An Approach for Detecting Potential Market Anomalies in the Balancing Power Market Using Screening Analysis and Regression Analysis

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Master in Electric Power Engineering
Date: December 12, 2019
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Examiner: Lina Bertling Tjernberg
School of Electrical Engineering and Computer Science
Host company: Svenska kraftnät (Swedish national grid)
Swedish title: Ett tillvägagångssätt för att upptäcka potentiella marknadsavvikelser i balanskraftsmarknaden med screeninganalys och regression
Abstract

In accordance to the insertion of the regulation "(EU) nr 1227/2011" (REMIT), responsibilities and duties for participants as well as a People Professionally Arranging Transactions (PPAT) comes to maintain a competitive and fair market. After recent clarifications of the term PPAT, directives from the Agency for the Cooperation of Energy Regulators (ACER) specify that system operators with responsibilities over a balancing power market should also be considered as PPAT’s. Thus, Svenska kraftnät (Svk) has an obligation to introduce an weekly automated ex post monitoring of the balancing power market to identify potential violations.

The study proposes a method to detect potential violations on the weekly data. The method is divided into two steps where the first step contains a comparison of two approaches for a screening analysis and the second step is a regression analysis. The two approaches compared in the first step is one where the data are approximated to normal distribution and one non-parametric approach called bootstrap. The purpose of the first step is to find anomalies in the weekly bids based on the price. The flagged bids are then used in a regression analysis where the actual bids are compared to predicted prices which are generated by using external variables.

It was concluded that the bidding data that was used could not be approximated to normal distribution. The results were more promising for the bootstrap approach in the screening analysis. Further, it was concluded that such a statistical analysis can be applied more efficiently on a market where the submitted bids reflect the companies bidding strategy, that is, by placing bids per regulation object (RO). The market design also had an impact on the regression analysis results. The $R^2$ value showed that the regression explained the price variations better on a market where the bids were connected to a RO.
**Sammanfattning**

I enlighet med införande av förordningen REMIT tillkommer ansvar och plikter, för deltagare såväl som en PPAT, att bibehålla en hederlig och säker marknad. Efter ett förtydligande av termen PPAT har det, enligt direktiv från ACER, kommit fram att systemoperatörer med ansvar över balanskraftmarknaden även ska anses som en PPAT. Svenska kraftnät har således en skyldighet att införa en automatiserad ex post övervakning av balanskraftmarknaden för att identifiera potentiella överträdelser.


Acknowledgements

We would like to thank Svenska kraftnät for the opportunity to conduct this master thesis. A special thanks to our supervisor at Svenska kraftnät, Linn Fröström, for her commitment and valuable feedback throughout the project and for spending time on continuously reviewing the report. We would also like to thank Dan Atsmon and Kristofer Låås at Svenska kraftnät for providing us with helpful advices and also reading and reviewing the report continuously. We also appreciate all of the people we reached out to at Svenska kraftnät who have taken the time to answer our questions.

We are very thankful to all the interviewees who spend their valuable time for a meeting with us and shared their useful knowledge.

Lastly we would like to thank our supervisor and examiner at the Royal Institute of Technology, Professor Lina Bertling Tjernberg, for taking on this project and supporting us throughout.
<table>
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<tr>
<td>ACER</td>
<td>Agency for the Cooperation of Energy Regulators</td>
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<tr>
<td>aFRR</td>
<td>Automatic Frequency Restoration Reserve</td>
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<td>BRP</td>
<td>Balance Responsible Party</td>
</tr>
<tr>
<td>BTI</td>
<td>Balance Responsible Engineer</td>
</tr>
<tr>
<td>CNMC</td>
<td>The National Commission on Markets and Competition</td>
</tr>
<tr>
<td>D-1</td>
<td>One Day Before Operation Hour</td>
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<tr>
<td>D-2</td>
<td>Two Days Before Operation Hour</td>
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<tr>
<td>DC</td>
<td>Driftcentraloperatör/Switching Supervisor</td>
</tr>
<tr>
<td>Ei</td>
<td>Energimarknadsinspektionen</td>
</tr>
<tr>
<td>EU</td>
<td>European Union</td>
</tr>
<tr>
<td>FCR</td>
<td>Frequency Containment Reserve</td>
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<tr>
<td>FCR-D</td>
<td>Frequency Containment Reserves Disturbance</td>
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<tr>
<td>FCR-N</td>
<td>Frequency Containment Reserves Normal</td>
</tr>
<tr>
<td>mFRR</td>
<td>Manual Frequency Restoration Reserve</td>
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<tr>
<td>MLP</td>
<td>Multiple Linear Regression</td>
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<tr>
<td>NEAS</td>
<td>Neas Energy A/S</td>
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<tr>
<td>NRA</td>
<td>National Regulatory Authority</td>
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<tr>
<td>PPAT</td>
<td>Person Professionally Arranging Transactions</td>
</tr>
<tr>
<td>REMIT</td>
<td>Regulation (EU) nr 1227/2011 on Wholesale Energy Market Integrity and Transparency</td>
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<tr>
<td>Svk</td>
<td>Svenska kraftnät/Swedish National Grid</td>
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<tr>
<td>SØIK</td>
<td>Statsadvokaten For Særlig Økonomisk og International Kriminalitet/State Attorney for Special Economic and International Crime</td>
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<tr>
<td>TSO</td>
<td>Transmission System Operator</td>
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<tr>
<td>UMM</td>
<td>Urgent Market Message</td>
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</table>
VHI  Vakthavande Ingenjör/Grid
Supervisor
Nomenclature

\( \alpha \)  
Significance level

\( \beta \)  
Constant representing the \( y \)-intercept from the regression

\( \beta_p \)  
Slope coefficient for independent variable \( x_p \)

\( C_{op} \)  
Opportunity cost

\( \epsilon \)  
Error term at time \( t \)

\( k \)  
Kurtosis

\( N \)  
Population size

\( N_{afR\text{-}u}^f \)  
Number of flagged bids in aFRR in up regulation

\( N_{afR\text{-}d}^f \)  
Number of flagged bids in aFRR in down regulation

\( N_{FCR\text{D}-D1}^f \)  
Number of flagged bids in FCR-D in D-1

\( N_{FCR\text{D}-D2}^f \)  
Number of flagged bids in FCR-D in D-2

\( N_{FCR\text{N}-D1}^f \)  
Number of flagged bids in FCR-N in D-1

\( N_{FCR\text{N}-D2}^f \)  
Number of flagged bids in FCR-N in D-2

\( M \)  
Number of bootstrap simulations

\( \bar{p}_{ico,s,st} \)  
Benchmark price level of company \( i_{co} \) in season \( s \) and state \( st \) [SEK/MW]

\( \bar{p}_{iro,s,st} \)  
Benchmark price level of company \( i_{ro} \) in season \( s \) and state \( st \) [SEK/MW]

\( \bar{p}_{ico,s,st}^* \)  
Bootstrap benchmark price level of company \( i_{co} \) in season \( s \) and state \( st \) [SEK/MW]

\( \bar{p}_{iro,s,st}^* \)  
Bootstrap benchmark price level of company \( i_{ro} \) in season \( s \) and state \( st \) [SEK/MW]

\( P_{ico,s,st,\text{Boot}}^* \)  
Bid price bootstrap population of company \( i_{co} \) in season \( s \) and state \( st \) [SEK/MW]

\( P_{iro,s,st,\text{Boot}}^* \)  
Bid price bootstrap population of regulator object \( i_{ro} \) in season \( s \) and state \( st \) [SEK/MW]

\( \bar{p}_{ico,s,st,n} \)  
The historic \( n \)-th bid price of company \( i_{co} \) in season \( s \) and state \( st \) [SEK/MW]
\( p_{Hist}^{i_{ro}, s, st, n} \) The historic \( n \):th bid price of regulator object \( i_{ro} \) in season \( s \) and state \( st \) [SEK/MW]

\( p_{Week}^{i_{co}, s, st, n} \) The weekly \( n \):th bid price of company \( i_{co} \) in season \( s \) and state \( st \) [SEK/MW]

\( p_{Week}^{i_{ro}, s, st, n} \) The weekly \( n \):th bid price of regulator object \( i_{ro} \) in season \( s \) and state \( st \) [SEK/MW]

\( p_{Hist}^{i_{co}, s, st} \) Bid price data set of company \( i_{co} \) in season \( s \) and state \( st \) [SEK/MW]

\( p_{Hist}^{i_{ro}, s, st} \) Bid price data set of regulator object \( i_{ro} \) in season \( s \) and state \( st \) [SEK/MW]

\( \sigma \) Standard deviation

\( s \) Skewness

\( \mu \) Mean

\( V_t \) Water value at time \( t \)

\( \tau \) Benchmark level

\( X^* \) Bootstrap population

\( X_{Root} \) Summarised bootstrap population

\( X^*_m \) Bootstrap simulation \( m \)

\( x_i^* \) Random sample drawn from population \( X \)

\( x_i \) Observation \( i \) of the random variable \( X \)

\( x_{pl} \) Observation \( t \) of independent (explanatory) variable \( X_p \)

\( X \sim \mathcal{N}(\mu, \sigma^2) \) Mean

\( y_t \) Observation \( t \) of dependent (response) variable \( Y \)

\( \hat{y}_t \) Expected value of dependent variable \( Y \) at time \( t \)

\( z_{\alpha} \) \( z \)-score for \( \alpha \)

\( z_i \) \( z \)-score for observation \( x_i \)

\( Z \sim \mathcal{N}(0, 1) \) Standard normal distribution
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Chapter 1

Introduction

This chapter presents the motivations of the study and the main objectives. It includes why the study was initiated, what the scope includes and how the objectives are going to be achieved.

1.1 Motivation

In 2011 the European Union (EU) introduced the "Regulation (EU) No 1227/2011 of the European Parliament and of the Council of 25 October 2011 on wholesale energy market integrity and transparency" (REMIT) [1]. The main purposes of the regulation is to prohibit insider trading and market manipulation in any wholesale energy market. The Agency for the Cooperation of Energy Regulators (ACER) was introduced by EU to be responsible for the regulation and supervision of all wholesale energy markets under the REMIT guidelines [2].

