Universitat Politècnica de Catalunya (UPC)

Escola Tècnica Superior d'Enginyeria Industrial de Barcelona (ETSEIB)

Master's Thesis Degree Project

Trading Techniques for European Electricity Markets

External Supervisor: Vadim Gorski
Center For Energy Markets
TUM School of Management
Technische Universität München

Director: Andreas Sumper
CITCEA, ETSEIB
Universitat Politècnica de Catalunya (UPC)

Study program: EIT InnoEnergy - Energy for Smart Cities

Composed by: Ákos Baldauf

Submitted on: April, 2018

Abstract

The high penetration of wind based electricity production has a notable effect on the electricity market prices in Germany. It is important to properly integrate the high level of wind generation into the liberalised electricity markets in order to make them more competitive and representing the actual costs.

Two markets, the German EPEX Day-ahead Spot and the Intraday Continuous can hold potential arbitrages between them.

This thesis is aiming to investigate nature of the listed markets and their trading opportunities.

Firstly, a testing method is introduced and applied on the markets to justify the search of arbitrage.

Secondly, the correlation of the actual wind generation and forecasts regarding to the market pricing is investigated. Thirdly, the intraday continuous market's order book is analysed in regards of trading potentials.

Lastly, strategy development steps are introduced in order to create profitable trading strategies between the day-ahead and intraday continuous markets.

The goal of this thesis is to investigate and provide a guide for the creation of such trading algorithms. Hopefully, this thesis can provide a good start, justification and viewpoint for further projects on this topic.

Contents

Glossary

AR autoregressive

ARMA autoregressive–moving-average

DA Day-Ahead

EEG Renewable Energy Sources Act

EMH efficient market hypothesis

EPEX European Power Exchange

EU European Union

FIP feed-in premium

FIT feed-in tariff

GARCH generalized autoregressive conditional heteroscedasticity

HFT high-frequency trading

iid independent and identically distributed

LSTM Long Short-Term Memory

MA moving average

order book an electronic list of ask (buy) and bid (sell) orders

Phelix German/Austrian Physical Electricity Index

REG renewable energy generation

RES renewable energy sources

RNN Recurrent Neural Network

TSO Transmission System Operator

VWAP Volume Weighted Average Price

List of Figures

1 Introduction

This work is aiming to give an introduction to trading strategies on the electricity market by exploiting inefficiencies in its pricing process. The methodology is based on finding arbitrage by using high-frequency trading (HFT) techniques.

A more detailed introduction into the financial processes and market mechanisms is consequent to the engineering background of the writer and perhaps also the reader of this thesis.

In this *Introduction* the necessary definitions of the workflow of this thesis are introduced.

The following *Test for Market Efficiency* contains the required steps and proofs for the efficient market hypothesis (EMH) that verifies the opportunity of constructing profitable trading strategies on the market.

The *Trading on EPEX SPOT* firstly introduces the operation of electricity market and then explores and introduces profitable trading strategies using the arbitrage between the Day-Ahead (DA) and Intraday markets via deep learning techniques.

In *Model results and outcome* the outcome and results of the model example algorithm is discussed. The final section, *Conclusions* gives a summary the outcome of this thesis.

1.1 Electricity sector in Germany

Over the last few decades Germany has gained a reputation for its endeavor to implement an environmentally friendly and sustainable electricity system. However, in the past the political and social climate was not always in favour of this undertake. Starting from the 1950s, the fast growth of the German industry was predominantly supplied by coal and lignite power plants (almost 90 % share). In the late 1960s nuclear power started to gain ground, although the coal industry remained its political support and subsidies. The energy efficiency in the form of governmental measures came about after the the oil crisis in 1973, in order to make the security of supply of the country less dependent on external factors. Investments have also been made in the nuclear sector mostly for the sake of energy security, predominantly to gain more oil independence.

A larger change towards sustainability, efficiency and renewable energy sources (RES) has come by a new government in 1998 that has emphasised these concerns in its energy policy. The policies mainly contained agreement on the reduction of CO2 emissions and the phase out of nuclear power. These aims were intended to be reached by growing renewable generation and increasing energy efficiency. At the same time, in line with the

Table 1: Quantitative targets of the *Energiewende* and status quo (2014) [8]

	2014	**2020**	**2030**	**2040**	**2050**
Greenhouse gas emissions					
Greenhouse gas emissions (base year 1990)	−27%	−40%	−55%	−70%	−80 to −95%
Renewable energy					
Share of gross final energy consumption	13.5%	18%	30%	45%	60%
Share of gross electricity consumption	27.4%	35%	50%	65%	80%
Share of heat consumption	12%	14%			
Share in transport sector	5.6%				
Efficiency and consumption					
Primary energy consumption (base year 2008)	−8.7%	−20%			−50%
Final energy productivity (2008–2050)	1.6%/year (2008–2014)	2.1%/year (2008–2050)			
Gross electricity consumption (base year 2008)	−4.6%	−10%			−25%
Primary energy consumption in buildings (base year 2008)	−14.8%				−80%
Heat consumption in buildings (base year 2008)	−12.4%	−20%			
Final energy consumption in transport(base year 2005)	1.7%	−10%			−40%

EU competition law and policy, Germany has liberalized the electricity market.

The accident at the Fukushima nuclear power plant in Japan had a great impact on the balance of the political decision makers and the public awareness. As a consequence the so called *Energiewende* (energy transition) law was ratified by the German Bundestag (the German legislative body) in 2011. The *Energiewende* law had a mandated to the complete phase out of all nuclear power plants by 2022. The law also includes other targets in favour of the RES and energy efficiency. The detailed *Energiewende* targets can be seen in *Table 1*. [7, 8]

Since 2000 the Renewable Energy Sources Act (EEG) provides the supporting scheme for RES through guaranteed feed-in tariff (FIT) by granting investment protection and connection requirement. FIT is a form of policy that is focused on supporting the development of RES projects by offering long-term price and purchase agreements for the renewable electricity sales.

In 2012 the EEG has been modified. A new support scheme has been introduced in the form of feed-in premium (FIP). The FIP is intended to foster the market integration of the RES, hence a premium is payed on top of the direct production sales on the EPEX spot market. The average market price and the FIP add up to the guaranteed FIT. [9]

The economical and legislative incentives have had a great impact on the German electricity generation mix. The wind and solar based generation that is mainly supported by the EEG has gone through a significant growth as it can be seen in *Figure 1.1* between the years 2002 and 2017.

The growth of the renewable energy generation (REG) capacity amounts in the net power generation as it is displayed in *Figure 4*.

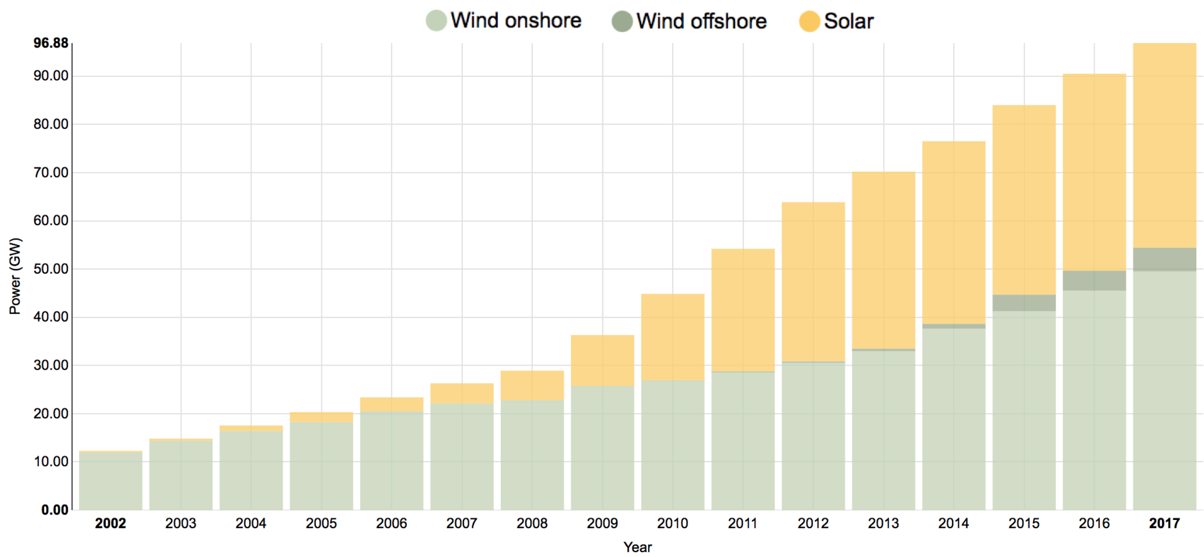


Figure 1: Net installed wind and PV electricity generation capacity in Germany [1]

The growth of the intermittent renewable capacity brings more fluctuation of the electricity production into the grid. In 2015 the total share of the wind energy of the total production was 14.5 % (Germany was net exporter in 2015). Hence the wind based production is situated with lower prices in the merit order (see in *Figure 12*). Based on the merit-order principle, the supply change caused by the wind in the market, brings extra fluctuation to the electricity prices too.

Also, looking at and *Figure 4*, it is quite telling that the share of the wind based generation *capacity* and the share of actual *generation* significantly differ in numbers.

A good demonstration for the tendency for fluctuation is the capacity factor of the wind based production.

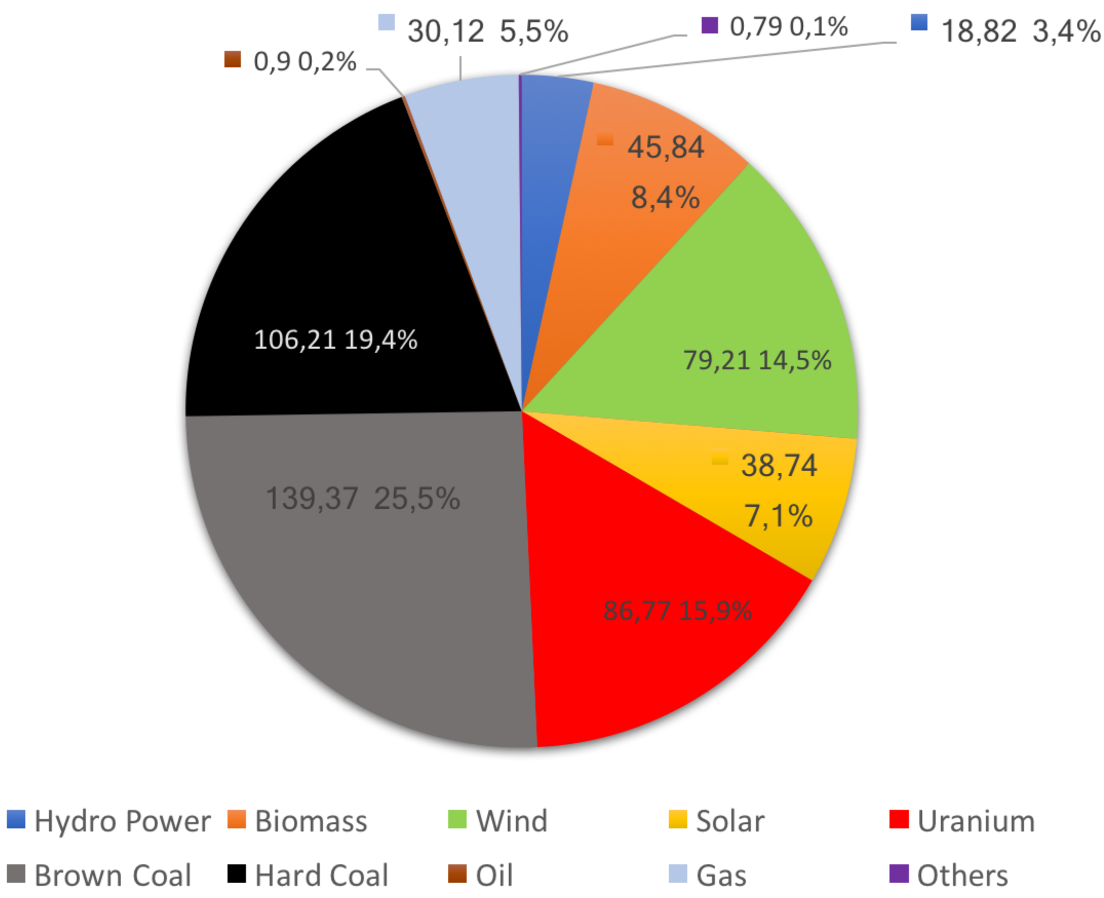


Figure 2: The German net power generation from power plants for the public power supply in TWh end percentages for 2015.[1]

$$\textit{capacity factor} = \frac{\textit{average generated power}}{\textit{rated peak power}} \tag{1}$$

As a demonstration based on the introduced indicators and numbers, looking at *Figure 4* and *Figure 5* a good proxy to the rated peak power could be the installed wind based generation capacity and the yearly generated energy transformed to average generated power as

$$\textit{average generated power} = \frac{\textit{yearly energy production}}{\textit{8760 h}} \tag{2}$$

Thus, the calculation yields *capacity factor = 20.27 %* which seems to be proper a approximation based on [10], where the *capacity factor* is calculated as *20.47 %*

The duration curve is also a good indicator of the intermittent nature of the RES. The duration curve of onshore wind based production in Germany is displayed in *Figure 3*. This curve indicates the level of production in the amount of hours throughout a year period. The area under the curve adds up to the total yearly production. There are relatively less hours when the level of production is higher, but the number of hours is high when it is lower. The nature of wind production is also described by its low capacity factor.

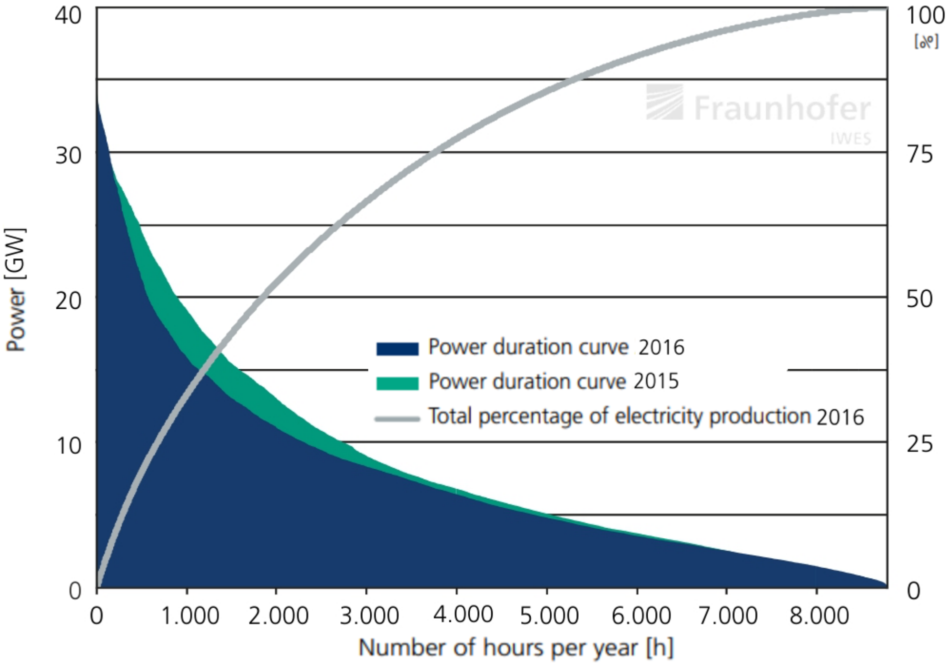


Figure 3: Wind power duration curves in Germany [2]

The high share of intermittent renewables and its FIP subsidization system in the German grid, and hence its impact on the electricity market prices leads us to consider trading techniques based on the nature of RES, especially on the relatively less decentralized and predictable wind based energy sources.

