price has on the intraday price varies between months and season. Except for January, there is a great difference on how the import and export Elspot price affect the intraday price trough the seasons. For April and July, the intraday price is more sensitive to the spot price set in the export areas. In October, it is the opposite, while in January there is only a small difference.

According to Illieva and Bolkesjø (2014) the spot price affected the regulating down price more during the summer than in the winter. The authors assume that during the summer the balancing parties have more free capacity and use it to trade in the spot market, rather than reducing the production to trade in the regulating market. This could explain the reason why the Elspot price (export) coefficients for April and July have such a large impact on the intraday price, compare to the other months.

Both prediction criteria had quite low values, which suggests a good prediction power for the models. However, because of a lower R^2_a compare to the full model, an additional prediction criterion was used; $R^2_{prediction.}$ This criterion creates an out-of sampled test (further described in chapter 3), and the result is showed in table 7. The result showed that the models had a lower prediction ability than the full model, except October. The colder months had a higher fit and prediction ability than the warmer months. This indicates that the intraday price can be more explained by the Elspot and regulating power prices during the colder months.

4.2.8 Variation among the Norwegian price areas

To examine how the different Norwegian price areas could impact the analysis, the model was run for each area. Table 8 presents a summarized result and indicates a good model fit in all the areas.

Table 8: Estimated coefficients from each price area. The coefficients, besides the ones in brackets, are statistically significant with a 5% level of significance.

Coefficients	NO1	NO2	NO3	NO4	NO5
Intercept	[0.584]	0.729	2.126	1.142	1.937
Elspot price (import)	0.527	0.453	0.223	0.559	0.517
Elspot price (export)	0.220	0.268	0.505	0.160	0.217
Up reg. price (import)	[-0.014]	[0.0009]	0.020	0.055	[0.003]
Down reg. price (import)	0.097	0.145	0.070	-0.082	0.046
Up reg. price (export)	0.081	0.063	[0.014]	[0.016]	[-0.009]
Down reg. price (export)	[0.073]	0.047	0.126	0.267	0.170
R^2_a	0.841	0.722	0.817	0.805	0.809
PRESS	27907	153583	110637	48109	84445
RMSEP	3.08	4.56	3.83	3.81	3.86

In NO1, NO4, and NO5, the intraday price increases with more than 0.5 Euro/MWh as a result of increases in Elspot price (import). In general, the Elspot coefficients have higher values than the regulating coefficients. For each area, at least one regulating price becomes insignificant.

All the areas have lower PRESS and RMSEP values and a better explanation rate (except NO2) than the full intraday price model. Dividing the Norwegian price areas in separate models indicates a better prediction power and a better fit. The motive of the price areas is to handle regional bottlenecks; thus the electricity prices are adapted to the areas with surplus or deficit in the transmission system. As the results show, the model is more accurate when operating within an area with uniform prices.

4.3 Limitations of the data and the analyses

This section will specify and discuss the main limitations of the data and the overall statistical analysis.

The data used in the regression analysis was limited to the Norwegian price areas. In comparison to other price areas the liquidity in the Norwegian intraday market is low. When the trading activity is not high enough, the market is not able to make transparent prices which has a low impact from individual market participants. Although the result probably represents Norway well, it would be an advantage to analyse other areas with higher trading activity where the prices are more transparent. This would give a better understanding on how the intraday price is developed.

The autocorrelation test stated that the data in the model is autocorrelated. Autocorrelation is one of the characteristics for electricity prices, and several studies have used times series models to manage the strong autocorrelation in the spot price; (Huisman et al. 2007; Levin 2011; Raviv et al. 2015). A disadvantage with autocorrelation is that it often prompts an underestimation of the coefficients, thus creating a lack of confidence in the estimation results (Mendenhall & Sincich 2014). In this analysis, this problem was not dealt with sine it occurred late in the process. Switching to a time series model could have resolved the problem, and should therefore be considered for future work. However, a time series model would have lacked the information that a regression model provides about the relationship between variables.

The model contained only price variables from the spot and regulating power market. Although, these variables can explain a large share of the intraday price, the model struggles to forecast prices with either extreme low or high values. A way to manage this weakness is to add variables as discussed.