One of the responsibilities of the Swedish transmission system operator (TSO) Svenska kraftnät (Svk) are the Swedish balancing power markets. According to Prohibition of market manipulation (article 5), in the REMIT regulation Svk should monitor the balancing power market and report suspicions of market abuse to the Swedish national regulatory authority (NRA), Energi-marknadsinspektionen (Ei). Also, as stated in Prohibition of insider trading (article 3) in REMIT, Svk should also report suspicions of insider trading or an attempt to doing insider trading to Ei.

Currently, Svk does not have a market monitoring system but the bids are manually observed during operation, to continuously accept and activate bids in the balancing energy market and to procure automatic reserves. At the request of Ei, Svk are now working to improve the market monitoring. Therefore, a method to systematically scan through weekly bids will be developed,
to detect any potential market anomalies, which might indicate market violations.

1.2 Scope and Objective

This report is a master’s thesis at the master’s programme Electrical Power Engineering (TELPM) at The Royal Institute of Technology (KTH) initiated by and in collaboration with Svk and consists of a work load equivalent to 20 ECTS (30 hp). The scope of the study is initially provided by Svk. The main objective of this thesis is to develop a method for supervision of the balancing power markets where one focus will be on the energy activation market and another will be on the capacity market. The project is divided in the following two main objectives:

\( i \) To investigate market manipulation in the balancing power market. To assess the types of manipulations and violations that are applicable on the balancing power market and analysing the risks if the market would change.

\( ii \) To propose a method designed in order to enable weekly automatic surveillance with the purpose of finding potential market violations by processing the weekly data of received bids.

All the data analysed in this study are classified information and were provided by Svk. Hence, the data is not open for public so the actual data that is used will not be published in this report. Although no numerical values of the data will be shown information about the bids’ different properties will be necessary for the description of the analysed data.

1.3 Activities

- Literature studies on REMIT, balancing power markets, energy market surveillance and market violations.
- Acquire a deeper understanding on data analysis to create constraints for the analytical model.
- Interviews with relevant parties both externally and internally to obtain information about market abuse and methods to detect it.
• Development of an analytical method for detecting potential market abuse.
• Development of a model in R based on the analytical method.
• Testing of the model and corrections for improvements.

Figure 1.1 presents the initial idea of the method. The historical data is evaluated such that benchmarks can be drawn. The weekly data will be compared with the benchmarks to flag the anomalies. When the anomalies have been found in the weekly data, the flagged data will be used in a regression analysis to find potential violations if the external variables can not explain the flagged data.

1.4 Limitations

To prove if it is market manipulation in the Swedish balancing power markets is outside the scope of this study. The algorithm presented in this study is simply intended to flag for scenarios which might call for further investigation. Also, the algorithm does not take into account bids that belong to the disturbance and power reserve. The algorithm will check for deviating bids in weekly data based on the historical bid data provided by Svk and other external factors. Section 3.2 presents different types of manipulation that ACER has provided and deemed to be relevant in wholesale energy markets. The algorithm will not provide an idea of which type of manipulation a deviating bid correspond to. More on this in Chapter 7.
Gas turbines are part of the disturbance- and power reserve and thus not traded as regular market bids. Therefore, gas turbines will not be analysed in this study.

Since Svk does not currently have a market monitoring system in place, the data that has been provided can likely contain data that might constitute some kind of market manipulation. The result of this study depend on historic data in the balancing power market and if the data includes market anomalies or potential market manipulation the benchmarks used to flag deviant bids will be biased as well. This is an important note since this study will not undergo any investigation whether or not the historic data contain any potential market manipulation.

This study will only include bids with the purpose of correcting and restoring imbalances. It will not include accepted bids under the special regulation.

There are various production sources in the balancing power market. However, the majority of these sources are hydro power generation which is why this study will solely focus on hydro power.

1.5 Outline of the Report

In Chapter 2 the relevant background of the market will be presented. In Section 2.2 there is a short overview of the Swedish electricity market. Section 2.3 describes the balancing power market.

In Chapter 3 market manipulation is addressed. In Section 3.1 the underlying regulation is explained. It is followed by different types of manipulations and a interview summary in Section 3.2. Lastly, Section 3.3 presents examples of sentences of market violations.

In Chapter 4 the proposed method is presented. Section 4.1 present the motivation of the proposed method. Section 4.2 presents the theory behind the method and Section 4.4 introduces the detailed proposed method.

Chapter 5 presents the validation of the method with the historical data. Section 5.1 validates if the data can be approximated. Section 5.2 presents the validation results from the screening analysis and Section 5.3 shows the results from the regression in the different markets.

In Chapter 6 the results drawn from the validation of the method is presented. Section 4.3 presents the proposed algorithm. In Section 6.1 the decisions on the manipulation types are assessed. Section 6.2 presents the results of the screening analysis after the validation and Section 6.3 presents the results of the regression.
Chapter 7 is a discussion of the results and the proposed method followed by a conclusion of the report in Chapter 8.

This study is conducted by two master students and the work has been divided as shown in Table 1.1. The parts that are not listed in the table below are jointly written.

Table 1.1: Division of the study and thesis. Here JW=jointly written, KR=Kristoffer Ravudd and LG=Lilian Gren

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<td>Validation of proposed method</td>
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Chapter 2

Swedish Electricity Markets

This chapter will give an overview of the Swedish electricity wholesale market and the different market participants in it. A more in depth description of the Swedish balancing power market will be provided here as well.

2.1 Generation Mix in Sweden

Sweden relies mainly on nuclear- and hydro power for their electricity production. With an annual electricity production of 160 TWh in Sweden in 2017, nuclear power and hydro power covered about 40% each of the production [3]. There are several types of generation sources in the electrical grid. They differ in many aspects such as technology, generation cost, generation capacity and unit commitment time. They can be grouped into three main categories [4].

*Baseload power generation:* The baseload power in Sweden is the nuclear and parts of the hydro power [5]. The baseload power can be planned regardless of weather conditions and covers the base load so it is not directly connected to fluctuations in supply and demand [4].

*Interruption generation:* Wind and solar energy is of intermittent character and depend on ambient conditions. Due to their volatile characteristics intermittent energy sources cannot guarantee continuous generation and are non-dispatchable [5].

*Balancing power generation:* With the expanding adoption of renewable energy sources the need of handling the variations in the energy production increases [6]. Not only does the uncertainty of the intermittent energy sources needs to be handled, the varying load and the
variation in generation due to unexpected production shortfall also need to be taken cared of [4]. To meet the varying generation and demand, balancing power is used in order to ensure a reliable and stable grid. The balancing power production in Sweden mainly consists of hydro power but gas turbines are also used in some cases to secure the electricity demand during critic hours, e.g. during cold winter days. Gas turbines belongs to the disturbance- and power reserve and are not activated with consideration to the merit order.

As mentioned above, the use of renewable energy sources is increasing and according to [7] the Swedish government set up a goal to reach an electricity supply consisting of 100% renewable energy sources by the year of 2040. However this is not a deadline of banning the nuclear power production or closing of nuclear power plants but initiatives are made through support to solar cells and energy storage as well as investments in energy efficiency in households.

2.2 Overview of the Swedish Wholesale Electricity Market

Electricity is a unique commodity in the aspect that it cannot be stored and the production must be consumed simultaneously to not hazard the electrical grid.

The Swedish electricity market consist of four bidding zones SE1, SE2, SE3 and SE4. A visual overview of the bidding zones is shown in Figure 2.1.

They are apart of the same synchronous system, known as the Nordic synchronous system which involves Denmark, Finland, Norway and Sweden. Nord Pool is the power trading exchange which operates the power trading markets in Sweden amongst other countries. The trading platform was introduced in 1993, becoming the worlds first international wholesale energy exchange [9].

2.2.1 Day-ahead market

In the day-ahead market, market participants are able to sell and buy power for the next day in a closed auction. The day ahead market sets reference prices for all 24 hours of the next day. The Nordic market operator, Nord Pool, process the traded data from the closed auction to provide an electricity price for all hours of the next day which maximises the social welfare subject to some
Figure 2.1: The different bidding zones for the Nordic Countries and Baltic from Nord Pool [8].

constraints e.g. network constraint, supply- and demand constraint [10]. Nord Pool announces the available transmission capacity provided by the TSOs at 10:00 CET and market participants have until 12:00 CET to submit their final offers to the trading platform Elspot. The prices set at the day-ahead market are announced at the Elspot platform at 12:42 CET or later.

2.2.2 Intraday market

The majority of the volume which is traded at Nord Pool is done at the day ahead market and the balance between production and consumption is secured there [11]. However there might occur events after the day ahead market is closed and before hours of delivery that causes imbalances in the system. That might be that a nuclear stops operating which causes production shortfall or unexpected weather changes due to faulty prognosis which causes intermittent generation sources to generate more or less electricity than planned. So, as a complement to the day ahead market, the intraday market resolves these unplanned market imbalances by letting traders buy and sell volumes closer to real time of operation. The trading at the intraday market is a continuous process and trading takes places as close to one hour before delivery. Prices are set based on a principle where best prices come first that is the highest buy
price and the lowest sell price.

As already stated, more intermittent production sources are implemented in the system which makes the intraday market increasingly important.

### 2.2.3 Market participants

The electricity market consists of several actors which play different roles in the electricity market [12].

*Producers:* The producers are the participants in the production of power. In the Nordic there are over 370 companies producing power for trading in wholesale energy markets.

*Transmission system operator:* The TSO is responsible for securing the supply in its area and maintaining a stable and secure grid. It is entrusted to take care of the transmission grid.

*Distribution system operator:* There is currently around 500 distribution system operators in the Nordic and Baltic area. The distribution system operators are responsible for ensuring that power reaches the end-users. To maintain, operate and develop the distribution grid within a given area.

*Retailer:* A retailer in the Nordic buys power through the wholesale energy market platform Nord Pool or directly from producers to supply it to their customers. Their customer base are small and medium-sized companies and households. There are around 380 companies supplying power to end-users in both the Nordic and the Baltic.

*Traders:* The trader is defined as the owner of the power during the time trading takes place. Traders can buy power directly from producers and sell it to retailers or buying from one retailer and selling it to another one.