Based on the principles of the *Energiewende* and the EU directives, the share of the intermittent RES in the grid both in Germany and in the EU is and will be increasing, it is important to improve the electricity system not strictly on a physical level, but also on market level in order to incentivize the technological innovations and developments in order to accommodate the bulk of intermittent RES. On the liberalized electricity market, smartly constructed trading techniques can potentially facilitate the aforementioned goals and generate profit for the trading entity.

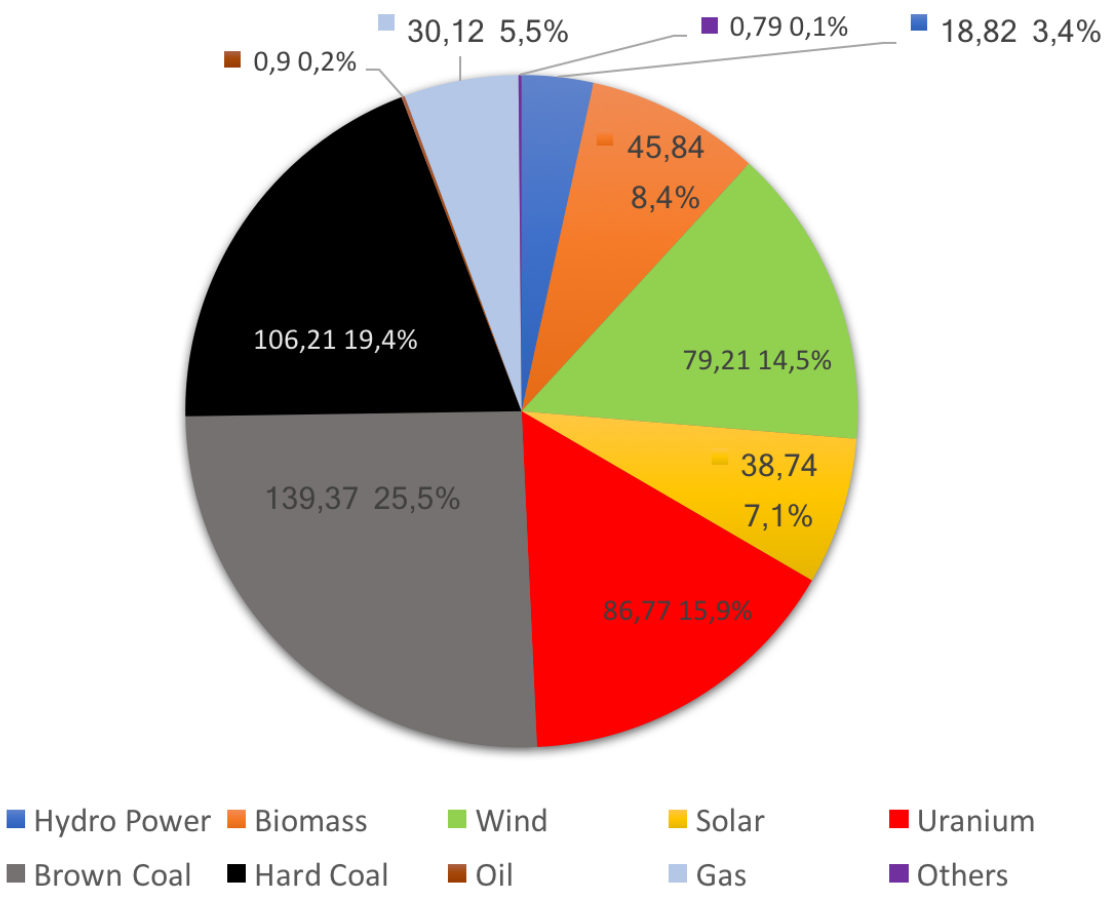


Figure 4: The German net power generation from power plants for the public power supply in TWh end percentages for 2015.[1]

1.2 EPEX SPOT Market Design

With the release of the EU Directive on Internal Energy Markets, the basis was set for the wholesale energy markets in the EU and it has also became implemented in the German law in 1998. In line with the legal framework, the electricity market became liberalized and the precursor of the EPEX SPOT was established in Germany. After several iteration, the market developed its current structure and products as it is described in this section.

EPEX is a market for power spot trading in Europe operating in Germany, France, the United Kingdom, the Netherlands, Belgium, Austria, Switzerland and Luxembourg.

The spot market consists of two major segments, the DA and the continuous intraday markets. Apart from these two major segments, capacity auctions are also organized.

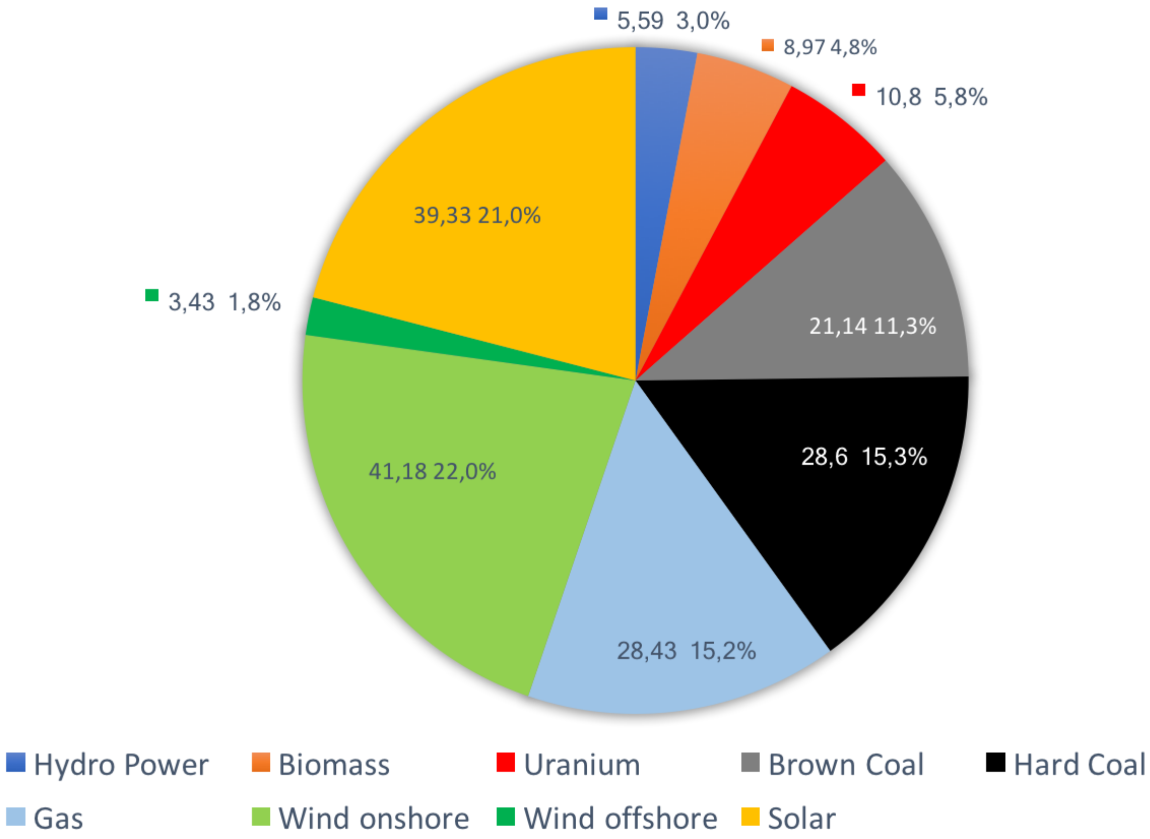


Figure 5: Net installed electricity generation capacity share in Germany in 2015. Capacities in GW.[1]

Futures, options and other derivatives can be traded on the European Energy Exchange (EEX) Derivatives market.

The EPEX SPOT is organized as follows: price index for the hourly, half hour and quarterly DA market in the German and Austrian area is called the German/Austrian Physical Electricity Index (Phelix). The intraday continuous market of EPEX in Germany is also indexed by the weighted averages of its hourly, 30 min and 15 min products.

The following list provides an overview of various kind of markets on EPEX with delivery in the German Transmission System Operator (TSO) zones [11–15]

- DA hourly
  - electricity traded for delivery the following day in 24 hour intervals
  - the daily auction takes place at 12.00 pm, 7 days a week, year-round, including statutory holidays

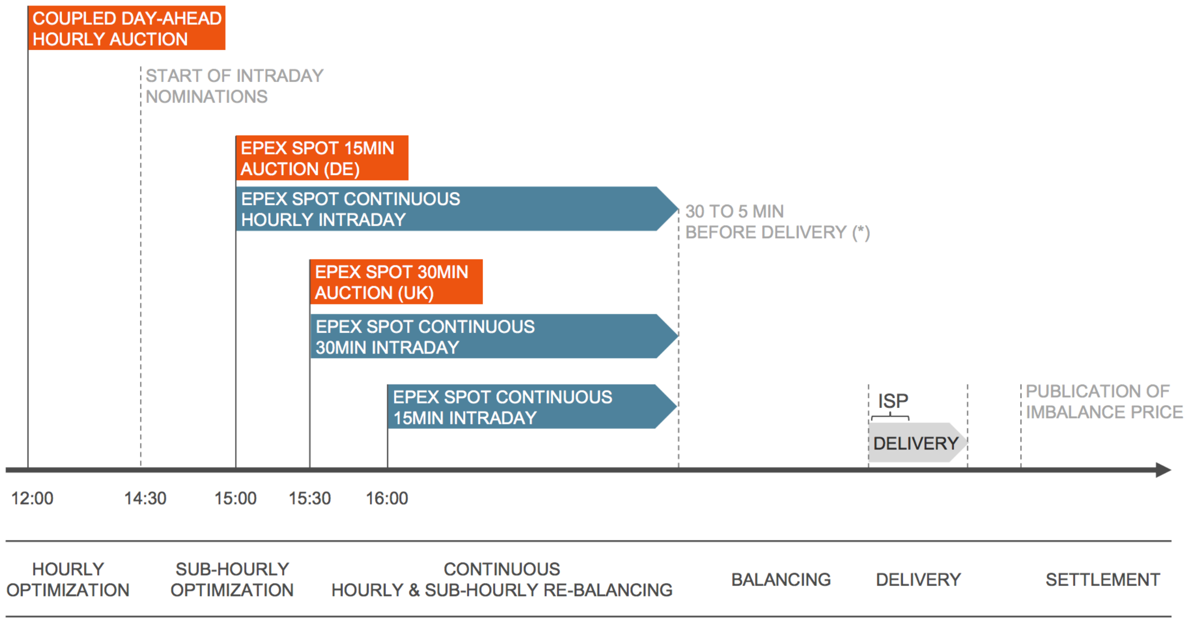
  - the order book opens 45 days in advance and closes one day before delivery at 12 pm
  - the market clearing is performed after and the market-clearing prices are released right after the submission deadline

- Intraday 15-min auction
  - electricity traded for delivery the following day in 96 quarter hour intervals.
  - the daily auction takes place at 15.00 pm, 7 days a week, year-round, including statutory holidays
  - the order book opens 45 days in advance and closes one day before delivery at 3.00 pm
  - the market clearing is performed after and the market-clearing prices are released right after the submission deadline

- Intraday hourly, 30 min and 15 min continuous
  - continuous trading 7 days a week, 24 hours a day, all year around
  - hourly contracts for the next day open at 3.00 pm (d-1) and the 15-min contracts at 4.00 pm (d-1)
  - if there is a match between orders, they are immediately executed
  - the index of each market is characterized by the weighted average of the executed orders in the assigned time period
  - the lead time between the neighbouring countries is 60 minutes, within the German bidding area is 30 minutes and within the control (within TSO) zones is 5 minutes [1]

The timeline of the trading on the markets is shown in *Figure 6.*
The clearing algorithm of the intraday continuous markets is visualized in *Figure 11.*

[1]before 16 July 2015 the lead time was 45 minutes within Germany and 5 minutes lead time was introduced in 14 June 2017



(*) Both local and cross-border lead times are country-specific

Figure 6: Timeline of EPEX SPOT markets [3]

1.3 Efficient Market Hypothesis

In order to develop profitable trading strategies, the instrument intended to trade has to exhibit inefficiencies in its pricing process. Thus, if the inefficiencies can be exploited in the time frame for the intended trading period, profitable trading strategies can be constructed.

The EMH was described by Fama in [16] as the market is efficient if it ”fully reflects” all available information. Thus, if the EMH is true to a market, with applying technical or fundamental analysis to the market would make no profit. If there's profit made based on the analyses that is only random, and the sum of profits and losses converges to zero on the long run. Hence, an expert would not do any better than a layman holding a randomly selected portfolio (considering equal risks). Namely, it suggests that profiting from predicting price movements is mostly unlikely and can only based on luck.

On the other hand, if the EMH is rejected, in other words, the market is inefficient, the potential exists for developing profitable trading systems. The EMH suggests that profiting from predicting price movements is very difficult and unlikely. [16–18]

The methodology for EMH testing is explained in the *Test for Market Efficiency* section.

1.4 High-Frequency Trading

HFT is a trading methodology, not a trading strategy. It has appeared on stock markets in the late 2000s and advanced by the developing technology and computer algorithms.

HFT on stock markets can be charaterized by its propriety as a type of trading algorithms that is executed with the help of superfast computers to generate profit. The rapid entry and exit from the order stream may fetch a small fractional profit, but by large quantity it can turn into a substantial profit. The algorithms are formed on the basis of informational speed advantage measured in milliseconds.

Although, this thesis relies on an other main property of the HFT algorithms that describes how they work by exploiting the inefficiencies in the pricing process (mainly in its speed). As it can be proved by the rejection of the EMH that an instrument one intends to trade exhibit inefficiencies in the pricing process at the time frame that one intends to exploit that by the HFT algorithms. [18, 19]

Fama in [16] describes the ideal market is the market in which prices provide accurate signals for resource allocation. As it can be read in *Trading on EPEX SPOT*, HFT trading strategies help to facilitate the directives of the European Union (EU) on the efficiency of the electricity market by advancing their pricing process. [20]

2 Test for Market Efficiency

Test for the EMH is required in order to justify the search for arbitrage opportunities in the market. Very efficient markets either have the arbitrage opportunities quickly removed by market participants or they don't have at all, since the market immediately (or very quickly) "fully reflects" all available information. [16, 17, 21]

In a technical point of view the efficient market can be boiled down to the unpredictability of the market's behaviour, it is entirely random, and can only be described by a random process, such as in the form of a random walk.

An efficient market has to exhibit a random walk. The random walk process can be described in a periodical manner as follows

$$x_t = x_{t-1} + \varepsilon \tag{3}$$

Here, taking the electricity market as an example x_t can be described as the electricity price at period t; ε as an independent and identically distributed (iid) random variable (e.g. white noise) and x_{t-1} as the electricity price in previous period $t-1$ (e.g. sequential hourly products on the DA spot market). [22]

If the market is not efficient, its behaviour cannot be described by a random walk.

In order to reject the EMH, autocorrelation in the time series data has to be proven. In other words, the price volatility on a market cannot be described by a random walk, therefore there is a way to predict the movements of prices to a certain degree.

Since the intention of this thesis to propose trading strategies between the EPEX DA Spot and the Intraday Continuous markets, the EMH has to be tested on both.

In the following subsections a testing methodology is introduced and applied on the EPEX DA Spot and Intraday Continuous markets.