5 Conclusion

This thesis has presented an analysis of the trading behavior and price determinants on the Nordic intraday market; Elbas. The aim has been to examine the trading pattern, volume and number of trades between price areas in the market, and to develop an intraday price model to examine how the prices in the spot and regulating power market impact the intraday prices. A successful model would also be a sufficient tool of prediction for the intraday prices.

Firstly, I will present the main findings from the market activity analyses. The result showed that the number of trades and volume varies strongly between price areas. Areas with elevated trading activity often had a large share of intermittent energy (Denmark, and Germany), high imbalance costs (Finland) or a high level of generating power (Sweden). In Norway, the trading activity is one of the lowest, which is a result of a high share of flexible hydro power and a low share of wind power, the capacity limitations to continental Europe and a well implemented regulating power market.

For the intraday price model, the results for the estimated coefficients showed that both the spot price and the regulating power price impacts the intraday price, but the spot prices had the most influence. The model could explain 77 % of the intraday prices and its prediction ability was overall good, but it struggled when the prices were either extremely high or low.

Furthermore, the model was developed into several sub models, and the results showed that the impact of the price variables on the intraday price varied between the Norwegian price areas, time periods within a market session, and season. The spot price had a larger impact when looking at the trading that takes place in the day-ahead period of the market, while the regulating power prices had a larger impact during the intraday period. Also, the intraday price was more influenced by the prices in the spot and regulating power market during the colder months.

Additionally, a model with all the selected variables had the best prediction ability and the prediction ability increased when the model was limited to data from one price area at the time. On the other hand, the estimated coefficients appeared more valid when using a model with fewer variables.

The intraday price model manages to give useful information regarding the relationship between the price variables and the intraday price. It gives an idea of when the spot and regulating power price impact the intraday price the most. The model itself is not a complex model, and is built upon basic regression analysis. The information used in the model is from public electricity prices. An advantage with this is that it is not difficult to interpret the outcome. The model can be used to get an idea on how the future intraday prices will be, without having to handle large amount of raw data.

While the intraday price model can explain a large share of the intraday prices, I would recommend to further improve it by:

- adding more valuables, so that the model is more robust in predicting extreme prices.
- expanding the model to include other price areas that have a higher trading activity, so that the prices used in the model are more transparent.
- using another type of model. For example, a times series model to manage the autocorrelation in the data.

Europe is moving towards a sustainable zero emission energy system where renewable energy, such as solar and wind power, dominates. The short-term markets´ advantage of trading closer to real time will be fundamental to manage the imbalance from intermittent energy. Intraday markets will play an important role to enable the increasing share of renewable energy, thus we need to further improve our understanding of the mechanisms behind this market.

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Appendices

Appendix A: The number of intraday trades between price areas in 2015

Table I: The number of trades between price areas in the intraday market. The rows represent the seller areas and the columns represent the buyer areas. For example, NO1 region have sold power to FI 92 times. The regions are organised alphabetically.