*Market operator:* The market operator provides the service of trading wholesale energy. In the Nordic and Baltic region, Nord Pool is the market operator.

### 2.3 Swedish Balancing Power Market

The synchronous power system in which Sweden is a part of always strives to withhold a frequency of 50.00 Hz. Deviations from the nominal frequency
has to be corrected as soon as possible in order to keep the synchronous system stable and to reduce the risks of damaging the grid and its components [13]. Deviations will put the system in one of two states depending on if the frequency increases or decreases. If the synchronous frequency decreases the system is set into up regulation and down regulation if it is the opposite [14].

- Up regulation: When the frequency drops the TSO regulates the deviation by increasing the production or reducing the consumption.

- Down regulation: When the frequency increases the deviation is counteracted by decreasing the production or by increasing the consumption.

A party that is participating in one or more of the balancing power markets is called a Balance Responsible Party (BRP). The regulation is typically handled in three different steps as in Figure 2.2 [4].

The first step is regulation with automatic reserves to stabilise the frequency referred as the frequency containment reserve (FCR). The second step involves restoring the frequency with the reserve called automatic frequency restoration reserve (aFRR) which also is handled automatically. The third and last step is the manual correction, manual frequency restoration reserve (mFRR), to release strain on and replacing the already activated reserves to sustain the available volume of automatic reserves.

There are two types of products traded in the balancing power markets which are both used in Sweden. These are balancing capacity markets and balancing energy markets.

*Balancing capacity:* In the balancing capacity market a BRP place bids for a capacity that they will reserve for eventual future disruptions and frequency deviations. The aggregated bids are not connected to any
specific generator that the BRP possess. It is just connected to the BRP itself, that is to the company that the BRP is connected to. It is therefore difficult to determine the geographical location of where the power will be dispatched by looking at the bids. One could regard it as a proactive measurement to ensure that the demand of energy can be met if deviations in the production from the spot market and real-time market would arise. If Svk chooses to procure capacity from a BRP, the BRP is compensated for reserving the procured capacity. However, the BRP does not necessarily need to deliver the procured capacity during the given hour of operation in situations where there is no need for balancing capacity.

**Balancing energy:** Compared to the balancing capacity market, balancing energy markets solely compensate for the produced and delivered energy. There is no possibility of being compensated without delivering as in balancing capacity markets. The aggregated bids that are received by Svk contain bids for individual regulation objects (ROs) with capacity and price. Since the bid is directly connected to a RO, each bid can be linked to a bidding zone. If there is any frequency deviation the bids are examined and the best fit bids are accepted according to a merit order and activated to support and unburden the automatic reserves.

The capacity markets that exist in the balancing market today are all the automatic reserves, that is FCR-N, FCR-D and aFRR. The mFRR market is the only balancing energy market. Although, there are plans of introducing a balancing energy market in the aFRR and also to present a balancing capacity market for mFRR.

All the reserves has to fulfil certain technical requirements, as in [14], such that it may not destabilise the system further or cause additional problems. The BRPs should have real time monitoring to detect deviations from the nominal value. If deviations are detected, the BRP must be adaptive and able to regulate the frequency according to their availability stated in their bid. It also has to meet the requirements that is set for the activation time and the capacity.

### 2.3.1 FCR

The FCR is the first step in the process of regulating the frequency in the synchronously integrated system and the reserve nearly consist of 100% hydro power. As mentioned above, the reserve is operating automatically. The aggregated bids that are placed by the BRP in the FCR market contain the capacity
that the BRP is willing to reserve and to which price. The FCR consists of two different products that are bought separately. There is the normal operation FCR-N and the disturbed operation FCR-D.

### 2.3.2 aFRR

The aFRR is activated in order to restore the frequency to 50.00 Hz. As FCR only stabilises the frequency there is no certainty that the frequency has reached 50.00 Hz when stabilised. Therefore, aFRR is activated as a first reserve to restore the frequency before manual measures can be taken.

### 2.3.3 mFRR

The automatic reserves that are available are limited. To retain those reserves, manual actions has to be taken to replace the automatic reserves. The reserves should be unburdened as quickly as possible such that remaining capacity could be used for eventual future disturbances. The automatic reserves are replaced by the manual reserve mFRR.

### 2.3.4 Procurement and activation of balancing reserves

The reserves are bought by SvK in order to enable frequency corrections when it is required. They are procured during different time spans which is represented in Figure 2.3.

![Figure 2.3: Representation of balancing market procurement of reserves and bidding schedule before operation hour [15].](image)

The FCR reserves are procured during the day before (D-1) and two days (D-2) before the operation hour. The aFRR reserves are procured weekly for the upcoming week of operation to secure restoration reserves. For the mFRR market, a BRP is allowed to place bids until 45 minutes prior to the operation hour in question. When the bidding period is closed manual reserves are bought during the remaining time period if the system requires it.
**FCR-N:** The FCR-N is activated when the frequency is deviating from 50.00 Hz in the interval $49.90 \text{ Hz} - 50.10 \text{ Hz}$ [14]. Outside the interval, when the frequency is below 49.10 Hz or above 50.10 Hz, the FCR-n reserve is using 100% capacity. When the frequency is changing gradually the reserve should activate 63% within 60 seconds and 100% within 3 minutes. The capacity of the reserve should always consist of at least 600 MW in Nordic countries and new reserves should be bought continuously such that the requirement of capacity is met [14].

**FCR-D:** The FCR-D is activated when there is more deviation than - 0.1 Hz from the nominal frequency. The reserve is activated when the frequency goes below 49.90 Hz. It is only available for up regulation. The reserve should activate 50% capacity within the first 5 seconds and reach full capacity within 30 seconds [14].

**aFRR:** In the aFRR, the activation is automatically managed by a control signal at Svk and should be fully activated within 120 seconds [14]. The aFRR requires real time measurements that Svk retrieves from the BRP.

**mFRR:** The mFRR are activated within 15 minutes and are required to have real time measurements [14]. Svk requires, according to the agreement in [14], that the measurements should be delivered every 36:th second with an error of less than 5%. Measurements include the produced reactive and active power.

When the BRP has determined how much capacity they can offer to the balancing power market, they place their available capacity or how much they can reduce their generation with their offered price for up- and down regulation. The bids are placed for individual RO’s in the balancing energy market and for each company in the balancing capacity market. The bids are delivered to Svk and received by the control room responsible of the operation and monitoring of the national grid.

### 2.3.4.1 Svk control room

The control room is operated around the clock to ensure that the system stability is maintained and the frequency is held around 50,00 Hz. The balance responsible engineer, henceforth referred to as the BTI, supervises the national grid and the frequency. The BTI is responsible for taking action to preserve the balance. If the system requires manual corrections of the frequency the BTI goes through the aggregated bids and accept bids after the merit order. In
some cases certain bids can be prioritised due to their location and regarding their activation time. Aside from the BTI, the control room comprises of the person responsible for the operation of the national grid and connections between countries and is called the central operator, DC. There is also one person with the responsibility of regulating the voltage to maintain the same level in the national grid in order to reduce transmission losses, the VHI.

2.3.5 Market configuration

There are a few differences between the balancing power market and other wholesale energy markets. The main differences which is important in the aspect of market monitoring is:

- **Svk is the only buyer** so trading between BRPs is not possible in the balancing power market.

- **Procurement requirements** results in Svk needing to buy reserves regardless of price, i.e. Svk is not price sensitive.

- **Few market participants** makes the balancing power market at risk for market power, that is a few BRPs having influence over the price.

- **A fixed demand** removes the possibility of disseminating false information about the demand.

2.3.6 Main price drivers in the balancing power market

The cost of automatic reserves varies during the year between seasons due to seasonal variations in demand and weather. They also vary from year to year from different external factors affecting the cost. These factors include whether it is a dry or wet year which affect the spot price, the temperature, hydrology and other external factors. The parameters with the biggest impact on the cost in the balancing power markets that should be accounted for is the spot price and the hydrology as the share of hydro power in the generation mix is large in Sweden [3].

2.3.6.1 Opportunity costs

The main price driver for hydro power costs is the opportunity cost [16]. Opportunity cost is a cost to represent a value that could have been attained if the
most valuable choice was made compared to the actual choice that was made. When the value of something is fluctuating over time, one might not wish to spend their resources when the value is at a minimum. The opportunity cost is therefore the cost of the willingness to spend a resource even though the value of it will increase by time. It can also be seen as the loss of opportunity to use the resource at a later time when the value of the resource is higher. It could be the difference in value between night and day or up to the difference between different seasons. The opportunity cost is given by,

\[ C_{op} = \max(V_{t+n}) - V_t \]  

(2.1)

where \( C_{op} \) is the opportunity cost, \( V_t \) is the value at the given time, \( t \), and \( V_{t+n} \) is the value in a future time period, \( t + n \). The opportunity cost can be affected by limitations in resource storage, value fluctuations and other factors.

2.3.6.2 Balancing capacity market

In the capacity market there are different price driving factors separating the markets between each other. There are also some factors that are affecting the prices in the same way but to different extents. As mentioned in 2.3, a BRP participating in capacity markets is reserving parts of their capacity in order to be available to supply if sudden disruptions occur or there are any other deviations in the frequency. The need to reserve capacity when cleared is typically one of the price drivers that can be seen in all of the automatic reserves. Following describes the different price drivers in each separate capacity market.

2.3.6.2.1 FCR-N The FCR reserve consists of 100% hydro power as mentioned in Section 2.3.1. The variable cost of generation for a hydro power is considered to be negligible [17] and the price of FCR is mainly affected by the opportunity cost. The FCR-N reserves is especially affected by the spot price which is directly connected to the available energy [18]. The cost of the reserve is typically expensive during the hours when the spot price is low, most common during summer nights. The demand is lower than during the day hence the spot price will fluctuate. The BRP is aware that the water value will be higher at a later point in time and the opportunity cost from Section 2.3.6.1 is thereby increased such that the BRP recieves the same revenue as they would have done if they conserved the water until a latter time when the spot price is higher. FCR-N is typically expensive during the nights when the spot price differs excessively between the night and the day. The BRP wants to
dispatch all the capacity during the day where they would gain more revenue and will therefore place expensive bids for FCR-N during the night.