2.1 Testing Methodologies

If it is possible to prove that there is a method to characterize the market's behaviour, then the EMH is rejected. In order to describe the time series data of a market, the most commonly used method is the first-order autoregressive (AR) model, where subject variable depends linearly on its own previous values and on a stochastic term.

The AR(1) model can be described as follows:[23, 24]

$$\alpha_t = \alpha_0 + \pi\alpha_{t-1} + \varepsilon_t \tag{4}$$

where π is a parameter, α_0 is a constant, and ε is a iid random variable (white noise).

An other widely used extension of the AR is the first-order moving average (MA) model. The output variable of a MA depends linearly on the current and past values of a stochastic iid term.

The MA(1) model can be described as follows:

$$a_t = \mu + \kappa\varepsilon_{t-1} + \varepsilon_t \tag{5}$$

where κ is a parameter, μ is a constant, ε_{t-1} is a propagated error term, and ε is a iid random variable (white noise).

Together the AR and MA has a joint description as the autoregressive–moving-average (ARMA) model. The first-order ARMA(1,1) model can be described as follows:

$$\alpha_t = \alpha_0 + \pi\alpha_{t-1} + \kappa\varepsilon_{t-1} + \varepsilon_t \tag{6}$$

where π and κ are parameters, α_0 is a constant, ε_{t-1} is a propagated error term, and ε is a iid random variable (white noise).

Although, the ARMA(1,1) can be a good model to describe a market's behaviour, in case of EMH rejection it does not perform sufficiently, since it does not take into account the heteroskedasticity of the time series data.

A time series is heteroskedastic if the variances of the regression disturbances are not constant, but changes over time.[25]

An improved version of the ARMA(1,1) process that allows MA components in the heteroskedastic variance is the generalized autoregressive conditional heteroscedasticity (GARCH) process.

In order to yield a GARCH(1,1) the ARMA(1,1) process should be modified as follows: [17, 26]

$$\gamma_t = \alpha_0 + \pi\alpha_{t-1} + \varepsilon_t \tag{7}$$

where the ε_t is defined as follows:

$$\varepsilon_t = \eta\sqrt{h_t} \tag{8}$$

$$h_t = \kappa + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1} \tag{9}$$

Here, $\kappa > 0$, $\alpha \geq 0$, $\beta \geq 0$ and η_t are iid random variables.

In this thesis, the test for market efficiency follows the *GARCH* model with two endogenous structural breaks, since its higher likelihood of rejection compared to other methods as it is proposed in both [17] and [26]

$$\gamma_t = \alpha_0 + \pi\alpha_{t-1} + D_1 B_{1t} + D_2 B_2 t + \varepsilon_t \tag{10}$$

Here, T_{Bi} are structural break points where $i = 1, 2$; D_1 and D_2 are break dummy coefficients, hence $B_{it} = 1$ for $t > T_{Bi}$ otherwise $B_{it} = 0$.

The endogenous structural breaks represent certain structural changes in the time series data. In case of electricity markets it can be e.g. changes in the regulation or subsidy system.

Important to notice, that it is sufficient if there's any test exists that can reject the EMH. Thus, it is sufficient if the proposed GARCH model rejects the EMH on a data set with one or without any endogenous structural break implementation.

In order to accept or reject the EMH on the market data, weighted Ljung-Box test on the standardized residuals of the GARCH is carried out.

The Ljung-Box test indicates whether any of a group of autocorrelations of a time series are different from zero. It tests the "overall" randomness.

The Ljung-Box test is a portmanteau test, in which case the null hypothesis is very specified, but the alternative hypothesis is more loosely.

The hypothesis for the Ljung-Box test is defined as follows:

H_0 - The time series data is independently distributed (i.e. the correlations in the population from which the sample is taken are zero)

H_a - The time series data exhibit serial correlation, not independently distributed

Thus, the EMH is consequently rejected in the case of H_0 is rejected by the Ljung-Box test. [26, 27]

In order to evaluate the statistical significance of the H_0 hypothesis, the Ljung-Box test uses the *chi-square* distribution table. The method yields the P-value and the statistic value, that are indicators of the likelihood of the tested hypothesis.

As it is described in [28], in order to get the proper *chi-square* distribution, the degree of freedom of the $GARCH(p, q)$ is necessary. Its value depends on the p, q variables and the number of lags during testing.

The number of lags describes how many consecutive samples of the tested time series data is included in the Ljung-Box test.

In this thesis the **R** programming language and its functional packages are used to implement the algorithms and mathematical expressions.

2.2 Market Data Test

The test runs on two data sets: EPEX DA Spot hourly index and EPEX Intraday Continuous hourly products.

The test on the DA Hourly Market Indices is simply run through the historical data set of the year 2015.

Although, on the prices of the transactions of the Intraday Continuous Market is also run the same time period, but it is broken down two 24 separate tests. Since there are three time horizons of the data:

- the actual ”real” time of the events (the time hoizont)
- the delivery time of the hourly products
- the time of the transactions of the products (match of buy and sell orders - a tick)

The tests are run for each and every of the 24 hours. Hence, it is considered as 24 different markets for 24 different kind of products.

Both cases are tested by the *rugarch* library package in **R** with the above-mentioned combination of the GARCH and Ljung-Box methods [26]

2.2.1 Testing the EPEX SPOT Day-Ahead Market

The first data set, the hourly DA EPEX Spot market prices from 2015 is visualized in *Figure 7.*

Searching historical events for structural breaks throughout 2015, one can notice the change of the cross-border capacity allocating algorithm from the Available Transfer Capacity to the Flow-Based methodology. [12]

Although, as it can be seen later in *Figure 10*, the first test can be implemented without the structural break(s), since if the EMH got rejected, it is redundant and unnecessary to implement the break(s).

2.2.2 Testing the EPEX Intraday Continuous Market

The prices for four different hours on the intraday continuous market throughout the year 2015 can be seen in *Figure 8* and *Figure 9.* The dataset shows significant differences in prices both for different hours (products) and for clearings. The methodology of the

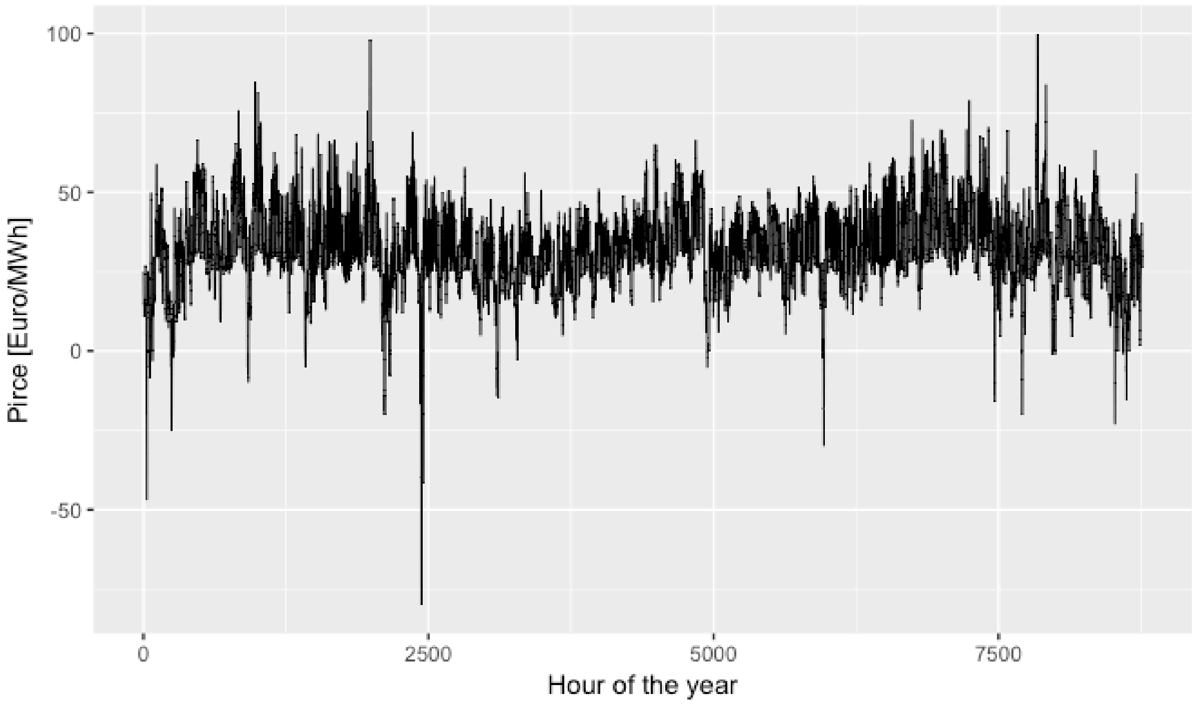


Figure 7: DA hourly prices in 2015

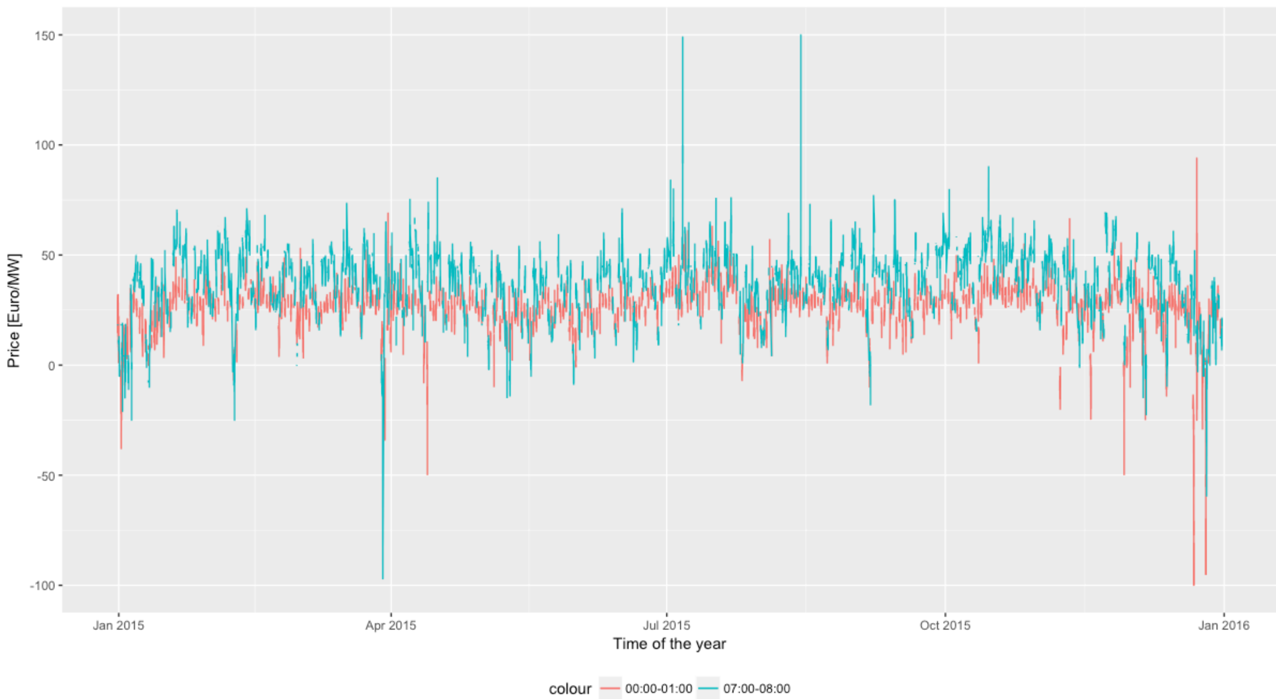


Figure 8: Intraday prices in 2015 for the products between 00:00-01:00 and 07:00-08:00

testing in this case is similar to the previous one in the *Testing the EPEX SPOT Day-Ahead Market* subsection.

The combination of the GARCH and Ljung-Box test is run on the data on the hourly product prices one by one. The same **R** *rugarch* [26] library package is used, except in case of non-convergence a back-up algorithm from the **R** *fGarch* [29] package is used.

Also, as in the case of the test on the DA prices, the GARCH test has been implemented without indigenous structural break.

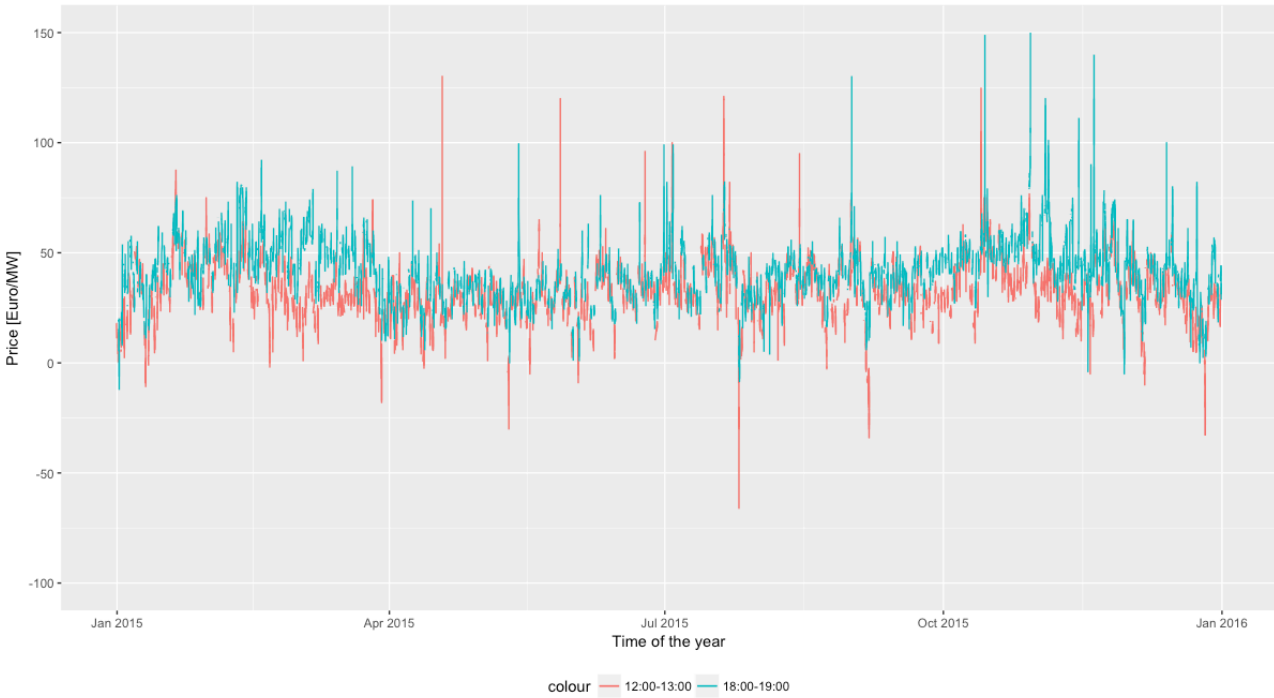


Figure 9: Intraday prices in 2015 for the products between 12:00-13:00 and 18:00-19:00

2.3 Results and Discussion

2.3.1 EPEX DA Market

The results of the hourly EPEX SPOT DA Market dataset test in **R** can be seen in *Figure 10*.

The EMH is rejected without implementing endogenous structural breaks. The $H : 0$ hypothesis in the Ljung-Box test got rejected with a p-value of zero at all of the lags values (4; 5; 9).