	50HZ	**AMP**	**BE**	**DK1**	**DK2**	**EE**	**FI**	**LT**	**LV**	**NL**	**NO1**	**NO2**	**NO3**	**NO4**	**NO5**	**SE1**	**SE2**	**SE3**	**SE4**	**TBW**	**TTG**	***Total***
50HZ	3	238	0	20	41	2	18	1	2	0	0	1	3	3	0	5	19	34	2	5	68	*465*
AMP	190	5614	12	1210	1195	119	2790	67	74	16	69	223	467	152	218	448	2338	3217	307	180	1485	*20391*
BE	0	6	9457	42	23	0	94	2	3	5279	0	14	36	3	4	25	73	78	2	0	7	*15148*
DK1	92	941	53	2006	1459	163	2407	45	82	29	76	605	394	102	283	1077	2053	3075	546	2	523	*16013*
DK2	120	1661	30	4207	667	113	1899	43	43	12	35	162	314	76	81	561	1381	2716	562	3	2747	*17433*
EE	1	130	8	205	133	258	5859	376	134	3	12	51	151	25	31	138	419	752	37	0	24	*8747*
FI	21	2186	191	2490	1154	3268	37615	1939	1771	148	149	363	1007	442	321	1113	3772	6197	406	3	693	*65249*
LT	1	34	7	56	22	150	1419	5005	968	0	13	31	44	16	13	91	109	242	5	0	7	*8233*
LV	0	25	3	33	21	34	488	242	105	4	5	6	12	10	2	26	77	112	4	0	12	*1221*
NL	0	42	11362	193	32	4	223	9	21	12402	6	86	36	5	41	56	164	208	10	0	7	*24907*
NO1	2	63	2	135	19	6	92	2	3	0	**49**	**299**	**55**	**44**	**440**	29	89	165	15	0	26	*1535*
NO2	5	192	26	596	71	22	315	23	12	26	**311**	**287**	**208**	**231**	**933**	71	294	439	39	0	78	*4179*
NO3	5	111	3	177	35	19	175	10	21	3	**42**	**108**	**169**	**274**	**182**	63	235	322	23	0	31	*2008*
NO4	1	25	2	51	18	4	90	3	8	0	**45**	**91**	**251**	**41**	**83**	25	99	103	8	0	3	*951*
NO5	4	89	8	235	50	14	201	14	9	6	**296**	**763**	**187**	**116**	**30**	31	194	321	17	0	35	*2620*
SE1	1	347	36	949	415	91	777	61	43	19	49	116	286	76	41	154	2697	3469	624	0	194	*10445*
SE2	25	1732	190	2205	856	249	3265	114	211	69	114	269	853	327	220	2809	2326	7820	1151	2	599	*25406*
SE3	50	3806	270	4111	1765	654	8399	388	553	133	377	675	1964	657	582	2519	9701	6550	1564	7	1380	*46105*
SE4	4	350	16	577	407	38	978	42	35	10	21	81	181	55	65	545	1083	1873	70	2	128	*6561*
TBW	12	223	0	7	2	1	15	0	0	0	0	0	1	4	0	3	13	6	0	5	65	*357*
TTG	33	1546	7	582	1906	26	815	8	9	8	8	73	143	40	46	196	634	892	90	53	259	*7374*
Total	*570*	*19361*	*21683*	*20087*	*10291*	*5235*	*67934*	*8394*	*4107*	*18167*	*1677*	*4304*	*6762*	*2699*	*3616*	*9985*	*27770*	*38591*	*5482*	*262*	*8371*	*285348*

Appendix B: Variable selection test

Table II: The result from the sStepwise regression test. The best result is highlighted.

	In	Out	AIC	R^2_{pred}	C_p	F-value	p-value
β_1	1	1	67390	0.71038	6852.096	53410.664	< 2.2e-16
β_2	1	1	71441	0.71038	6852.096	40644.700	< 2.2e-16
β_3	1	1	83982	0.71038	6852.096	13312.247	< 2.2e-16
β_4	1	1	74619	0.71038	6852.096	32166.401	< 2.2e-16
β_5	1	1	78709	0.71038	6852.096	22929.103	< 2.2e-16
β_6	1	1	75578	0.71038	6852.096	29842.430	< 2.2e-16
β_2	2	1	62872	0.76462	1487.944	5023.393	< 2.2e-16
β_5	2	1	64114	0.76462	1487.944	3537.556	< 2.2e-16
β_6	2	1	63137	0.76462	1487.944	4699.173	< 2.2e-16
β_6	3	1	61966	0.77419	540.413	926.689	< 2.2e-16
β_3	4	1	61523	0.77871	91.433	449.196	< 2.2e-16
β_4	5	1	61463	0.77928	30.603	62.759	2.448e-15
$\boldsymbol{\beta_5}$	**6**	**1**	**61439**	**0.77950**	**7.000**	**25.603**	**4.227e-07**

Table III: The result from the all-possible regression selection procedure. The best result is highlighted.