### 2.3.6.2.2 FCR-D

When placing bids to FCR-D, BRP have the knowledge that the disturbance reserve does not have to be activated that often. The BRP has to reserve an amount of their total capacity such that they are capable of delivering FCR-D reserves if necessary. This typically affects the cost of FCR-D during hydrological strain due to, for example, heavy rain or the spring flood. Knowing that they have to reserve some of the total capacity, an increased amount of inflow imposes a potential risk of having to spill water [18]. The cost of the FCR-D reserve is thus expensive during hydrological strains as BRP accounts for the potential value of the spillage amount. It is also a potential price driver in FCR-N but, knowing that FCR-D is dispatched less frequently, there is greater risk of having to spill water in FCR-D during hydrological strains.

### 2.3.6.2.3 aFRR

The aFRR market presently consists of 100% hydro power. The hydro power price, as mentioned above, is typically controlled by the capacity they have to reserve. Considering that there are limits on the reservoirs, a continuous inflow together with a generator that is not fully dispatched increases the risk of being forced to spill water. Water that could have been dispatched if some of the generator capacity would not have been reserved. The price is thus set by that prediction of lost opportunity to dispatch.

### 2.3.6.3 Balancing energy market

The majority of the traded energy in the mFRR markets consist, much like the other balancing power markets, of hydro power. Similar to the capacity markets, the price reasoning for hydro power is the same.
Chapter 3

Market Manipulation

In this chapter market manipulation will be described according to the ACER’s guidelines on REMIT as well as a summary of the interviews conducted in the initiation of this study. Especially, market manipulation applied in the balancing power market will be discussed.

3.1 Current Legislation in the European Energy Market

A market that is afflicted by market abuse is risking to suffer major consequences as a result. Examples of such situations and their following consequences where market abuse has been detected is brought up in Section 3.3. To maintain the transparency and stability of the European wholesale energy market EU introduced a new regulation in 2011 called REMIT, Regulation (EU) No 1227/2011 [1]. The regulation includes the prohibit of using or distributing insider information to limited sources for profitable purposes described in article 3. The regulation also prohibits actions and behaviour of manipulation and intentions to manipulate the wholesale energy market in article 5. REMIT also states, in article 4, the obligation to publish insider information within reasonable time such that no one can draw additional benefit from it. An example of insider information could typically be planned interruptions, maintenance and other operations. This information should be published without further ado in urgent market messages (UMM) which are messages containing necessary information that should be known to participating parties and the public. Information that could alter the bidding behaviour of people, similar to market abuse if someone is deliberately withholding the information.
To ensure that there are no violations of prohibitions, means of market monitoring is required. Thus, article 15 in REMIT obliges any person professionally arranging transactions (PPAT) to possess effective measures to identify breaches of article 3 or 5. If a PPAT has reason to believe that a bid is in violation of article 3 or 5, the incident is to be reported to the NRA for further investigations to determine whether it is a violation or not.

Up until recently TSO’s have not been recognised as PPAT’s and the monitoring at Svk has solely been performed manually from the control room. Although, ACER has now made the assessment that TSO’s are to be considered as PPAT’s. Therefore, there is a requirement for Svk to introduce well maintained and functioning monitoring of the balancing power market. The suspicions that are alerted in the Swedish balancing power market will be sent to Ei. Ei reviews any suspicions that PPAT’s has recognised and initiates an investigation to establish the reason for why the bid was flagged as a suspicion in the first place to conclude if there was any intention of market abuse.

3.2 Market Manipulation

As the author suggest in [19] market manipulation can take any form and attempting to state all types of manipulations in an energy market is not possible because of its complex nature. Although, the guidelines for REMIT supplied by ACER in [20] mention types of manipulation with a possibility to be applied on the electricity market.

3.2.1 Examples of market manipulation in REMIT

(i) Wash trades: Wash trading is when a market participant simultaneously buys and sells the same energy wholesale product to create artificial and misleading activity in the market. It is done by first placing a sell order and then placing a buy order from himself or vice versa. This can lead to artificially increasing the volume of the traded product which leads to the impression that the product is more in demand.

(ii) Abusive squeeze or market cornering: This is when a party or parties have significant influence over supply or demand of a product and uses the influence to materially distort the price in which others have to supply or receive in order to satisfy their own obligations.

(iii) Cross-market-manipulation: It is where a party is trading in one market to impact the price of another market in order benefit from it. Trading
on one market to improperly influence the price on another market with the same or related whole energy product.

(iv) *Physical withholding:* When a party chooses not to offer the available capacity to the market without any justification in order to influence the price to a higher level. The supply will be considerably low to influence the price when the available capacity is higher in reality.

(v) *Transmission capacity hoarding:* This is when a party acquires part of or the whole transmission capacity without the intent of using it or to use it inefficiently. It may interrupt trades between different price areas such that the price differences arise.

(vi) *Improper matched orders:* Transactions where buy and sell orders are done at the same time at the same price and quantity by different but colluding market participants. In other words when company A conducts a selling transaction at a certain price and quantity and company B puts a buying transaction at the same time for the same quantity and price as company A. This can indicate that company A and B are colluding parties which constitute market manipulation unless both companies has a legitimate reason for the carried out transactions according to the rules of the trading platform.

(vii) *Layering:* When a market participants places multiple non genuine buy or sell orders at different price levels to be able to enter into one or more sell or buy transactions.

(viii) *Spoofing:* This is similar to layering but in spoofing a market participants lays a single large or multiple orders at the same price level.

(ix) *Other order-based behaviours:* Behaviours that involve issuing orders to trade when actually not having an interest in execution themselves. It gives out misleading signals over either the supply, demand or the price of an energy wholesale product which leads to prices being on artificial levels.

(x) *Marking the close:* This is the a party is deliberately buying or selling wholesale energy products right before the close of the market to with the intent to influence the closing price.

(xi) *Scalping:* This is when false or misleading information is spread through media influencing the price to a more favourable level for the disseminating party.
(xii) Pump and dump: When a party has taking a long position in a wholesale energy product and then continues to buy or spreads misleading information with the intent to trick more market participant to buy. The party then takes the opportunity to sell the wholesale energy product for the inflated price.

(xiii) Circular trading: This is when a party is initiating a sell order with the knowledge that a buy order is placed at the exact same time. Illegal as it excludes other competition.

(xiv) Pre-arranged trading: When two parties are trading with each other at their own agreed prices to exclude other competition in the market. It can also be used to gain a tax advantage. Much similar to circular trading where insider information is used, pre-arranged trading is when the two parties have an agreement with each other.

3.2.2 Interview summary

In the initiation of the project interviews were conducted in order to get an understanding of which types of manipulation that could potentially be exploited on the balancing power market. Further, the interviews gave suggestions on mentionable methods of market monitoring. They also included the thoughts around the potentiality of having public bids in the future.

- An interview with [21] mentions the possibility of cartels that collude to drive up the price of the market. It is suggested that an understanding should be acquired of what is driving the demand in the balancing power market. A possible method would be to do an estimation of the markup where the cost would be estimated and compared to the bid. It is also suggested to use a non parametric solution to avoid distributional assumptions. The potential risks of cartels were according to the interview considered to be higher if the bids were to be public but the transparency would at the same time invite more research in the monitoring area.

- From the interview with [22] it was considered to get an understanding of what normal behaviour is. A benchmark method is proposed to find indexes to flag cases that would require to take a closer look at. They both agree on that manipulation on the balancing power market is feasible but that the profit would be marginal. They also mention that research implies that publication of bids would facilitate cartels.
• [23] mentions the possibility of collaboration in wholesale energy markets. An analytical method is proposed in order to detect anomalies in the data. He mentions that the seasonal factor is important to include for monitoring over a energy wholesale market. He says that the openness of the customers to give out information will affect the method. He mentions that public bids could enable collaboration and that honest players might be affected by the now public bids.

• From [24] it is mentioned that one should compare the bid to what the price should reasonably be. They suggest looking at flagged bids according to a trading pattern, to find anomalies from a behaviour in historical bids. They also mention that no particular tendencies of market manipulation has been mentioned in any wholesale energy market in Sweden. They also believe that the risk of cartels is increased when the bids are public but that the overall purpose of the transparency is positive.

• In [25] it is mentioned that the possibility of cartels could increase with more players in a wholesale market. A question that was risen during the interviews was if it would be possible to model a player’s cost. She believes that the problem of modelling the cost is due to the complex evaluation of it. As most of the interviewees, she believes that the increased transparency would allow for easier collusion.

• [26] proposed a non parametric method called bootstrap that could be used to find anomalies. He argued that a non parametric method as such would be of choice as it disregards distributional differences in the data sets since it does not assume any specific probability distribution.

To summarise the interviews, the proposed method could be a non parametric solution that would flag anomalies from a statistical analysis. The seasonal factor should be considered in the method and the behaviour should be analysed. It was mentioned that it could be problematic to model the cost of a party, making it more difficult to make a comparison to the bid.

Many of the interviewees agreed that cartels could be a potential manipulation risk, especially with the increased transparency if the bids would be public. No other manipulation type was mentioned or considered during the interviews as possible violations in the balancing power market.
3.3 REMIT Sanction Decisions

Since REMIT entered into force in 2011, punitive measures have been taken on market participants behaving in misconduct according to the regulation. REMIT covers both the gas and the energy wholesale market hence the cases which will be described down below include market manipulation in both of these markets. Up until this day, no market participant in Sweden has been taken under appeal for breaches against the REMIT regulation [27]. The REMIT sanctions which will be described in this section are all the reported market abuse decisions involving breaches of article 3 and 5 so far.

3.3.1 Denmark

There has been two REMIT sanctions in Denmark on the two market participants Neas Energy A/S (Neas) and Energi Danmark A/S [27]. Neas and Energi Danmark violated article 5 of the REMIT regulation and were fined 153 000 DKK and 1 104 000 DKK respectively for involvement in market manipulation.