Also the statistic values are high and increasing as the number of lags are increasing. One would assume, that this can be interpreted as it is easier to find a pattern in the time series data if more samples are looked at.

```
Weighted Ljung-Box Test on Standardized Residuals
------------------------------------
                        statistic p-value
Lag[1]                      74.63       0
Lag[2*(p+q)+(p+q)-1][5]    381.46       0
Lag[4*(p+q)+(p+q)-1][9]    615.33       0
d.o.f=2
H0 : No serial correlation

Weighted Ljung-Box Test on Standardized Squared Residuals
------------------------------------
                        statistic p-value
Lag[1]                       77.1       0
Lag[2*(p+q)+(p+q)-1][5]      90.0       0
Lag[4*(p+q)+(p+q)-1][9]     107.8       0
d.o.f=2
```

Figure 10: Results of the *rugarch* test on the DA hourly market

2.3.2 EPEX Intraday Continuous Market

The results yielded by the Ljung-Box test via *rugarch* are in the same form as it is in *Figure 10* and summarized in *Table 2*.

In case of all markets the H_0 hypothesis are rejected. As it can be seen in *Table 2* certain markets, in other words, for some time periods they have higher p-value than zero and lower statistic value. This means that these markets are more efficient than others.

Both the EPEX Spot Day-Ahead and (all the) Intraday markets have rejected the EMH. This serves as a justification for the opportunity of arbitrage both within and between the markets, although does not proves its existence.

Table 2: Results of the intraday market test one by one

Hour of the Day	**Lag = 1**		**Lag = 5**		**Lag = 9**	
	Statistic	*P-value*	*Statistic*	*P-value*	*Statistic*	*P-value*
1	307.3	0	314.9	0	337.2	0
2	290.3	0	309.8	0	361	0
3	110.5	0	111.8	0	119.3	0
4	281.4	0	286.9	0	304.9	0
5	213.2	0	2017.2	0	226.2	0
6	380.9	0	385.8	0	390	0
7	287.9	0	317.7	0	381.9	0
8	260.5	0	350.5	0	528	0
9	267	0	270.4	0	281.2	0
10	230.7	0	231.3	0	237.2	0
11	163.4	0	183.7	0	194.6	0
12	177.1	0	204	0	211.5	0
13	194.6	0	239.3	0	251	0
14	663.2	0	676.4	0	682.6	0
15	42.71	6.34E-11	43.51	0	44.8	0
16	11.93	5.11E-04	19.44	0	22.18	4.25E-09
17[2]					283.24 (lag=10)	0
18	570.3	0	579.3	0	586.7	0
19	282.6	0	290.5	0	299.3	0
20	356.1	0	375.4	0	419.9	0
21	252.8	0	258.9	0	288.2	0
22	421.2	0	444.1	0	454	0
23	438	0	448.7	0	505.8	0
24	425.2	0	426.8	0	461.9	0

[2]the *rugarch* test in this case was not converging, thus the very similar *fGarch* test was used

3 Trading on EPEX SPOT

In this section the operation of the market and trading on it is introduced followed by steps of creating trading strategies. The methods are based on the market data of the year 2015.

3.1 Operation and Clearing Algorithm of EPEX SPOT Intraday Market

In order to develop the later proposed trading strategies it is crucial to understand the operation of the EPEX SPOT Intraday Continuous hourly market, especially its clearing algorithm. In this section the definitions are explained and the important algorithms are laid out.

The simplified flowchart of the clearing algorithm can be seen in *Figure 11.* As it is explained in the *EPEX SPOT Market Design* section, the Intraday Continuous hourly market opens at 3.00 pm the day before (d-1) and closes 30 min (in the Germany area) before the delivery hours.

As the order book opens, various kind of sell and buy orders can be submitted. If there are orders, in which case the price of the buy order is higher or equal than the sell order's the orders are executed, a transaction is made (in other words: the market is cleared). If the quantity to sell or buy of the orders are not equal and if the orders can be partially executed, new, so called child order or orders are created of the remaining quantities and re-added to the order book.

If the execution time is closer then the highest lead time of orders depending on the physical location of delivery, matching is not possible.

If the delivery time is closer than the smallest lead time (in Germany 5 min), the order book is closed for the subject day.

On the intraday market, every time there is buy and sell orders match, the market clearing algorithm makes a so called tick or in other words, a transaction is made. A tick represents the clearing price of the subject market, until a new tick is made.

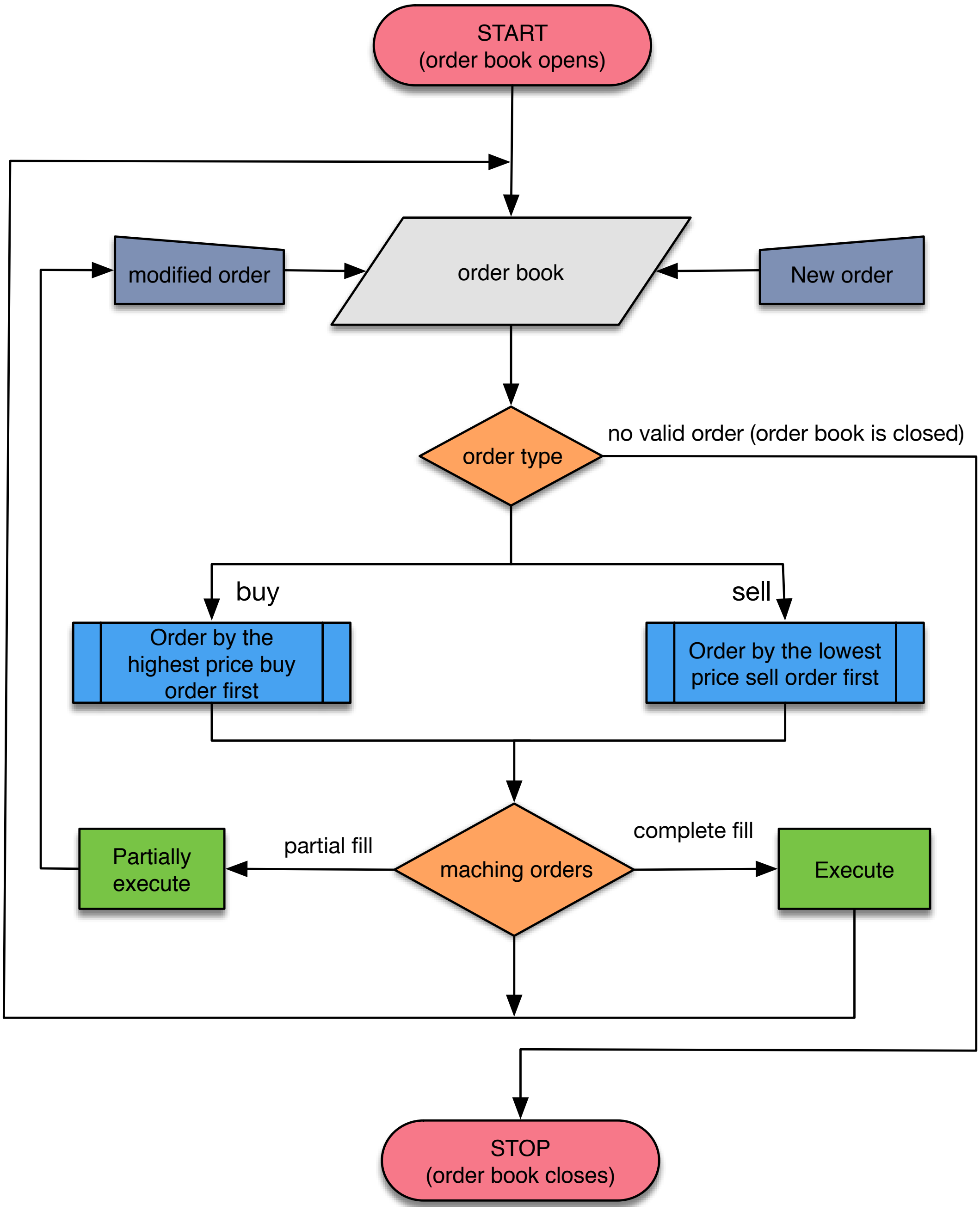


Figure 11: The flowchart of the clearing algorithm

3.2 Analysing Wind Forecast Data

There is a great reason to analyze and consider wind production forecasts for trading strategies. Since the short-term marginal cost of wind production is very low, it is positioned high on the merit order list. Hence, alternation in wind production has a great effect on the electricity prices. This phenomenon is called the *merti-oder effect*. The merit order curve ranks all available generators according to their short-run marginal costs.

The structure of the merit order in Germany and the position of renewable (included wind) is shown in *Figure 12*. [4]

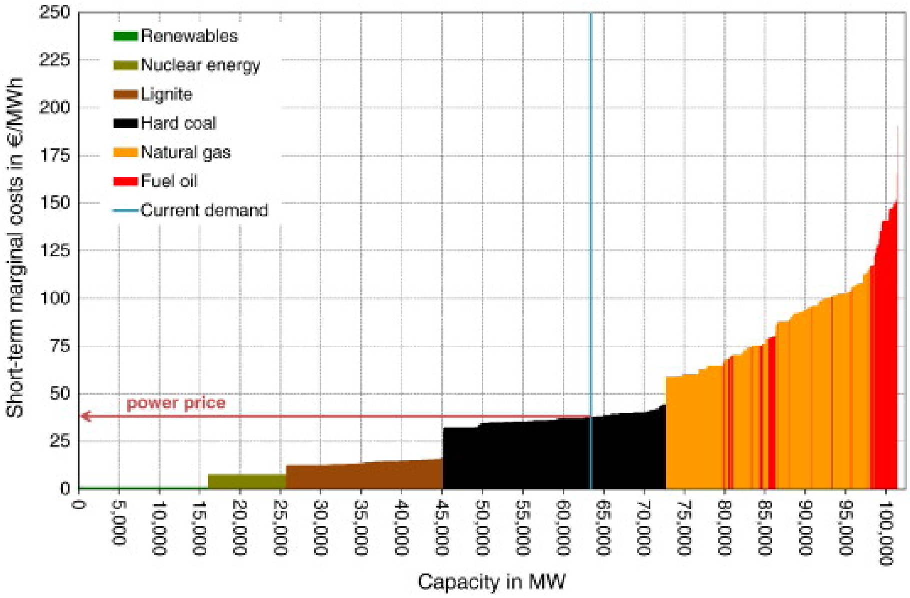


Figure 12: Stylized German merit order curve [4]

A plausible start is to look at the error between the day-ahead forecast and real wind production, since the intraday continuous market's function is to balance out the inefficiency of the day-ahead "predictions". In this thesis two different forecasts are deployed for creating trading strategies. One is provided by the German TSOs and the other one is by the EWeLiNE project by the German Federal Ministry of Economics and Technology (BMWi) [30].

Firstly, in *Figure 13* and *Figure 14*, based on the two different sources, the hourly wind error between the day-ahead forecast and actual production are visualized, respectively. In the figures, the black dots represents the magnitude of the errors in the year 2015, the blue bars are indicating the yearly averages. As it shows the forecast in average deviates from the actual.

The figures are clearly showing the inaccuracy of the forecasts and the differences between the two forecasts. In average, in most of the hours the forecasts exceeds the actual production and only in a few hours are below the actual.

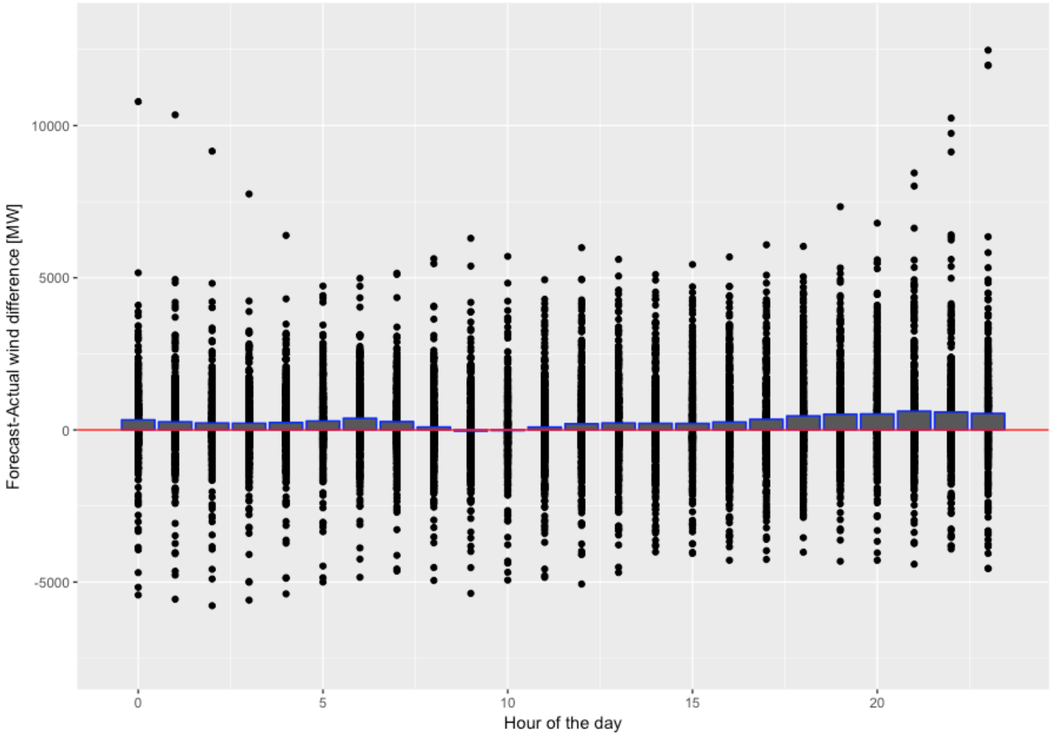


Figure 13: The error between the actual and hourly wind forecast (TSO's forecast)

3.3 Analysing the Market Pricing

This thesis focuses on the leverage opportunity in the pricing inefficiencies between the day-ahead and intraday markets. Thus, based on the data of the EPEX Spot market in 2015 the following figures give a glimpse of the differences in their prices.

Each intraday tick's (transaction) deviation from the day-ahead prices can be seen in *Figure 15* visualized on hourly basis throughout the whole year. The deviations are obviously visible and proved by the traded volume weighted average in *Figure 16*. Depending on the purpose, this average difference between the prices can be used for profit maximizing or cost minimizing trading strategies.

In this case the weighted average difference means, if someone would be able to buy everyday (throughout a year) 1 MWh of energy and sell on the intraday market at every tick's clearing price. This is very unlikely, although a rather suitable approximation of the market potentials.