	β_1	β_2	β_3	β_4	β_5	β_6	R^2	R^2_{adj}	C_p
1 (1)	*						0.7104876	0.7104743	6852.09641
1 (2)		*					0.6512666	0.6512505	12705.23138
1 (3)				*			0.5964428	0.5964243	18123.76101
1 (4)						*	0.5782696	0.5782502	19919.91987
1 (5)					*		0.5130345	0.5130121	26367.46353
2 (1)	*	*					0.7647814	0.7647597	1487.94439
2 (2)	*					*	0.7618994	0.7618775	1772.78304
2 (3)	*				*		0.7509676	0.7509447	2853.23669
2 (4)		*		*			0.7322625	0.7322379	4701.96316
2 (5)	*			*			0.7281961	0.7281711	5103.86610
3 (1)	*	*				*	0.7743885	0.7743574	540.41305
3 (2)	*	*		*			0.7740389	0.7740077	574.97296
3 (3)	*	*	*				0.7708323	0.7708007	891.89868
3 (4)	*	*			*		0.7695566	0.7695249	1017.97885
3 (5)	*				*	*	0.7669881	0.7669560	1271.83923
4 (1)	*	*	*			*	0.7789515	0.7789109	91.43285
4 (2)	*	*		*		*	0.7771434	0.7771024	270.13814
4 (3)	*	*		*	*		0.7767398	0.7766987	310.02743
4 (4)	*	*	*	*			0.7756593	0.7756181	416.81343
4 (5)	*	*			*	*	0.7795872	0.7754277	435.62557
5 (1)	*	*	*	*		*	0.7790592	0.7795365	30.60329
5 (2)	*	*	*		*	*	0.7790592	0.7790085	82.78518
5 (3)	*	*		*	*	*	0.7783215	0.7782706	155.69705
5 (4)	*	*	*	*	*		0.7773855	0.7773344	248.20491
5 (5)	*		*	*	*	*	0.7685299	0.7684767	1123.45868
6 (1)	*****	*****	*****	*****	*****	*****	**0.7798462**	**0.7797855**	**7.00000**

Appendix C: Correlation scatterplot matrix

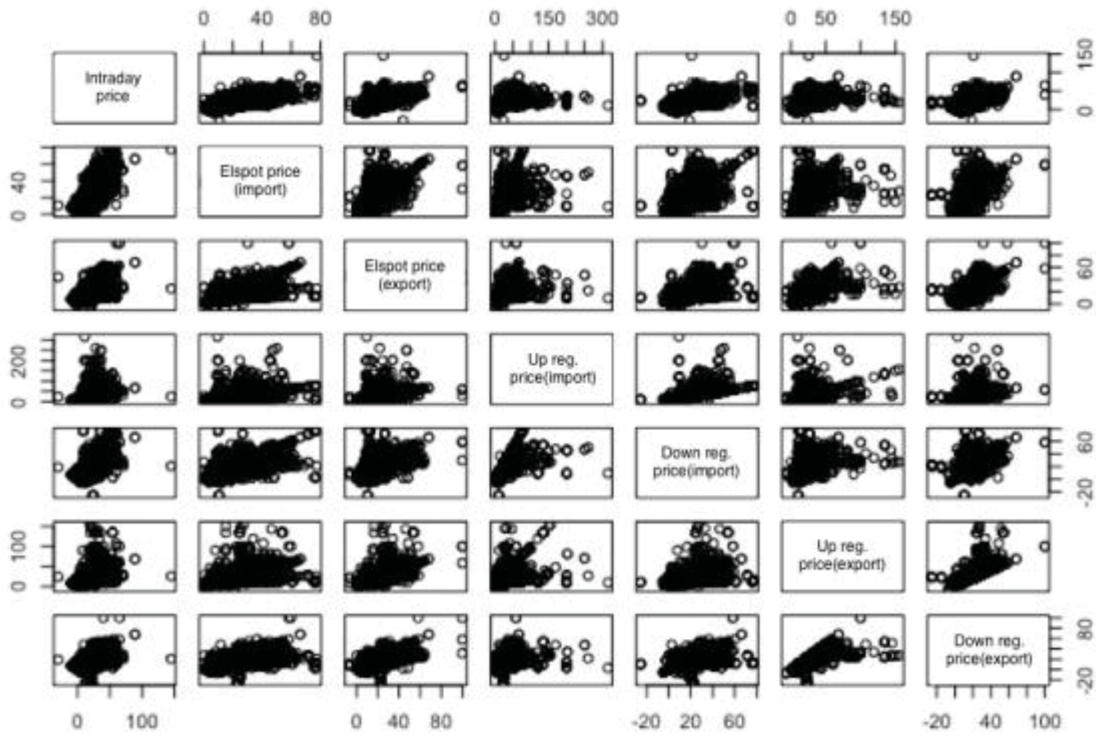

Figure IV: Display the correlation between all the variables in the full intraday price model.

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