During 2015, Neas conducted manipulation of the wholesale energy market and The Danish State Prosecutor for Serious Economic and International Crime (SØIK) charged them with a fine of 150 000 DKK [28]. Additionally, Neas had to pay back the revenue of 3 000 DKK they were given as a result of the market manipulation. In total, Neas had to pay 153 000 DKK in fines. The reason for the charges was that Neas hoarded capacity on the transmission lines between Sweden and Denmark by trading electricity with itself which resulted in barriers for other market participants from trading between bidding zones and thereby impeding competition. This capacity hoarding resulted in or were likely to result in the creation of misleading and/or artificial prices in the intraday market according to SØIK.

Energi Denmark conducted market manipulation on the Nordic wholesale energy market during 2015 and SØIK charged them with a fine of 750 000 DKK in addition to the revenues the company received through its 10 counts of market manipulation [29]. This resulted in that Energi Denmark had to pay 1 104 000 DKK in fines. Similar to Neas, Energi Danmark traded capacity with itself without a genuine need between bidding zones and therefore occupied the capacity of the interconnectors. This led to other market participants not being able to trade between the corresponding bidding zones which led to detrimental effects on competition and also created or were likely to create price differences between bidding zones. Energi Danmark’s capacity hoard-
ing occurred during 10 different bidding hours in 2015 between May 5 and September 1.

### 3.3.2 Germany

On the European gas trading platform PREGA, a market participant in Germany was involved in market manipulation [30]. The Bundesnetzagentur has imposed fines to the company responsible, Uniper Global Commodities SE, of 150 000 EUR. In addition to this, two traders working at Uniper are risking to pay 1 500 and 2 000 EUR in fines for participating in a case of gas market manipulation. The two trader’s bidding behaviour resulted in the ability to deliberately exclude other market participants to trade with the trading point NetConnect Germany. The manipulative behaviour was that the two traders split up one big order into several small ones, an iceberg order, making other participants unable to submit lower bids causing the trading point to be misled about the offer situation. While investigating this case the Bundesnetzagentur discovered more information about Uniper in their lack of duty of supervision.

### 3.3.3 France

The NRA in France, CoRDiS, has imposed a fine of 5 000 000 EUR to the energy trading company VITOL for engaging in market manipulation on the gas trading point PEG Sud. The events occurred between the beginning of June 2013 and the end of March 2014 with 65 cases of manipulation spread over 54 days [31].

During these events Vitol would generally lay several sell orders at the beginning of the trading day and as the day moved along Vitol gradually decreased the prices of the sell orders. Once the prices had decreased Vitol laid buy orders and cancelled its sell orders. This course of action was likely to give misleading signals to the market in the supply and demand and with Vitol not having reasonable arguments for their behaviour, Vitol’s approach was not considered rational.

CoRDiS therefore decided to charge Vitol for engaging in market manipulation during the 54 trading days.

### 3.3.4 Spain

Three different market participants in Spain are under appeal for breaches of article 5 in the REMIT regulation [27]. The National Commission on Markets and Competition (CNMC) are charging Multienergía Verde SLU, Galp
Gas Natural, S.A. and Iberdrola Generación S.A.U. with 120 000, 80 000 and 25 000 000 EUR respectively in fines for their involvement in market manipulation.

Multienergía Verde SLU was sanctioned by CNMC with a fine of 120 000 EUR for handling and attempting to manipulate the prices on the organised gas market managed by MIBGAS [32]. Multienergía tried to fix the price of several of the products in the gas market on an artificial level. They made transactions of the minimum allowed trading volume or for a reduced volume at prices much lower than those offered by other participants. These anomalous price offers marked an auction price between 24% and 97% lower than the rest of the market participant’s prices for the same product and trading days. These actions gave false price signals of a market price drop which led to the CNMC fined them for breach of the prohibition of market manipulation according to article 5 in REMIT.

CNMC fined Iberdrola Generación with 25 000 000 EUR for participating in electricity market manipulation in 2013 [33]. Iberdrola affected the electricity prices by raising its offer price on three different hydro power plants during November 30 and December 23 for no legitimate reason.
Chapter 4

Proposed Method

In this chapter a proposed method will be presented and the motivation behind the proposed method will be described in Section 4.1. Furthermore, the theory behind the proposed method will be presented in Section 4.2. In Section 4.4 a detailed proposed method will be described on how the proposed method is applied in this study.

4.1 Motivation of Proposed Method

From the interviews it could be concluded that one of the main concerns regarding market manipulation in the balancing power market is colluding companies. This study will not analyse the potential existence of cartels in the balancing power markets due to limited time, resources and complexity of that sort of research.

Svk is a state owned company and its obligation lies in securing the national electrical supply by transmitting electricity between generators and distribution networks and maintain the nominal frequency in the grid. As described in Section 2.3 the different products in the balancing power market is there to maintain and restore the frequency. With this said, SvK is not price sensitive, i.e. SvK’s demand will not decrease with increasing prices in the balancing power market. The imbalance need to be restored and corrected at any cost to not hazard the electrical grid. With SvK not being price sensitive the risk for expensive procurements increases and the focus in the proposed method for a monitoring system of the balancing power markets will lie in finding outliers in the bid price data. These outliers might be an indication of market participants bidding high prices with the intent of raising the prices in order to get a higher revenue. This is somewhat related to abusive squeeze or
market cornering listed in Section 3.2 in terms of observing high prices in the bidding data.

4.2 Statistical Analysis

Two types of statistical analysis will be conducted in order to find potential violations in the bidding data. First an outlier detection will be conducted through a screening analysis. Second, a regression analysis will be made in an attempt to find potential price indicators of an outlying bid in order to accept the bid if it is reasonable in terms of explaining external factors. If not accepted, the bid is treated as a potential violation that requires further investigation. The external factors include bid volume, spot price, inflows and storage. Seasonal factors is important to take into account which was a conclusion drawn from the interviews. Also the spot price can also have an impact on the bid prices in the balancing power market according to [18]. The bid volume is taking into account to analyse possible relations between bid price and volume.

4.3 Proposed algorithm

The flowchart of the proposed model can be seen in Figure 4.1. The historical data are divided into objects, capacity and season intervals according to Eq. 4.18a for aFRR and FCR and Eq 4.18b for mFRR. The historical data comprise of all the data from the beginning of time up until one week before the hour of monitoring. The idea is to compare the remaining 1 week of data to the historical bids, as in Eq. 4.18, to find potential outliers with Eq. 4.20. The bids that are flagged, i.e. when $p \geq \overline{p}$, are then used in the regression analysis to predict prices by using different external factors as influencing variables.
Figure 4.1: Flowchart of the model implementation.
4.3.1 Screening analysis

The screening analysis presents two approaches that can be used to find anomalies in the data. The first approach is approximating the data to normal distribution to find outliers and the second one is a non-parametric approach called bootstrap statistics.

To find outliers, the both approaches finds the observations that are considered as the extremes compared to the rest. In the case of finding anomalies in the bidding data, a benchmark is set to find bids with values higher than the maximum benchmark. The decision rule for the benchmark can be defined as,

$$Pr(x_i > \bar{x}) < \alpha$$

where $x$ is an observation of the random variable $X$, $\bar{x}$ is the benchmark and $\alpha$ is the significance level which states the probability of an observation to attain a certain value outside the selected acceptable boundaries of the distribution. The observations that are obtained outside the boundaries are the outliers. The decision rule is the same for both screening analysis approaches.

4.3.1.1 Approximating data to normal distribution

To determine whether the data are normally distributed or can be approximated as such, tests can be made on the data. Descriptive statistics are used with the intent to get a visual overview of the data. Normality tests are performed to analyse the data to see whether it resembles normal distribution or not.

4.3.1.1.1 Descriptive statistics A simple and efficient way to analyse if the data are approximately normally distributed is to use descriptive statistics. Two methods will be explained, the first is simple visual interpretation of the data and the second is quantile-quantile or Q-Q plots.

*Visual interpretation:* To get a visual interpretation of the data distribution a histogram can be plotted. The histogram is used to get a graphical overview of what values the data adopt and how many times it occurs. It is a first good step to see whether the data resemble normal distribution or if it is skewed in any way.

*Q-Q plot:* To better assure that the underlying data follow an approximate normal distribution a Q-Q-plot can be made to compare the shape of two probability distributions with each other. In the case of assuming normality in the analysed data, theoretical quantiles are compared to empirical quantiles.
4.3.1.1.2 Normality test  Aside from the descriptive statistics, there are other ways to determine if the data set is normally distributed. Normality tests such as the kurtosis value and the skewness value allows someone to comprehend if the data have elongated tails or is asymmetric.

Kurtosis: Kurtosis is a measure to see the behaviour of the tail of the distribution plot. It is a measure to see the likeliness of more deviating values in any given distribution. The higher the kurtosis value, the heavier the tails are, e.g more values that are deviating from the mean. The kurtosis value of a discrete time series distribution can be calculated by Eq. 4.2.

\[ k = \frac{1}{N} \sum_{i=1}^{N} \frac{(x_i - \mu)^4}{\sigma^4} \]  

(4.2)

where \( N \) is the size of the data set, \( x_i \) is the data in the distribution, \( \mu \) is the mean and \( \sigma \) is the standard deviation. The kurtosis value will be 3 if the distribution would be perfectly normal. An approximate margin of \( k = 3 \pm 2 \) is acceptable to assume normal distribution.

Skewness: Skewness is used to test the asymmetry of the distribution set. As real life data almost always is not perfectly normal distributed it is reasonable to investigate how skewed the data are. The skewness value is recieved by using Eq. 4.3 for the given data.

\[ s = \frac{1}{N} \sum_{i=1}^{N} \frac{(x_i - \mu)^3}{\sigma^3} \]  

(4.3)

The value of the skewness is for a perfectly normal distributed set equal to 0. To approximate to normal distribution the skewness is acceptable within a interval of \( s = 0 \pm 1 \).