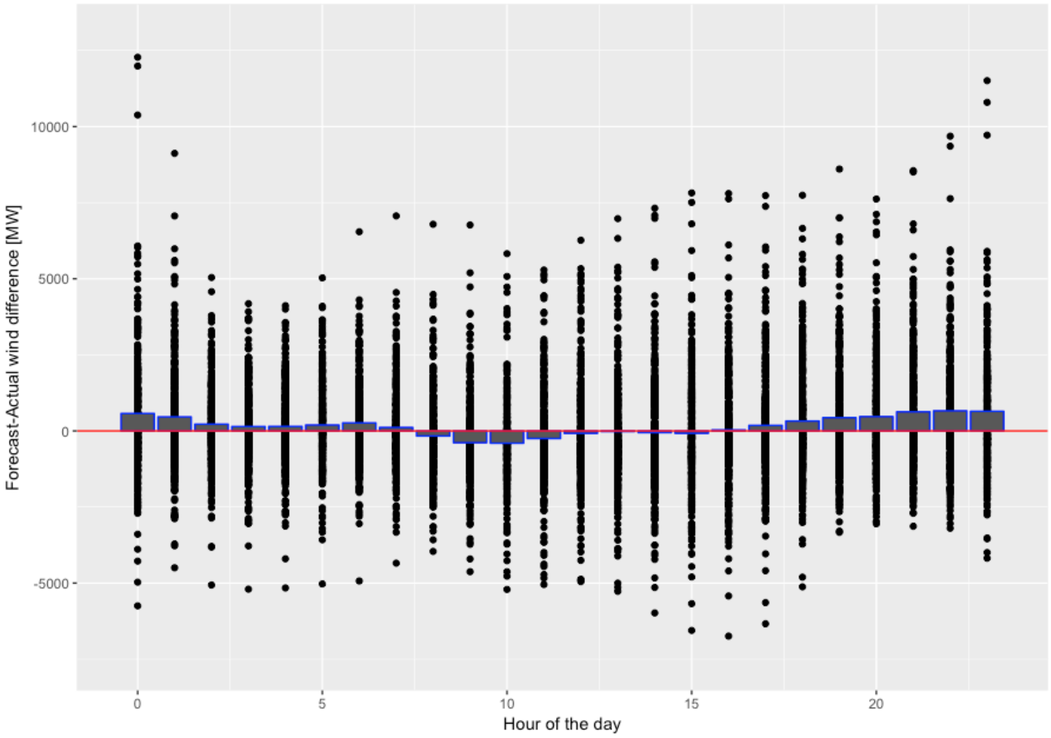


Figure 14: The error between the actual and hourly wind forecast (EWeLiNE's forecast)

In *Figure 17* the correlation between the day-ahead wind forecast error and the hourly average intraday prices can be seen based on the data from 2015.

The blue smoothened curve clearly shows as the actual wind production deviates to the positive direction (surplus production), then the average price decreases, and as it deviates to the negative direction, down to a certain value (about 600MW). This can be explained, as if there is a surplus actual wind production comparing to the forecast, it lowers the prices, since the low marginal cost of the wind production. If it lacks the forecasted wind, the prices go up, because of the shortage of "cheap" electricity production as it can be seen in the merit-order *Figure 12*.

Figure 18 shows the distribution of the profits (or) costs in a hypothetical manner, as if all of the energy traded on the intraday market would have been purchased on the day-ahead prices (as a price-taker). *Figure 18* gives a good glimpse of the potentials of making profits or losses trading between the DA and intraday market.

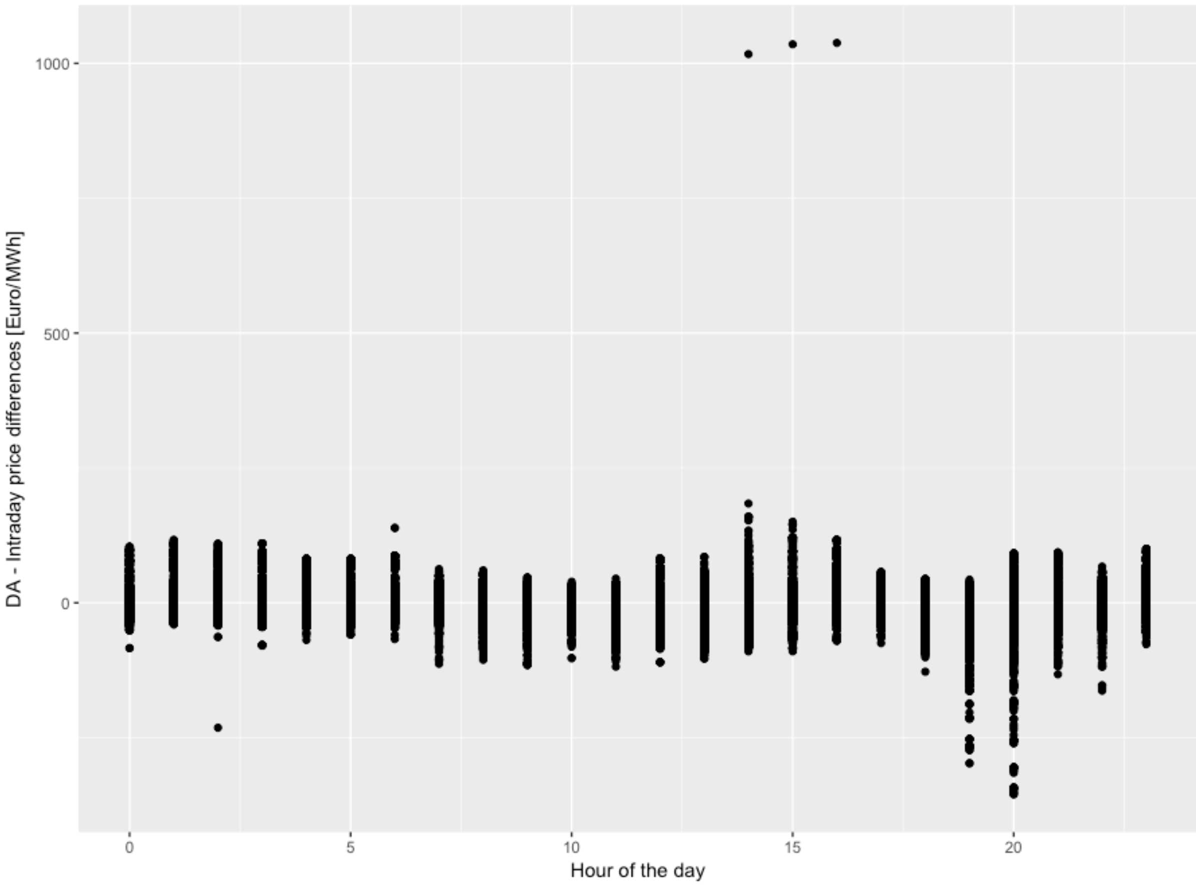


Figure 15: The price difference between the DA prices and each tick (transaction) of the intraday market on a year long hourly resolution

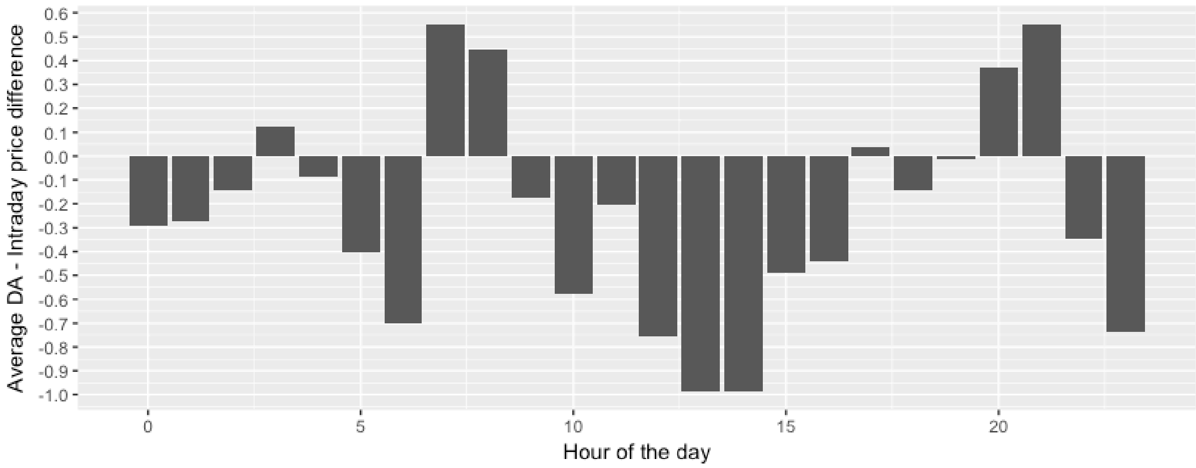


Figure 16: The average price difference between the DA prices and each tick of the intraday market on a year long hourly resolution

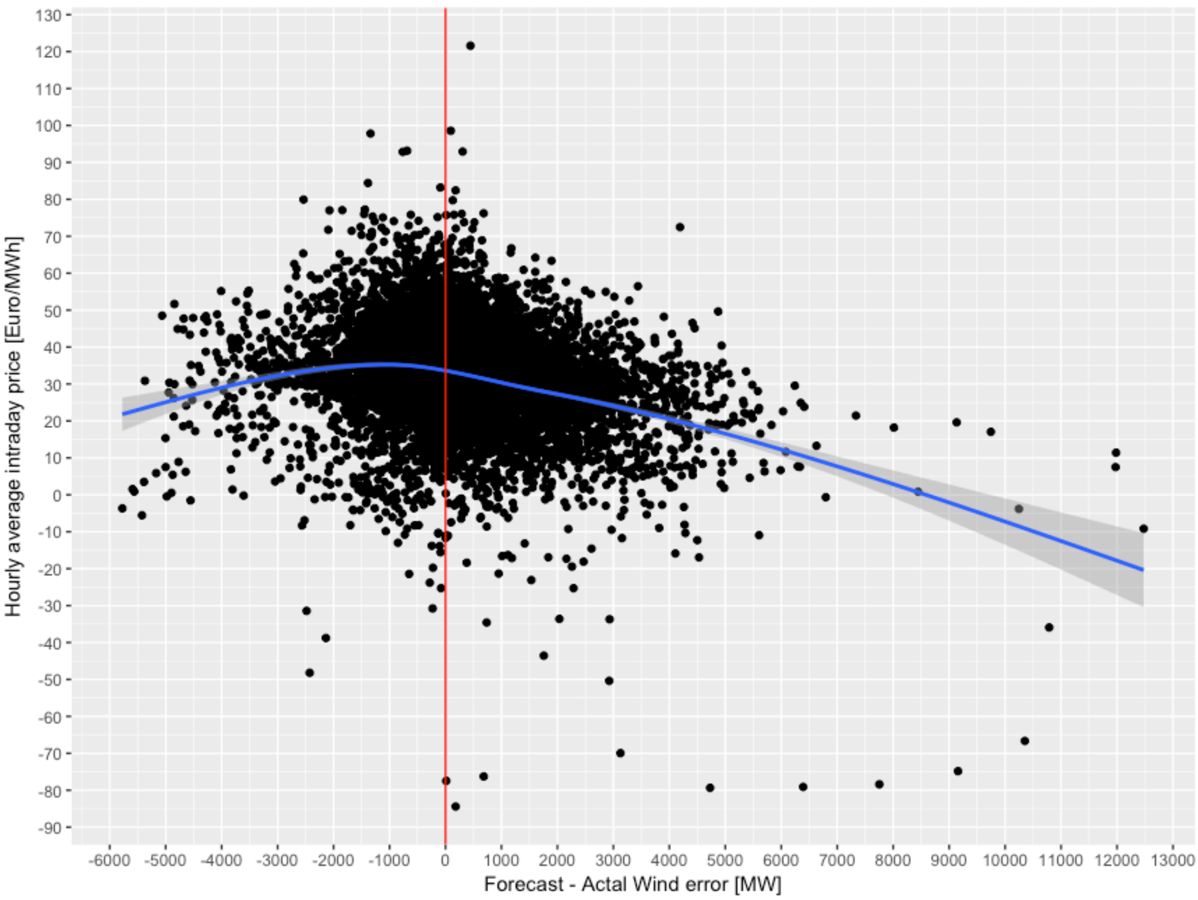


Figure 17: Correlation between the hourly average intraday price and the wind forecast error

In order to demonstrate the potentials regarding to trading on the intraday market, if the day-ahead auction prices are used as the reference to the execution prices of the transactions on the intraday continuous market, the indicators and numbers are as follows:

- $profit = \sum_1^N if(p_n^{id-da} > 0)$
- $loss = -\sum_1^N if(p_n^{id-da} \leq 0)$
- $market\ profit = profit - loss$

where N denotes the total number of transactions (ticks) in a year period and p_n^{id-da} denotes the price of each transaction (tick) on the intraday market minus the day-ahead market price for the same delivery time and date. The *market profit* denotes the hypothetical profit that could be made by all of the market participants by leveraging the price difference between the day-ahead and intraday continuous market as price-takers.

The simulated numbers based on the market prices in 2015 were as follows:

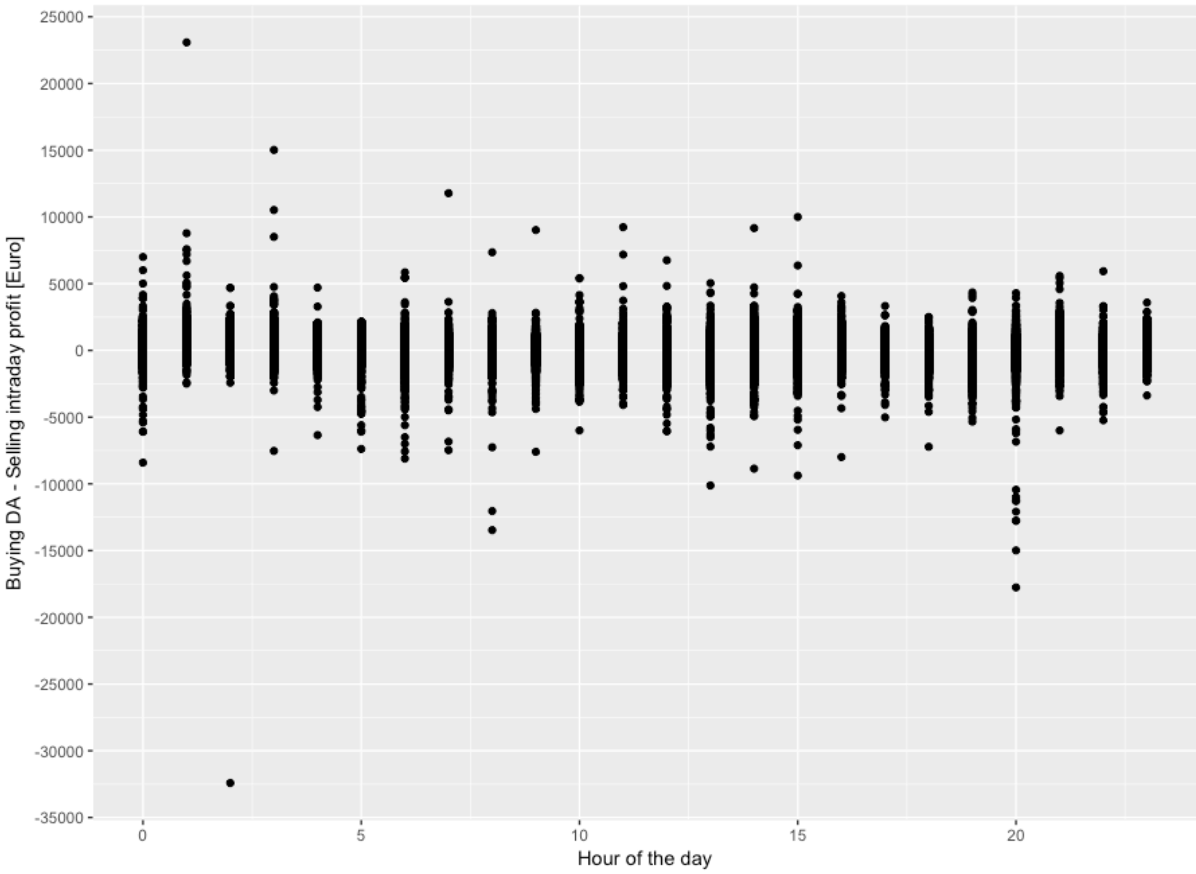


Figure 18: The error between the actual and hourly wind forecast (TSO's forecast)

- $profit$ = 82 224 699.506 €
- $loss$ = -90 168 291.727 €
- $market\ profit$ = -7 943 592.221 €

The numbers, especially the *market profit* indicates, if there is a hypothetical price-taker dummy strategy that would consist of only buying energy on the day-ahead market and then selling it on the intraday continuous market, would come with a negative profit on average, in other words it would come as a loss. Also, in average the prices on the intraday continuous market are lower than on the day-ahead spot (this was the case based on the EPEX data from 2015).