4.3.1.1.3 Outliers  An outlier, also known as an anomaly, is something that stands out to the majority of a data set. When an observation lies outside the overall pattern of the distribution it can be considered an outlier [34]. From a statistical analysis perspective the cause of outliers can be due to a heavy tailed distribution when the kurtosis value is high. Data sets with small populations are especially sensitive to outliers in the data as there is a risk that the distribution is not representative of the underlying data due to lack of data points. A sample can therefore be classed as an outlier even though it is a perfectly valid sample. When the population is larger the outliers are considered as the extremes meaning that outliers in samples taken from a larger population are considered to have a low probability of occurrence.
4.3.1.1.4 Outlier Detection  After \( \alpha \) is chosen, the benchmark, \( \bar{x} \), is calculated to be able to find potential outliers. In order to do this, the samples must be converted to their corresponding \( z \) scores to have the distribution in a standardised normal form. So for a given probability, \( \alpha \), the \( z \) score for that \( \alpha \) can be found. The normal distribution is converted to a standard normal distribution by Eq. (4.4)

\[
    z_i = \frac{x_i - \mu}{\sigma} \quad (4.4)
\]

where \( \mu \) and \( \sigma \) are the mean and the standard deviation respectively of the random variable \( X \sim \mathcal{N}(\mu, \sigma^2) \). The standard normal distribution has a mean of zero and a standard deviation equal to 1 and is denoted by \( Z \sim \mathcal{N}(0, 1) \). The standard normal table then gives the probability that an observation is \( x_i \geq z \).

When the observations have been converted to their corresponding \( z \) scores, depending on which \( \alpha \) is chosen, the \( z \) score for the benchmark price can be found in a standard normal table. The \( z \) score for a given \( \alpha \) can then be converted to its corresponding observation from the original normal distribution. By rearranging Eq. 4.4 the benchmark price is given by,

\[
    \bar{x} = \mu + z_\alpha \sigma \quad (4.5)
\]

where \( \bar{x} \) represents the benchmark price for a given alpha with its corresponding \( z \)-score, \( z_\alpha \). When observations are greater than \( \bar{x} \) they are considered as outliers.

4.3.1.2 Non-parametric statistics

Non-parametric statistics can be used as a statistical method that does not require that the data follow a normal distribution. In the section above, the outlier detection relies on assumptions of normality, therefore another approach to find outliers will be used in order to compensate for the fact that normality assumptions cannot be made.

4.3.1.2.1 Bootstrap statistics  The statistical method bootstrap is a non-parametric solution with the general idea of random data sampling with replacement. The objective of using it is to, given a data set, estimate a parameter such as mean, variance, quadratic error or the standard deviation [35]. Through the estimation the confidence interval can be constructed.
We introduce \( X = x_1, x_2, \ldots, x_N \) as the population or the data set where \( N \) is the size of the population. We define \( F_X \) to be the population distribution of \( X \). The simple idea of bootstrapping is then to draw samples from the population \( X \) with replacement to create a new bootstrap population distribution \( F_X^* \). From the bootstrap distribution we get a bootstrap sample estimate \( T(F_X^*) \). The bootstrap sample population is given by Eq. 4.6.

\[
X^* = x^*_1, x^*_2, \ldots, x^*_N
\]  
(4.6)

where \( X^* \) is the bootstrap population and \( x^*_i \) are the random samples drawn from the original population. As can be seen, the number of random samples drawn from \( X \) is equal to the size of the population. The new bootstrap population distribution \( F_X^* \) could for one resampling be identical to the original data but since the samples are randomly selected it is more likely that the distribution will be different than its original. If the procedure is repeated and \( n \) more samples are drawn we get another estimate \( T(F_{X,i}^*) \). By repeating the random sampling many times, new bootstrap estimates are gathered and a histogram of the gathered resampled populations can be made. The new bootstrap population is the sum of the sampled population,

\[
X^\text{Boot}_M = \sum_{m=1}^{M} X^*_m
\]  
(4.7)

where \( X^\text{Boot}_M \) is the summarised population after \( M \) bootstrap simulations. Figure 4.2 displays how the bootstrap distribution begins to resemble the original distribution when more simulations are made.

The histogram of all the resampled populations are called the Monte Carlo approximation of the bootstrap distribution. From the approximation a confidence interval is created with the significance level as in Eq. (4.1). From the confidence interval the lower and the upper limits are used as the lower and upper benchmarks. Similar to the method of approximating the data to normal distribution, the benchmarks are used to flag data that is greater than the benchmarks.

### 4.3.2 Multiple regression analysis

Regression analysis is a method used to measure the relationship between two or more data sets [36]. Multiple linear regression (MLP) is a statistical technique which uses several explanatory variables to predict a response variable. An MLP model with \( n \) observations and \( p \) predictor variables \( X_1, X_2, \ldots, X_p \) and a response variable \( Y \) can be written as,
Figure 4.2: Changes in bootstrap distribution for increasing simulations

\[ y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_p x_p + \epsilon \tag{4.8} \]

where,

\[
\begin{align*}
\mathbf{y} &= \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_t \\ \vdots \\ y_n \end{bmatrix}, & \mathbf{x}_1 &= \begin{bmatrix} x_{11} \\ x_{12} \\ \vdots \\ x_{1t} \\ \vdots \\ x_{1n} \end{bmatrix}, & \mathbf{x}_2 &= \begin{bmatrix} x_{21} \\ x_{22} \\ \vdots \\ x_{2t} \\ \vdots \\ x_{2n} \end{bmatrix}, & \mathbf{x}_p &= \begin{bmatrix} x_{p1} \\ x_{p2} \\ \vdots \\ x_{pt} \\ \vdots \\ x_{pn} \end{bmatrix}, & \mathbf{\epsilon} &= \begin{bmatrix} \epsilon_1 \\ \epsilon_2 \\ \vdots \\ \epsilon_t \\ \vdots \\ \epsilon_p \end{bmatrix} \tag{4.9}
\end{align*}
\]

In the notation above,

- \( y_t \) is the value of the dependent (response) variable \( y \) at time \( t \)
- \( x_{pt} \) is the value of the independent (explanatory) variable \( x_p \) at time \( t \)
- \( \epsilon_t \) is the value of the error term at time \( t \)

Moreover, \( \beta_0 \) is a constant which represents the y-intercept, \( \beta_1, \beta_2, \ldots, \beta_p \) is the slope coefficient for the corresponding explanatory variable. The error term of the model is represented by the term \( \epsilon \) also known as the residuals.

The expected value from the regression model in Eq. 4.8 is,

\[ \hat{y} = \hat{\beta}_0 + \hat{\beta}_1 x_1 + \hat{\beta}_2 x_2 + \ldots + \hat{\beta}_p x_p \tag{4.10} \]
The residual, \( \epsilon_t \), is defined as the deviation from the model’s predicted value of the dependent variable, \( \hat{y}_t \), at time \( t \) and the measured value of the dependent variable \( y_t \).

\[
\epsilon_t = y_t - \hat{y}_t
\]  

(4.11)

which, by substituting \( \hat{y}_t \) with Eq. 4.10, can be written as,

\[
\epsilon_t = y_t - (\hat{\beta}_0 + \hat{\beta}_1 x_{1t} + \hat{\beta}_2 x_{2t} + \ldots + \hat{\beta}_p x_{pt})
\]  

(4.12)

The parameters \( \beta_0 \) and \( \beta_1, \ldots, \beta_p \) can be estimated by the least square method [37]. This is done by finding the minimum of the sum of the squared errors, \( \epsilon \), of all \( n \) observations,

\[
S(\beta_0, \beta_1, \ldots, \beta_p) = \sum_{t=1}^{n} \epsilon_t^2 = \sum_{t=1}^{n} (y_t - (\hat{\beta}_0 + \hat{\beta}_1 x_{1t} + \hat{\beta}_2 x_{2t} + \ldots + \hat{\beta}_p x_{pt}))^2
\]  

(4.13)

By differentiating Eq. 4.13 with respect to each parameter and setting the derivatives to zero each parameter can be found by solving the equation system,

\[
\frac{\partial S}{\partial \hat{\beta}_0} = -2 \sum_{i=1}^{n} (y_i - \hat{\beta}_0 - \hat{\beta}_1 x_{1i} - \hat{\beta}_2 x_{2i} - \ldots - \hat{\beta}_p x_{pi}) = 0
\]  

(4.14a)

\[
\frac{\partial S}{\partial \hat{\beta}_1} = -2 \sum_{i=1}^{n} x_{i1}(y_i - \hat{\beta}_0 - \hat{\beta}_1 x_{1i} - \hat{\beta}_2 x_{2i} - \ldots - \hat{\beta}_p x_{pi}) = 0
\]

\[
\frac{\partial S}{\partial \hat{\beta}_2} = -2 \sum_{i=1}^{n} x_{i2}(y_i - \hat{\beta}_0 - \hat{\beta}_1 x_{1i} - \hat{\beta}_2 x_{2i} - \ldots - \hat{\beta}_p x_{pi}) = 0
\]  

(4.14b)

\[
\vdots
\]

\[
\frac{\partial S}{\partial \hat{\beta}_p} = -2 \sum_{i=1}^{n} x_{ip}(y_i - \hat{\beta}_0 - \hat{\beta}_1 x_{1i} - \hat{\beta}_2 x_{2i} - \ldots - \hat{\beta}_p x_{pi}) = 0
\]

When solving the above set of equations the following parameter estimations are found,

\[
\hat{\beta}_0 = \hat{\beta}_1 x_1 + \hat{\beta}_2 x_2 + \ldots + \hat{\beta}_p x_p
\]  

(4.15a)
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(a) First degree line fit.  
(b) Second degree line fit.  
(c) Third degree line fit.

Figure 4.3: Different degrees of line fits. The data are a built-in data set in R called "mtcars".

\[
\hat{\beta}_1 = \frac{\sum_{i=1}^{n} (x_{1i} - \bar{x}_1)(y_i - \bar{y})}{\sum_{i=1}^{n} (x_{1i} - \bar{x}_1)^2} \\
\hat{\beta}_2 = \frac{\sum_{i=1}^{n} (x_{2i} - \bar{x}_2)(y_i - \bar{y})}{\sum_{i=1}^{n} (x_{2i} - \bar{x}_2)^2} \\
\vdots  \\
\hat{\beta}_p = \frac{\sum_{i=1}^{n} (x_{pi} - \bar{x}_p)(y_i - \bar{y})}{\sum_{i=1}^{n} (x_{pi} - \bar{x}_p)^2}
\]

(4.15b)

where \(\bar{x}_1, \bar{x}_2, \ldots, \bar{x}_p\) and \(\bar{y}\) is the mean values of the independent variables and the dependent variable respectively.

4.3.2.1 Polynomial regression

It is possible that some predictive variables have a relationship to the dependent variable other than a linear one. If that is the case, adding polynomial terms to the predictive variable in question might be a better alternative. Figure 4.3 shows the relationship between two variables with different degrees of line fit. Here the response variable represents the y-axis and the predictive variable represents the x-axis.

From Figure 4.3 it can be seen that adding polynomial terms to the predictive gives a better fit to the response variable which can indicate that the polynomial regression model can capture more of the variation in the response variable than in a first degree polynomial regression model.
For a single quantitative predictor variable, $X$, a polynomial regression model of degree $k$ can be written as,

$$y = \beta_0 + \beta_1 x + \beta_2 x^2 + ... + \beta_k x^k$$  \hspace{1cm} (4.16)

### 4.3.2.2 Interaction between variables

An interaction term is added if there is some correlation between the independent variables. Interaction exists when the effect of an explanatory variable on the dependent variable changes, depending on the value of one or more other explanatory variables. The interaction term is added to the regression equation as,

$$\hat{y} = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_1 x_2$$  \hspace{1cm} (4.17)

where $x_1 x_2$ is the interaction term and $\beta_3$ its coefficient.

### 4.3.2.3 Statistical significance

The summary of a regression gives indications of how well each independent variable captures the behaviour of the response variable as well as indications of how good the model captures the response variable in a whole.

The $p$-value for the independent variable $x_p$ gives the probability that its coefficient $\beta_p$ is zero, i.e., it tests the null hypothesis that the coefficient is equal to zero. A $p$-value of 1 will not reject the null hypothesis and the corresponding coefficient is equal to zero. A lower $p$-value indicates that one can reject the null hypothesis and the $p$-value is significant. The significance level of $p$ is decided by $\alpha$, so for example if $\alpha = 0.05$ the $p-value$ should be less than 0.05 to be considered significant.

The $p$-value’s significance is based on assumptions concerning the error term, $\epsilon$. These assumptions can be tested by conducting a residual analysis.

### 4.3.2.4 Residual analysis

Residual analysis is conducted to validate the regression model and as mentioned in Section 4.3.2.3 it is important to check whether the assumptions of the error term are valid to be able draw conclusions about the significance of the model [38]. The statistical tests is based on that $\epsilon$,

1. is a random variable with a mean of 0
2. is a normally distributed random variable

3. has a variance that is the same for all values of the independent variables \( x_1, x_2, \ldots, x_p \)

4. has independent values

Residual analysis can be performed visually by plotting the residuals against the fitted values from the regression where the residuals, \( \epsilon \), are placed on the vertical axis and the fitted values from the regression, \( \hat{y} \), are plotted on the horizontal axis. If the assumptions of \( \epsilon \) are satisfied the residual plot will consist of points which are randomly distributed within a horizontal band.

### 4.3.3 Literature Review of the Proposed Method

The chosen method to find outliers using statistical analysis (explained in Section 4.3.1.1.4) is much related to the literature on finding outliers in a data set which is much used in engineering and other disciplines (see [39] for applications in engineering and [40] for price manipulation on the stock market). The basic idea is to find observations that ‘markedly’ deviates from other observations. The choice of ‘markedly’ is then based on deviations from a certain mean, such as one or two standard deviations from normalized mean. This choice is, in turn, related to the choice of probability for the existence of outliers. In present study, the acceptable probability is assumed to be given and simple probability theory is used to find the threshold price for markedly deviation prices. This approach of acceptable deviations has long tradition in the literature where it has been used for e.g. ensuring sufficient food for survival (e.g. [41]) and in the climate change literature for accepting a certain level of uncertainty in mitigation strategies [42].

There are also several other methods to find anomalies such as clustering, distance-based and density-based as discussed in [34]. [34] is a review of different ways to find outliers using both statistical methods and data science. The authors in [34] mention using statistical analysis by creating a distribution of the data set and find points that occur at the end of the distribution tails. Due to computational restrictions and a desire of simplicity in the model the statistical method is the one chosen for this study as the approach of finding outliers.

However, this method builds on the fact that the underlying data are normally distributed. There are methods for checking that a specific data set is normally distributed as the ones suggested in [43] and [44]. In [43] it is suggested to conduct all of the suggested methods to get both visual determination
and normality test of the data to see whether it is or can be approximated to normal distribution. The chosen methods of testing for normality is descriptive statistics with Q-Q plots and histograms as well as normality tests such as skewness and kurtosis analysis.

A non-parametric approach to estimate statistics can be used if the underlying data distribution cannot be approximated to a normal one. Bootstrap is an example of a non-parametric method to find statistics of interest if the data do not follow one of the more conventional distributions, such as the normal distribution. In [45] the authors find confidence intervals and other statistics of the tail of an empirical distribution using bootstrap statistics.

Regression analysis is used in a wide array of studies in different fields to predict future scenarios based on historical data. The authors in [46] presented a regression model on the relationship between natural gas and wholesale electricity prices. They used their suggested regression model to detect potentially anomalous wholesale prices by comparing the predicted wholesale electricity prices from the regression and the actual wholesale electricity price during one year.

4.4 Detailed Proposed Method

The data that will be used will be referred to as the historical bids and the weekly bids. The historical bids are all the bids from when the data began being collected up until one week before the monitoring is commenced. The weekly data are therefore the remaining data, which are the data that will be evaluated for anomalies with the proposed method. The method that will be used to process and analyse the data is carried out in two steps. First, the data will be evaluated through outlier detection methods which in this study is called screening analysis. It is conducted to obtain deviating bids without taking into account parameters that might affect the prices in the balancing markets. The screening analysis will include a comparison of two approaches, one where the data are approximated to normal distribution and the other one, a non-parametric approach called bootstrap.

Second, a regression analysis is made to account for certain parameters that might affect the bidding outcome. The deviation from the mean that will be considered as acceptable will be determined together with Svk.

In the first step, the two approaches are conducted accordingly:

1. Mean values and standard deviations are estimated for the market participants’ bidding data in the normal approximation from the historical
data. From this, benchmark prices for each participant can be found by analysing the observations that lies outside the acceptable level of deviation.

2. Benchmark prices are derived directly from the confidence interval of the distribution by conducting bootstrap statistics on the historical bids.

The weekly bids that exceed the value of the benchmark price will be flagged and used in the regression analysis to investigate if there are any external factors that might affect the price of the bid.

In the second step a regression analysis is carried out to determine if the flagged bid is reasonable according to certain parameters that might affect the price level. For the energy products, regression analysis is made for each RO and for the capacity products for each company. The regression analysis can give an indication of a reasonable price an object or company would bid given certain parameters that might affect the price. The outcome of the regression can then be compared to the actual price a participant has given for further investigation.

### 4.4.1 Balancing energy market

The BRP submit bids per RO, where one BRP can have several ROs in different bidding areas. As each RO has different properties that are influencing the bid, the BRPs are sure to have various behaviours depending on the RO. The historical data sets of aggregated bids are therefore divided into the participating ROs to differentiate behavioural differences between them allowing the model to more accurately detect anomalies.

### 4.4.2 Balancing capacity market

In the capacity market, aFRR and FCR, the BRP submits bids per company so the bids are not directly connected to a specific RO. Thus, the data sets of historical bids are consequently divided into the participating BRPs.

### 4.4.3 Screening analysis

As discussed in Section 2.3.6.1 a hydro power producer is assumed to bid according to its opportunity cost. Note that opportunity cost is a kind of marginal cost since it reflects the cost of producing electricity. Another important factor to take into consideration is the seasonal variations. The demand for electricity
in Sweden is generally higher during cold winter months compared to warm summer months. Therefore, the price for electricity varies with season. From this realisation, the bids are divided into seasons, see Table 4.1.

<table>
<thead>
<tr>
<th>Season</th>
<th>Month</th>
</tr>
</thead>
<tbody>
<tr>
<td>Winter</td>
<td>December (year ( y-1 ))-February (year ( y ))</td>
</tr>
<tr>
<td>Spring</td>
<td>March-May (year ( y ))</td>
</tr>
<tr>
<td>Summer</td>
<td>June-August (year ( y ))</td>
</tr>
<tr>
<td>Autumn</td>
<td>September-November (year ( y ))</td>
</tr>
</tbody>
</table>

Table 4.1: An example of an arbitrary year \( y \) and its season intervals.

In this study, a data set will be defined as a market participant’s historical bids within each season. A market participant is referred to as an RO in the energy activation market and as a company in the capacity market. The screening analysis is conducted separately for each market, that is mFRR, aFRR, FCR-N and FCR-D. As explained earlier in this section the bids are divided into season intervals. Also, the bids are divided into companies in the aFRR- and FCR markets and into ROs in the mFRR-market. Furthermore, the data are divided into up- and down-regulation. The division for the historical price bids set can be seen in Eq. 4.18a for aFRR and FCR and 4.18b for mFRR.

\[
p \_{i_co},s,st,n \in P^{Hist}_{i_co,s,st} \quad \quad (4.18a)
\]

\[
p \_{i_ro},s,st,n \in P^{Hist}_{i_ro,s,st} \quad \quad (4.18b)
\]

where subscript \( i_{co} \) represents company \( i_{co} = 1, 2, ..., CO \) in the aFRR- and FCR-markets where \( CO \) is the total number of companies and subscript \( i_{ro} \) represents RO \( i_{ro} = 1, 2, ..., RO \) in the mFRR-market where \( RO \) is the total number of ROs. Subscript \( s \) denotes the season as in Table 4.1 and \( st \) denotes the state in which the bid is placed, \( st = U, D \), where \( U \) is for up-regulation and \( D \) is for down-regulation. Subscript \( n \) represents the observation, \( n = 1, 2, ..., N \) where \( N \) is the total number of observations in \( P_{i,s} \).

Within each data set statistical analysis are made as an attempt to detect any potential outliers in the bidding data.