3.4 Possible Trading Strategies

In this section a few possible trading strategies are introduced to demonstrate the potentials.

Important to clarify that in this thesis the *trader* (the trading strategy) is considered to be a price-taker on the day-ahead market, that means its transactions are unable to affect the market prices or the acts of other traders.

In order to create a profitable trading strategy, it has to successfully execute the following tasks:

- decide the amount of energy to buy on the day-ahead to sell on the intraday market
- create a good partitioning (orders of smaller amounts) of the energy to sell on the intraday market
- decide the price of the orders
- find the most appropriate time to place the order(s) on the intraday market

In this case partitioning the amount of energy to sell into smaller orders gives more pricing options, thus more adaptive pricing can be achieved that can be promising in terms of profit gain.

The management of placing and keeping the orders in the order book and resubmitting with an other price in the right timeframe is also very crucial.

3.4.1 The best case

The first "best case" assumes the *trader* owns the (nearly) perfect wind forecast as if it would the actual one.

In this demonstration, the hourly product between 8:00-9:00 is chosen to trade, since as it can be seen in *Figure 16* the price difference between the intraday and day-ahead markets in average in favour of the buying day-ahead, selling on the intraday continuous market strategy.

The forecast used by the TSOs is considered to be a common knowledge that is public and known by the other market participants.

The following figures are aiming to give a comprehensive review of the order book in case of the 8:00-9:00 product.

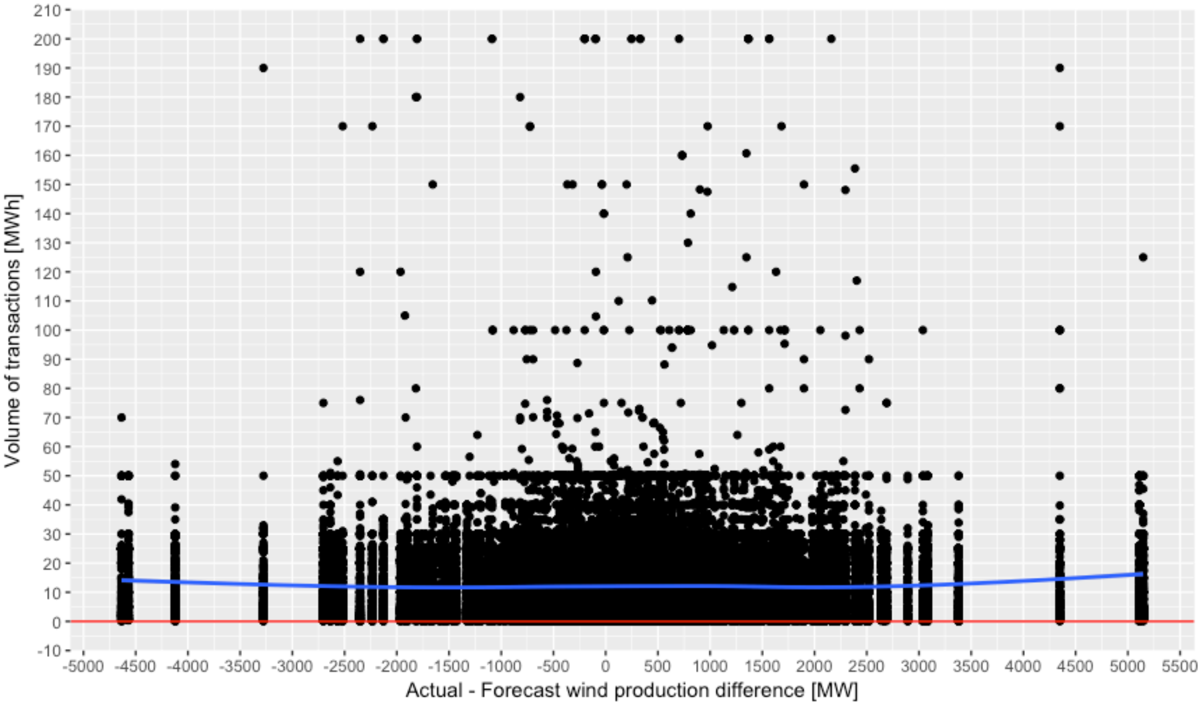


Figure 19: The volume distribution of the transactions on the intraday market for 8:00-9:00 product in regards of the wind production forecast error in 2015

Figure 19 shows the correlation between error of the wind forecast and the actual production, and the volume of each transaction executed at that error value. The smoothened line fitted on the data is an indication of the somewhat even distribution of the volumes at smaller wind production deviations.

Figure 20 and *Figure 22* show the distribution of the transaction volumes regarding to the time to delivery (in seconds). As it is explained in *Figure 6*, up until July 16, 2015 the lead time (gate closure to delivery) was 45 min (2700 sec) and was reduced to 30 min (1800 sec) afterwards, this should be considered during analysing the dataset. As the figures, especially *Figure 22* shows the density of orders in time grows as the time to gate closure is getting less.

The conclusion can be drawn that in case of considering to operate within the range lower wind production forecast errors, it is not that important to make distinction within the wind forecast errors regarding to the average order volumes.

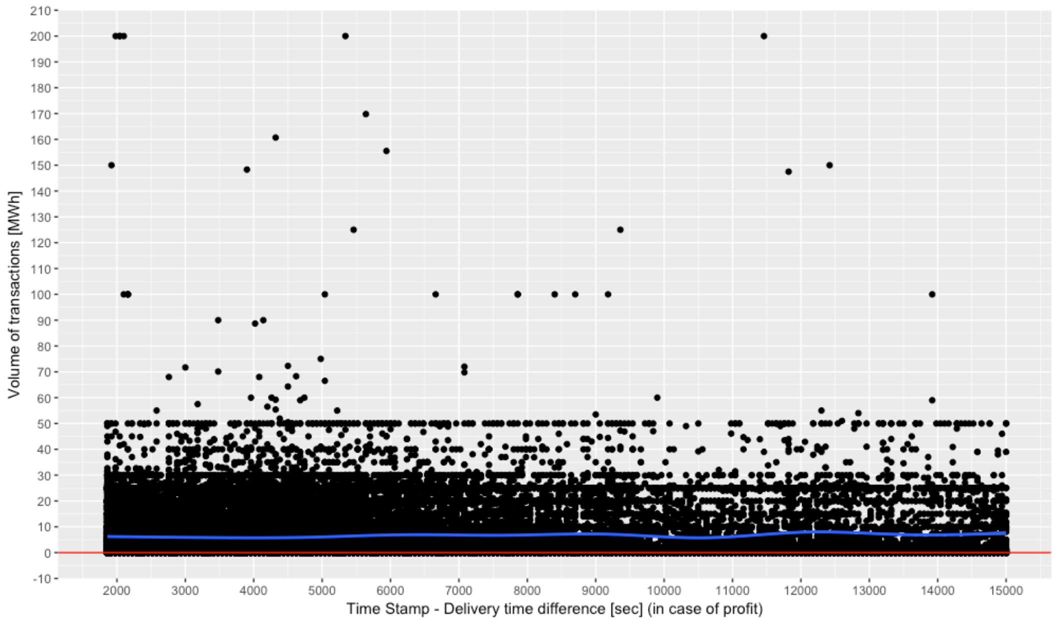


Figure 20: The volume distribution of the profitable transactions regarding to time to delivery

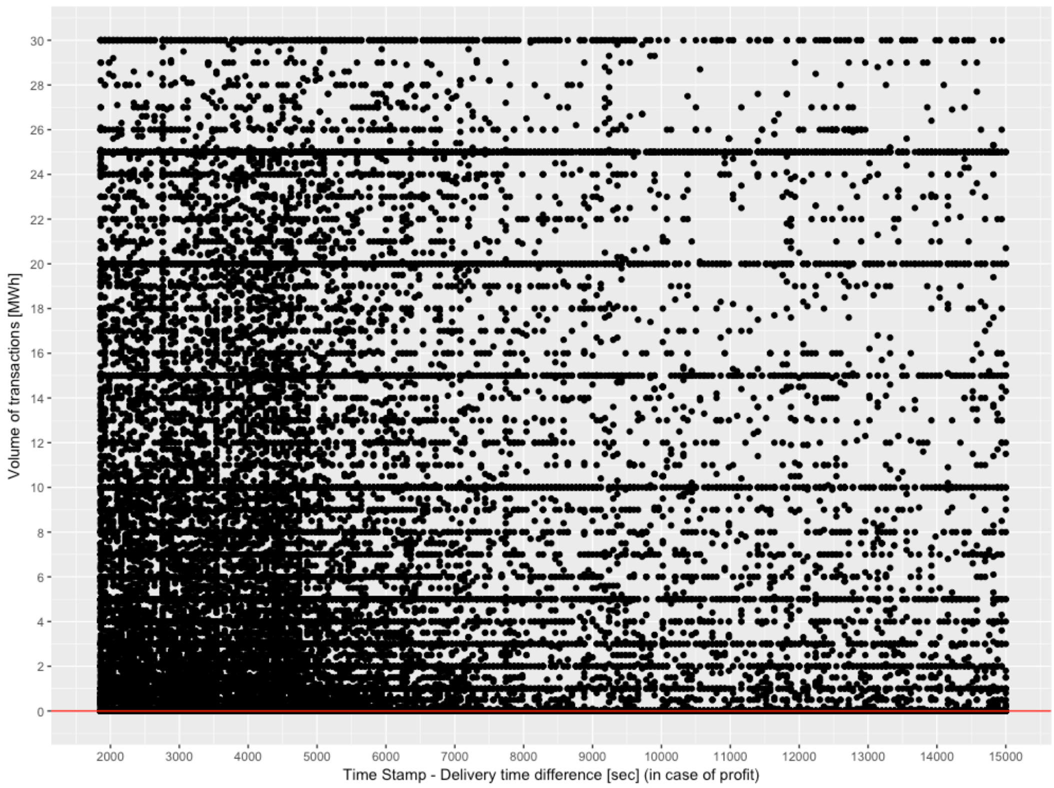


Figure 21: Zoomed in *Figure 20*

3.5 Trading Strategy Design

The task of a trading strategy is to make profit. It is more practical to construct a strategy for the long run, say, for year long. This means, at certain time period(s) it is likely that the strategy would not make profit or probably even make a loss. Although, considering a long period, the total sum of the transactions generates profit. In principle, the longer the trading period, statistically, it is more likely to make a trading algorithm converge to an average profit.

A strategy should consider the distribution of the orders both in time (to the gate closure) and regarding to the amount of wind production forecast or forecast error.

Also, the amount of energy to buy on the day-ahead spot market should be decided based on the previous points.

One way of implementation is the ”trial and error” method, that means tuning the trading algorithm manually, based on a priori data observations and posteriori adjustments based on the errors.

An other way of implementation involves machine learning algorithms, such as artificial neural networks or regressions. Having the historical data sets, the intelligent algorithms can be trained to predict future market situations and adjust the strategy to leverage the it's predictions.

3.6 Trading Strategy Requirements

In order to be able to place profitable orders on the intraday market (based on the DA prices), the prediction of the price and volume of orders to place in crucial.

The profit of a designated h hourly product made by trading based on the model is calculated as follows

$$P(h) = \sum_{1}^{N} (p_{hn}^{id-da} * v_{hn}) \tag{11}$$

where P is the profit, h is the designated hourly product, N is the total number of the placed orders on the intraday market, n is the number of a placed order, p_{hn}^{id-da} is the price difference between an intraday order and the DA price, v_{hn} is the volume of a placed order.

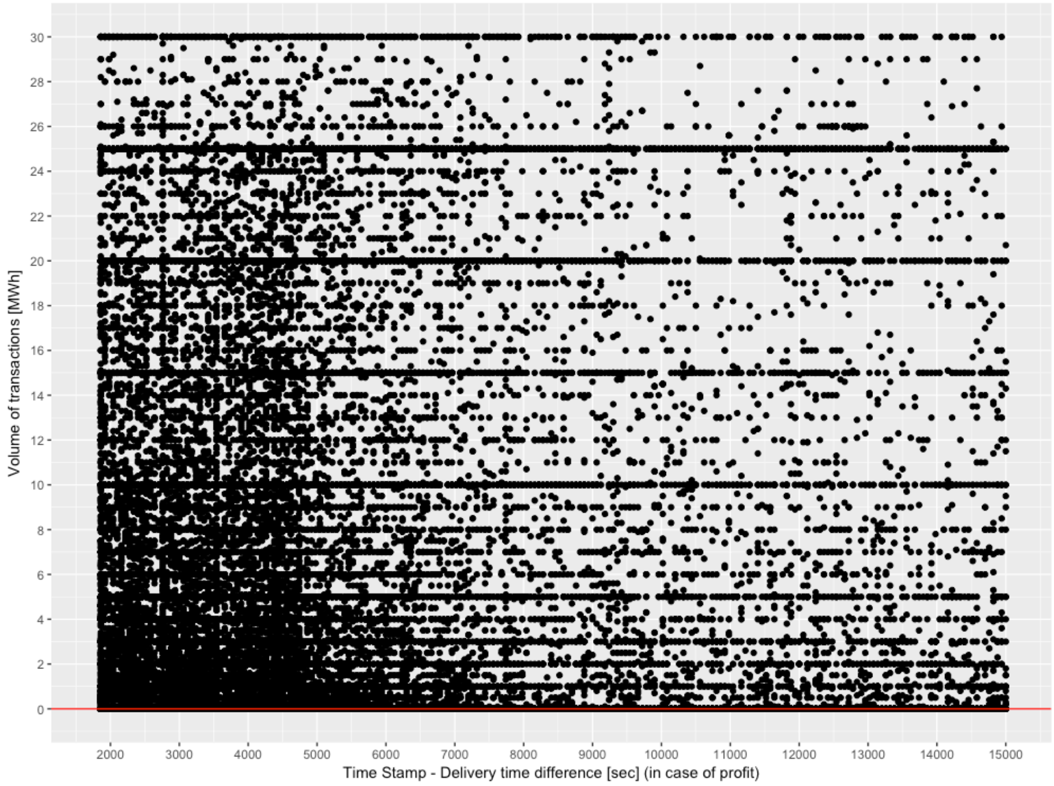


Figure 22: Zoomed in *Figure 20*

3.7 Long Short-Term Memory Recurrent Neural Networks - LSTM RNN

For the market prediction model Recurrent Neural Network (RNN) is utilized with Long Short-Term Memory (LSTM) structure.

3.7.1 Artificial Neural Network (ANN)

The Artificial Neural Network (ANN) can be demonstrated through *Figure 23*. The atomic element of an ANN is a neuron. A neuron has an activation function that describes the firing of a neuron. The neurons connected to each other via synaptic weights from other neurons, they add up and assigned to the activation function of the next neuron. There are various activation function depending on the application and kind of ANNs. The neurons are organized into layers as it is depicted in *Figure 23*. There are typically three kind of layers: input, hidden and output. The input layer represent the nuerons of the input ”data points”. The hidden is the doing the ”processing” of the network. Its size (amount of neurons and layers) and connections is up to the logic behind its tasks. The output represents the "answer" of the ANN to the input data. [5]

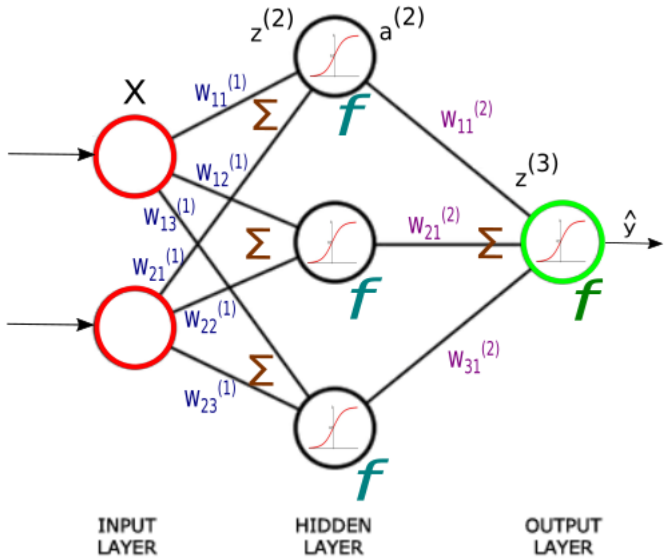


Figure 23: The principle of a basic Artificial Neural Network [5]

3.7.2 RNN

The Recurrent Neural Network (RNN) allow the information to persist within them. They do not give answer based on the prevalent input only, they remember previous inputs and consider them when they give the "answer". A RNN has loop in it that allows information to be passed between steps of the network.

An RNN cal be seen on the left side of *Figure 24*, it basically incorporates itself from previous steps as it is depicted in the right side of *Figure 24* as unrolled to previous steps.

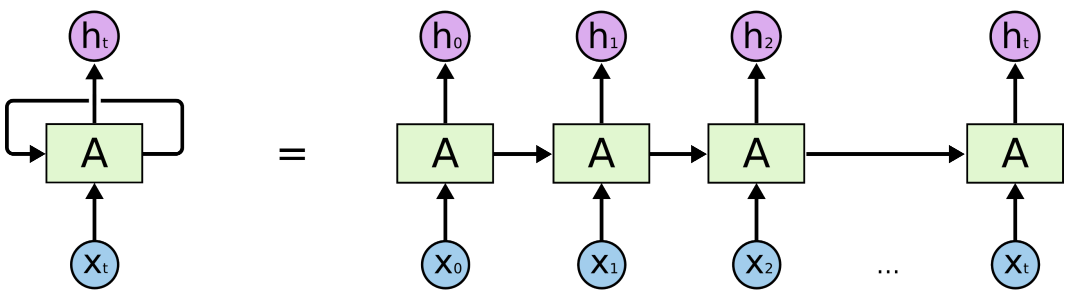


Figure 24: An RNN (with a loop) on the left and unrolled on the right [6]

3.7.3 LSTM

LSTMs have a daisy-chain structure like the RNNs. An LSTM network is depicted in *Figure 25*. The upper horizontal line running through the top of the diagram represents the cell state that is kay to LSTMs. The information can run strait down the whole chain, such the cell state working as conveyor belt, there is only some minor linear interaction to it.

The pink gates optionally run information through, they made up of a pointwise multiplication operation and a sigmoid neural net layer before the arithmetic operation. The sigmoid layer decides how much of each component should be let through. It is scaled between zero and one (noting and everything let through). There are three of these gates in order to control (or protect) the cell state. The training of the neural networks is based on the backpropagation algorithm.

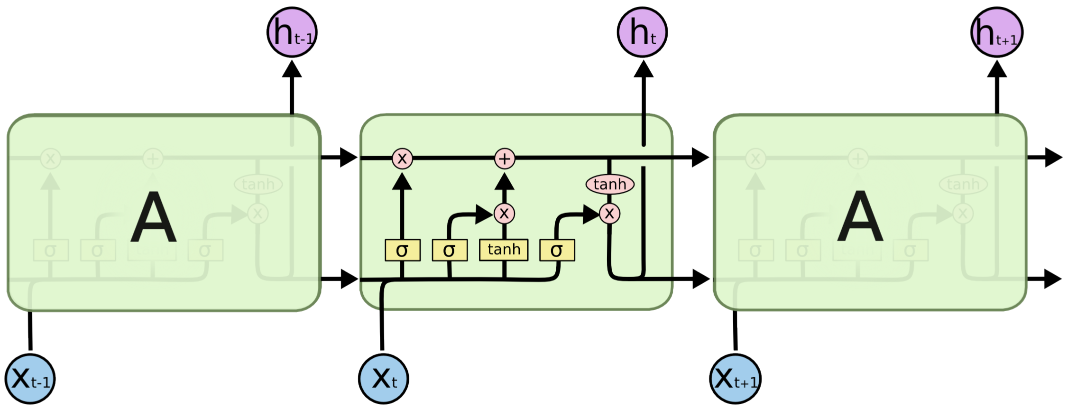


Figure 25: A repeating module in an LSTM in this case with four interacting layer within [6]

3.8 LSTM Model Structure

The basic "blackbox" model is depict on *Figure 26* and clearly defines the function of it. The input dataset is the day-ahead wind prediction and the output is the time, price and the volume of orders to place o the intraday market. The time frame of order placing is between a 9-32 hours, from the opening of the intraday market at 3 pm (D-1) until the delivery. Hence, the time-volume-price prediction of each hourly product requires customisations on the model.

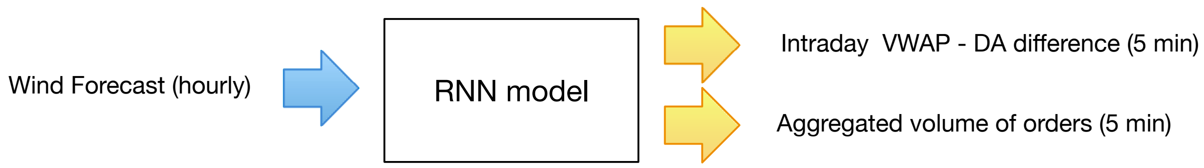


Figure 26: A simple description of the base model

The changing trading time frames are demonstrated in *Figure 27*

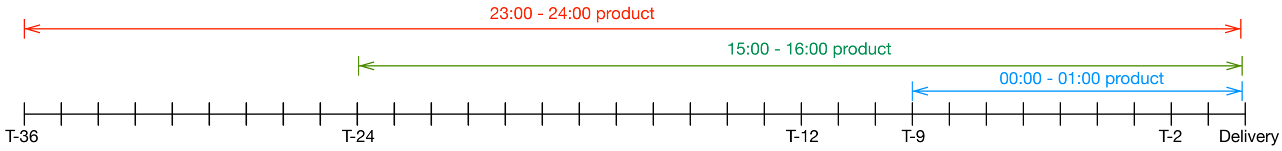


Figure 27: Time frames

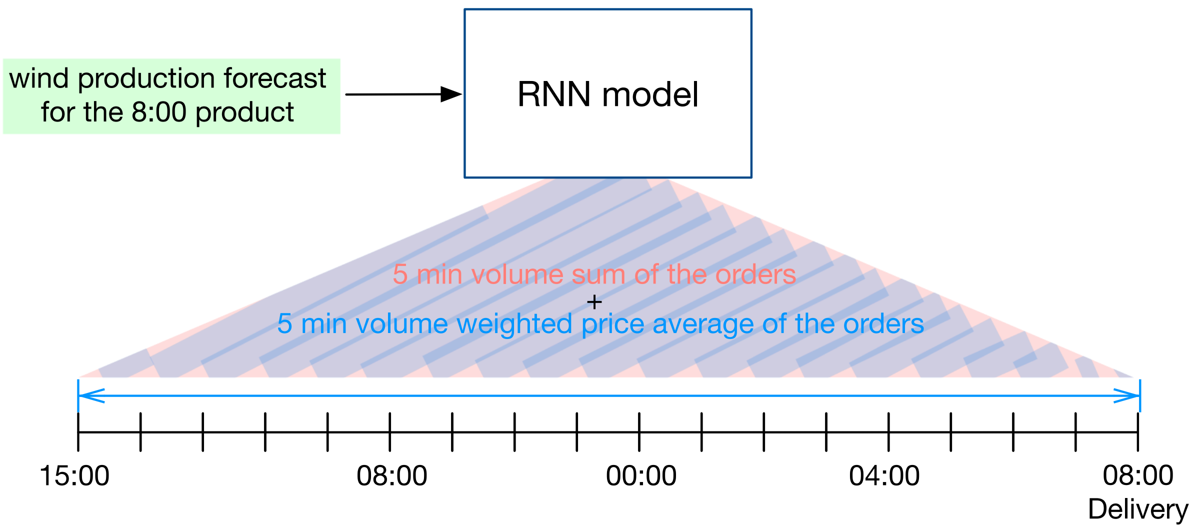


Figure 28: An example trading RNN model and its multiple training input and outputs (8:00-9:00 hourly product)

In order to leverage the periodicity of the data, the training periods are merged together as it can be seen in *Figure 29*. The trading algorithm should be customized according to the time frames. In case of the 8:00-9:00 product the structure of a trading algorithm is depicted in *Figure 28*. The input is the wind production and the output the a 5 minute resolution (12 tick per hour) of the Volume Weighted Average Price (VWAP). In case of the 8:00-9:00 product that means 199 tick throughout the 16.5 hours of trading period (in case of 30 lead time).

The daily historical data is merged into a continuous data flow in order to leverage the periodicity nature of the data that the LSTM can handle easier. The idea of the merged data based on *Figure 28* is visually explained in *Figure 29*.

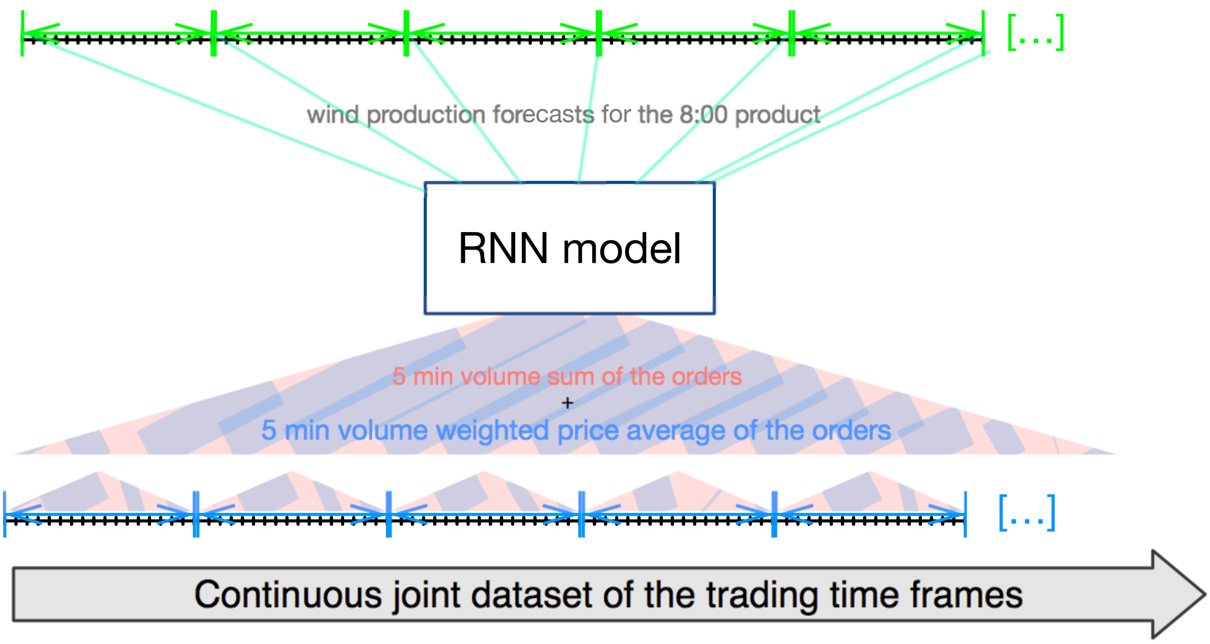


Figure 29: The continuous transformed model for the 8:00-9:00 hourly product

The LSTM algorithm is implemented in Python with the help of Keras library [31] that was developed to carry out such RNN and LSTM tasks. The implementation code of the algorithm can be seen in *Appendix - Python code for the LSTM RNN model* with brief comments for better the understanding.

In the demonstration case the used data columns from the 2015 historical order book data are as follows:

- the real historical wind based energy production
- VWAP in five minute resolution
- the sum of the traded quantity in the five minute periods

The data is prepared in *R* and then imported into Python.

4 Model results and outcome

The result of the working model has not come with the expected outcomes at all. As it can be seen in *Appendix - Python code for the LSTM RNN model* the results are totally wrong and devastating. Neural network can work properly if the input data is correct, easily understandable to it. If the nature of the input information is not correct or not in the correct form the processing of the neural network can go very wrong. Deploying deep learning needs profound knowledge, since the so to so ”randomness” in the network should be address with good competence.

Although, the results are not, but the idea and the steps of building up such model with detailed data analysis in big data (more than 10 Million data points) can be useful for future developments.

Detailed results are present in *Appendix - model results*.

5 Conclusions

As it has been proven in the *Test for Market Efficiency* section, the markets to trade between are not efficient, they reject the EMH. In oder words, it is justified to attempt to construct profitable trading strategies between them, although the existence of arbitrage cannot be proven by the test and it is not inherently incorporated in the inefficiency of the markets.

In the market analysis, the EPEX day-ahead and intraday continuous spot market's data from the year 2015 have been investigated.

The price differences between the markets, the price in correlation with the wind production and the distributions of the orders on the intraday market, show a promising chance to develop profitable trading strategies.

The steps and idea of an approach of a trading algorithm is laid out. Data grooming and fitting for the algorithm were carried out. Although the idea is promising, the complexity of a such development of a trading strategy and algorithm is very high.

The continuation of this project can be a deep analysis of the underlying neural network algorithm and correction both of the input data and algorithm if needed. Also, there can be found other correlation within the market data or with external data. Such correlations can be leveraged in prediction models that would help to create a successful strategy and an underlying algorithm model.

A Appendix - Python code for the LSTM RNN model

```
# importing modules
import numpy
import matplotlib.pyplot as plt
import pandas as pd
import math
import seaborn as sns

from keras.models import Sequential
from sklearn.metrics import mean_absolute_error
from keras.utils import plot_model
from keras.layers import Dense
from keras.layers import LSTM
from sklearn.preprocessing import MinMaxScaler
from sklearn.metrics import mean_squared_error


# import data and show the head of it
data = pd.read_csv("HOUR_DATA.csv")
data.head()
```

	Index	TimeToDelivery1	TimeToDelivery2	product	ActualWind	VolSum	SecToDelivery	VWAPMinusPriceDA	Index2
0	1.420185e+09	2700	3000	1420182000	26247.5	265.4	3000	-44.355313	1
1	1.420185e+09	3000	3300	1420182000	26247.5	549.5	3300	-50.863649	2
2	1.420186e+09	3300	3600	1420182000	26247.5	294.3	3600	-35.481532	3
3	1.420186e+09	3600	3900	1420182000	26247.5	161.0	3900	-30.268634	4
4	1.420186e+09	3900	4200	1420182000	0.0	0.0	0	0.000000	5

Figure 30: The head of the input data of the RNN

```
# scaling the input data between 0,1
in_scaler = MinMaxScaler(feature_range=(0, 1))
```

```
# scaling the output data between 0,1
out_scaler = MinMaxScaler(feature_range=(0, 1))

# sorting the scaled data columns
data_in = in_scaler.fit_transform(data[["ActualWind"]])
data_out = out_scaler.fit_transform(data[["VolSum","VWAPMinusPriceDA"]])
data["ActualWind_scaled"]=data_in[:,0] data["VolSum_scaled"]=data_out[:,0]
data["VWAPMinusPriceDA_scaled"]=data_out[:,1]
data.head() # head of the data
```

product	ActualWind	VolSum	SecToDelivery	VWAPMinusPriceDA	Index2	ActualWind_scaled	VolSum_scaled	VWAPMinusPriceDA_scaled
1420182000	26247.5	265.4	3000	-44.355313	1	0.857145	0.261555	0.049836
1420182000	26247.5	549.5	3300	-50.863649	2	0.857145	0.541539	0.000000
1420182000	26247.5	294.3	3600	-35.481532	3	0.857145	0.290036	0.117786
1420182000	26247.5	161.0	3900	-30.268634	4	0.857145	0.158668	0.157702
1420182000	0.0	0.0	0	0.000000	5	0.000000	0.000000	0.389479

Figure 31: The head of the input data of the RNN extended with the scaled columns

```
# setting up the model, choosing the input and output data
# choosing the proportion of the training and testing data
from sklearn.model_selection import train_test_split
x_train, x_test, y_train, y_test = train_test_split(
        data[["ActualWind_scaled"]].values,
    data[["VolSum_scaled","VWAPMinusPriceDA_scaled"]].values,
    test_size=0.2,
    shuffle=False,
    random_state=195)


#shaping the data
x_train = numpy.reshape(x_train, (x_train.shape[0], 1,
x_train.shape[1]))
x_test = numpy.reshape(x_test, (x_test.shape[0], 1,
 x_test.shape[1]))
```

```
# create and fit the LSTM network
model = Sequential()
model.add(LSTM(10, input_shape=(1, 1)))
#model.add(LSTM(10,input_shape=(1, 1)))
model.add(Dense(2,activation="sigmoid"))
#model.add(Flatten())
model.add(Dense(2, activation="linear"))
model.compile(loss='mean_squared_error', optimizer='adam')

# run the model fit
model.fit(x_train, y_train, epochs=10, batch_size=1, verbose=2)



# make predictions
trainPredict = model.predict(x_train)
testPredict = model.predict(x_test)
# invert predictions
trainPredict = in_scaler.inverse_transform(trainPredict)
trainY = out_scaler.inverse_transform(y_train)
testPredict = in_scaler.inverse_transform(testPredict)
testY = out_scaler.inverse_transform(y_test)
# calculate root mean squared error
trainScore = math.sqrt(mean_squared_error(y_train[:,0],
trainPredict[:,0]))
trainScore_abs = mean_absolute_error(y_train[:,0],
trainPredict[:,0])
print('Train Score: %.2f RMSE' % (trainScore))
print('Train Score - absolute: %.2f MAE' % (trainScore_abs))
testScore = math.sqrt(mean_squared_error(y_test[:,0],
testPredict[:,0]))
testScore_abs = mean_absolute_error(y_test[:,0],
```

```
testPredict[:,0])

print('Test␣Score:␣%.2f␣RMSE' % (testScore))
print('Test␣Score␣-␣absolute:␣%.2f␣MAE' % (testScore_abs))

# calculate mean absolute error
trainScore = math.sqrt(mean_squared_error(y_train[:,1],
trainPredict[:,1]))
trainScore_abs = mean_absolute_error(y_train[:,1],
trainPredict[:,1])
print('Train␣Score2:␣%.2f␣RMSE' % (trainScore))
print('Train␣Score2␣-␣absolute:␣%.2f␣MAE' % (trainScore_abs))
testScore = math.sqrt(mean_squared_error(y_test[:,1],
testPredict[:,1]))
testScore_abs = mean_absolute_error(y_test[:,1],
testPredict[:,1])

print('Test␣Score2:␣%.2f␣RMSE' % (testScore))
print('Test␣Score2␣-␣absolute:␣%.2f␣MAE' % (testScore_abs))

#plotting the true and predicted Volume data
plt.plot(y_test[:,0], color='red', label='true')
plt.plot(testPredict[:,0],  color='blue', label='predicted')
plt.grid(True)
plt.legend()
plt.show()

#plotting the true and predicted Price data
plt.plot(y_train[:,1], color='red', label='true')
plt.plot(trainPredict[:,1], color='blue', label='predicted')
plt.grid(True)
plt.legend()
plt.show()
```

B Appendix - model results

RMSE and MAE errors with the following model configurations:

```
# create and fit the LSTM network
model = Sequential()
model.add(LSTM(30, input_shape=(1, 1))) # input layer
model.add(Dense(2,activation="sigmoid")) # hidden LSTM layer
model.add(Dense(2, activation="linear")) # output layer
# optimizing algorithm
model.compile(loss='mean_squared_error', optimizer='adam')
```

Train Score: 895.44 RMSE
Train Score - absolute: 347.48 MAE
Test Score: 909.28 RMSE
Test Score - absolute: 354.38 MAE
Train Score2: 12005.25 RMSE
Train Score2 - absolute: 12005.19 MAE
Test Score2: 12004.98 RMSE
Test Score2 - absolute: 12004.91 MAE

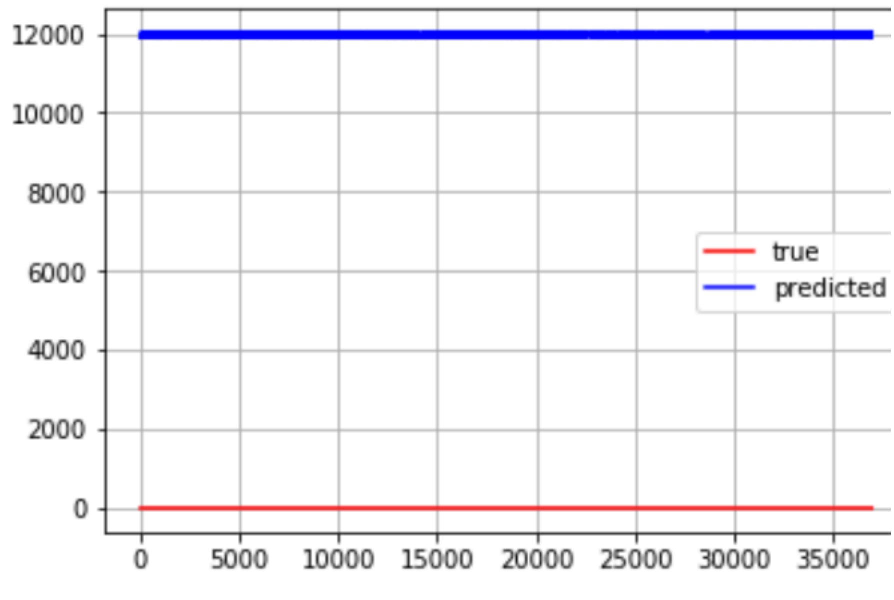


Figure 32: Graph of the true and predicted price data

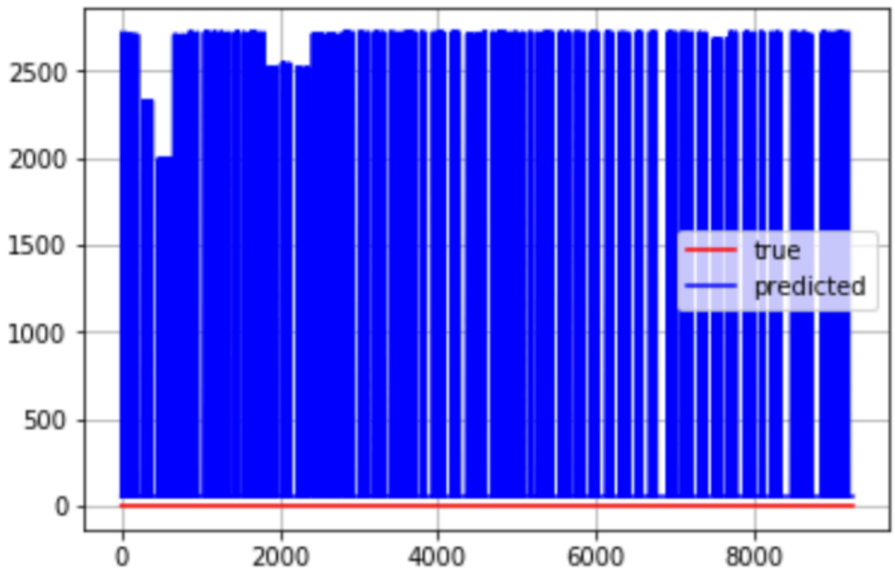


Figure 33: Graph of the true and predicted price data

References

[1] F. Institute, "Installed power in Germany | Energy Charts," 2017. [Online]. Available: https://www.energy-charts.de/power_inst.htm?year=all&period=annual&type=power_inst

[2] "WINDENERGIE REPORT DEUTSCHLAND 2016," FRAUNHOFER-INSTITUT FÜR WINDENERGIE UND ENERGIESYSTEMTECHNIK IWES, Tech. Rep. [Online]. Available: http://publica.fraunhofer.de/eprints/urn_nbn_de_0011-n-4456098.pdf

[3] P. Adigbli, "Kurzfristhandel in Europa – Day-Ahead & Intraday Märkte der EPEX SPOT," Berlin, Jun. 2017. [Online]. Available: http://www.strommarkttreffen.org/2017-06-02_Adigbli-Kurzfristhandel_in_Europa.pdf

[4] J. Cludius, H. Hermann, F. C. Matthes, and V. Graichen, "The merit order effect of wind and photovoltaic electricity generation in Germany 2008–2016: Estimation and distributional implications," *Energy Economics*, vol. 44, pp. 302–313, Jul. 2014. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0140988314001042

[5] "Artificial Neural Network (ANN) - Introduction - 2018." [Online]. Available: http://www.bogotobogo.com/python/scikit-learn/Artificial-Neural-Network-ANN-1-Introduction.php

[6] "Understanding LSTM Networks – colah's blog." [Online]. Available: http://colah.github.io/posts/2015-08-Understanding-LSTMs/

[7] O. Renn and J. P. Marshall, "Coal, nuclear and renewable energy policies in Germany: From the 1950s to the "Energiewende"," *Energy Policy*, vol. 99, no. Supplement C, pp. 224–232, Dec. 2016. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0301421516302294

[8] BMWi, "The Energy of the Future The Energy of the Future - Fourth "Energy Transition" Monitoring Report – Summary - The Federal Ministry for Economic Affairs and Energy (BMWi)," The Federal Ministry for Economic Affairs and Energy (BMWi), Berlin, Tech. Rep., Nov. 2015. [Online]. Available: https://www.bmwi.de/Redaktion/EN/

Publikationen/vierter-monitoring-bericht-energie-der-zukunft-kurzfassung.pdf?__blob=publicationFile&v=14

[9] C. Mitchell, D. Bauknecht, and P. M. Connor, "Effectiveness through risk reduction: A comparison of the renewable obligation in England and Wales and the feed-in system in Germany," *Energy Policy*, vol. 34, no. 3, pp. 297–305, Feb. 2006. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0301421504002411

[10] "Wind power in Germany," *Wikipedia*, Nov. 2017, page Version ID: 809513181. [Online]. Available: https://en.wikipedia.org/w/index.php?title=Wind_power_in_Germany&oldid=809513181

[11] "EPEX SPOT SE: Details." [Online]. Available: https://www.epexspot.com/en/press-media/press/details/press/FLOW-BASED_METHODOLOGY_FOR_CWE_MARKET_COUPLING_SUCCESSFULLY_LAUNCHED

[12] "EPEX SPOT Workshop," Zurich, Jul. 2015. [Online]. Available: https://www.epexspot.com/document/32776/EPEX%20SPOT%20Presentation_Zurich%20Workshop_2015%2007%2002_Final.pdf

[13] "EPEX SPOT SE: Trading Brochures." [Online]. Available: https://www.epexspot.com/en/extras/download-center/brochures

[14] "EPEX SPOT SE: Documentation." [Online]. Available: https://www.epexspot.com/en/extras/download-center/documentation

[15] EPEX, "Press Release - Epex Spot," Paris/Leipzig, Tech. Rep., Jun. 2017. [Online]. Available: https://www.epexspot.com/document/37626/170612_EPEX%20SPOT_Exchange%20Council.pdf

[16] E. F. Fama, "Efficient Capital Markets: A Review of Theory and Empirical Work," *The Journal of Finance*, vol. 25, no. 2, pp. 383–417, 1970. [Online]. Available: http://www.jstor.org/stable/2325486

[17] H. H. Lean, V. Mishra, and R. Smyth, "Chapter 4 - The Relevance of Heteroskedasticity and Structural Breaks when Testing for a Random Walk with High-Frequency Financial Data: Evidence from ASEAN Stock Markets," in *The Handbook of High Frequency Trading*, G. N. Gregoriou, Ed. San Diego: Academic Press, 2015, pp. 59–74. [Online]. Available: http://www.sciencedirect.com/science/article/pii/B978012802205400004X

[18] B. Vanstone and T. Hahn, "Chapter 3 - Data Characteristics for High-Frequency Trading Systems," in *The Handbook of High Frequency Trading*, G. N. Gregoriou, Ed. San Diego: Academic Press, 2015, pp. 47–57. [Online]. Available: http://www.sciencedirect.com/science/article/pii/B9780128022054000038

[19] T. Shabbir, "Chapter 7 - High-Frequency Trading: Implications for Market Efficiency and Fairness," in *The Handbook of High Frequency Trading*, G. N. Gregoriou, Ed. San Diego: Academic Press, 2015, pp. 113–122. [Online]. Available: http://www.sciencedirect.com/science/article/pii/B9780128022054000075

[20] EUROPEAN and European Comission, "REGULATION OF THE EUROPEAN PARLIAMENT AND OF THE COUNCIL on the internal market for electricity," European Comission, Brussels, Tech. Rep., 2017. [Online]. Available: http://ec.europa.eu/energy/sites/ener/files/documents/1_en_act_part1_v9.pdf

[21] "Arbitrage," Apr. 2008. [Online]. Available: http://www.investopedia.com/exam-guide/cfa-level-1/derivatives/arbitrage.asp

[22] A. S. A. E. Enien, "Efficient electricity markets," in *2013 IEEE Grenoble Conference*, Jun. 2013, pp. 1–6.

[23] H. Lütkepohl, *New Introduction to Multiple Time Series Analysis.* Springer Science & Business Media, Jul. 2007.

[24] W. Enders, *Applied Econometric Time Series, 4th Edition.* Wiley, Nov. 2014.

[25] W. H. Greene, *Econometric Analysis.* Prentice Hall, 2000.

[26] A. Ghalanos, "Rugarch: Univariate GARCH Models," Aug. 2015. [Online]. Available: https://cran.r-project.org/web/packages/rugarch/index.html

[27] "Ljung–Box test," *Wikipedia*, Jun. 2017, page Version ID: 788183631. [Online]. Available: https://en.wikipedia.org/w/index.php?title=Ljung%E2%80%93Box_test&oldid=788183631

[28] S. NIST, "E-Handbook of Statistical Methods," 2012. [Online]. Available: http://www.itl.nist.gov/div898/handbook/pmc/section4/pmc4481.htm

[29] "CRAN - Package fGarch." [Online]. Available: https://cran.r-project.org/web/packages/fGarch/

[30] W. Deutscher, f. W. E. Fraunhofer, and E. S. Technology, “EWeLiNE - Home,” 2017. [Online]. Available: http://www.projekt-eweline.de/en/index.html

[31] “Keras Documentation.” [Online]. Available: https://keras.io/