A benchmark is set for each data set to find bids with values higher than the maximum benchmark to find anomalies in the weekly bidding data. Using Eq. 4.1 in Section 4.3.1.1.4 the decision rule for the benchmark can be defined as,

\[
Pr(p > \bar{p}) < \alpha \quad \quad (4.19)
\]
which states the probability that a price, \(p\), takes a value higher than a certain benchmark price, \(\bar{p}\). \(\alpha\) is the acceptable probability that a price becomes larger than the benchmark price. Each approach in the screening analysis will have the same \(\alpha\).

### 4.4.3.1 Screening analysis with the assumption of normality

All the observations are converted to their corresponding z scores using Eq. 4.4,

\[
    z_i = \frac{p_i - \mu_p}{\sigma_p}
\]  

(4.20)

where \(\mu_p\) and \(\sigma_p\) are the mean and the standard deviation respectively of the random variable \(P \sim \mathcal{N}(\mu, \sigma^2)\).

The z score for the benchmark price is found in a standard normal table with a known \(\alpha\). The z score can then be converted to its corresponding observation from the original normal distribution. This is done by simply rearranging Eq. 4.20,

\[
    \bar{p}_{i,s,st} = \mu_{p_{i,s,st}} + z_\alpha \sigma_{p_{i,s,st}}
\]  

(4.21)

where \(\bar{p}\) represents the benchmark price for a given alpha with its corresponding z score, \(z_\alpha\) in season \(s\) and state \(st\) and \(i\) denotes either \(i = i_{co}\) or \(i_{ro}\). The z scores for the observations are then compared with \(z_\alpha\). When the z score of the observation is higher than or lower than \(z_\alpha\) the bids are flagged.

Outliers in the weekly data are detected as in Eq. (4.22).

Flagged Outlier: if

\[
    \begin{align*}
        & p_{i,s,st,n}^{\text{Week}} > \bar{p}_{i,s,st}, & \text{when } st = U \\
        & p_{i,s,st,n}^{\text{Week}} < \bar{p}_{i,s,st}, & \text{when } st = D
    \end{align*}
\]  

(4.22)

where \(p_{i,s,st,n}^{\text{Week}}\) is a bid in the weekly data, \(i = i_{co}, i_{ro}\) denotes either a company or a RO, \(\bar{p}_{i,s,st}\) is the upper benchmark price from the normal approximation of a data set and \(\bar{p}_{i,s,st}\) is the lower benchmark. If the bid is submitted as down regulation the lower benchmark is used to find outlier and if it is submitted as up regulation the upper benchmark is used.

The flagged bids are used in the regression analysis to find possible correlations between the flagged bids and other external factors such as electricity spot prices, gas prices and inflows to rivers.

The statistical analysis described is based on the assumption that the data set has a normal distribution. To check whether the data are normally dis-
tributed, or approximately normally distributed, distribution plots and normal-
ity tests, described in Section 4.3.1.1, are conducted for each data set.

4.4.3.2 Screening analysis using bootstrap statistics

The historical data are as mentioned divided into seasons as in Table 4.1 and
furthermore into ROs for the manual reserves and companies for the automatic
reserves. Up and down regulation are also separated into different data sets.
For each of the data sets bootstrapping is applied. Samples are drawn from
the population $P_{i_{co},s,st}$ for aFRR and FCR and $P_{i_{ro},s,st}$ for mFRR. From one
simulation we get the new bootstrap population as Eq. (4.6)

$$P_{i_{co},s,st}^* = p_{i_{co},s,st,1}^*, \ldots, p_{i_{co},s,st,n}^*$$  \hspace{1cm} (4.23a)

$$P_{i_{ro},s,st}^* = p_{i_{ro},s,st,1}^*, \ldots, p_{i_{co},s,st,n}^*$$  \hspace{1cm} (4.23b)

By performing multiple bootstrap simulations for each of data set, to get
new bootstrap estimations, a Monte Carlo approximation is made as described
in Section 4.3.1.2.1. The summarised bootstrap distribution is according to
Eq. (4.7) as

$$P_{i_{ro},s,st,Boot}^* = \sum_{m=1}^{M} P_{i_{ro},s,st,m}^*$$  \hspace{1cm} (4.24)

When the Monte Carlo approximation has been acquired for each data set,
the confidence intervals are used to get the lower and the upper benchmark
price. The benchmarks are used to test if the bids in the weekly data should
be flagged and used in the regression. The state determines if the lower or the
upper benchmark should be used. Outliers in the weekly data are detected as
in Eq. (4.25).

Flagged Outlier: if

$$\begin{cases} 
    p_{i_{s,s,1},n}^{Week} > p_{i,s,st}^*, & \text{when } st = U \\
    p_{i,s,s,1},n^{Week} < p_{i,s,st}^*, & \text{when } st = D 
\end{cases}$$  \hspace{1cm} (4.25)

where $p_{i,s,s,1},n^{Week}$ is a bid in the weekly data, $i = i_{co}, i_{ro}$ denotes either a company or a RO, $p_{i,s,st}^*$ is the upper benchmark price from the Monte carlo approx-
imation of a data set and $p_{i,s,st}^*$ is the lower benchmark. If the bid is submitted
as down regulation the lower benchmark is used to find outlier and vice versa.
4.4.4 **Multiple linear regression analysis**

The flagged bids from the statistical analysis is used in the regression analysis as an approach to further examine the bids from a market participant. The idea is to find correlation between the bid and factors that might cause the price of the submitted bid. When there is a strong correlation, the bid is assumed to have a reasonable price according to the factors that might affect it. If there is weak correlation the bid cannot be explained by affecting factors and might be subject to further investigation.

4.4.5 **Data**

The bid data analysed in this study is classified information and was provided by Svk, as mentioned in Section 1.2. The data will therefore not be published in this report.

As mentioned in Section 4.4.3 each bid is assigned a season according to Table 4.1. Furthermore, the bids are assigned a company or a regulation object depending on which market is analysed.

- **FCR**: The data for FCR-N and FCR-D are data between the year 2013 and 2019 on an hourly resolution. The data for FCR-N consist of both up- and down regulation bids while FCR-D consist of up regulating bids as well as data for D-1 and D-2.

- **aFRR**: The data for aFRR span from the year 2013 to 2019 on an hourly resolution. The data for aFRR consist of both up- and down regulation bids in D-1.

- **mFRR**: The data available for mFRR are in the range from late September 2017 to the end of August 2019.

The bid data are used in the screening analysis to determine benchmarks for each company and regulation object.

4.4.5.1 **Independent variables**

The external variables used in the regression (step 3 in Figure 1.1) are retrieved from various publicly available sources. The data which are used as independent variables in the regression are listed down below.

- **Capacity**: The bid volume in MW for each bid is provided in the bid data and is confidential.
**Spot Price:** Data for the spot prices are retrieved from Nord Pool’s historical market data and can be found in [47].

**Storage:** The total hydro storage levels in Sweden are gathered from *Energiföretagen Sverige* which can be found in [48].

**Inflow:** The total inflow from the larger rivers in Sweden are gathered from *Energiföretagen Sverige* which can be found in [48].

Table 4.2 describes the steps in Figure 1.1.

Table 4.2: Each step in the proposed method.

<table>
<thead>
<tr>
<th>Step</th>
<th>Description</th>
<th>Input</th>
<th>Output</th>
</tr>
</thead>
<tbody>
<tr>
<td>1a)</td>
<td>Confidence intervals are found for the historical price data using normal approximation</td>
<td>$p^{Hist}<em>{ico,s,st}$, $p^{Hist}</em>{iro,s,st}$</td>
<td>$\bar{p}<em>{ico,s,st}$, $\bar{p}</em>{iro,s,st}$</td>
</tr>
<tr>
<td>1b)</td>
<td>Confidence intervals are found for the historical price data using bootstrap</td>
<td>$p^<em>_{ico,s,st}$, $p^</em>_{iro,s,st}$</td>
<td>$\bar{p}^<em>_{ico,s,st}$, $\bar{p}^</em>_{iro,s,st}$</td>
</tr>
<tr>
<td>2a)</td>
<td>Screening analysis comparing benchmarks from normal approximation with one week of price data</td>
<td>$p^{Week}<em>{ico,s,st}$, $p^{Week}</em>{iro,s,st}$, $\bar{p}<em>{ico,s,st}$, $\bar{p}</em>{iro,s,st}$</td>
<td>$N_f$</td>
</tr>
<tr>
<td>2b)</td>
<td>Screening analysis comparing benchmarks from bootstrap distribution with one week of price data</td>
<td>$p^{Week}<em>{ico,s,st}$, $p^{Week}</em>{iro,s,st}$, $\bar{p}^<em>_{ico,s,st}$, $\bar{p}^</em>_{iro,s,st}$</td>
<td>$N_f$</td>
</tr>
<tr>
<td>3</td>
<td>Regression analysis with the flagged companies (balancing capacity market) and flagged ROs (balancing energy market)</td>
<td>Capacity [MW], spot price [SEK/MWh], inflows [MWh], storage [%]</td>
<td>$N_f$</td>
</tr>
</tbody>
</table>
Chapter 5

Validation of Proposed Method

The validation of the proposed method presented in this chapter are from an arbitrary week which was used to test the model. Due to secrecy, the week is not be specified and specific information about the bids are excluded. The validation of the regression model is made for the flagged companies and RO’s so no results from the regression will be shown from the remaining companies and RO’s. This is also due to confidentiality.

5.1 Testing Data for Normal Approximation

In this section, the normality tests for the flagged companies and ROs are presented. The descriptive tests for two arbitrary data sets in the balancing capacity market as well as two arbitrary data sets in the balancing energy market are also presented.

5.1.1 Balancing capacity market

In this section the balancing capacity normality tests and descriptive statistics are presented together due to having similar results. Two examples are shown for the descriptive statistics. The names of the companies are arbitrary and the names of the companies in the normality tests and descriptive statistics are not necessarily coherent. So for example, company A in the normality tests does not necessarily correspond to company A in the descriptive tests and so forth.

5.1.1.1 Normality tests

The values of the kurtosis and skewness for the flagged companies in aFRR during up regulation are shown in Table 5.1.
As can be seen in Table 5.1, the values for $k$ and $s$ are not close enough to the desired values of the parameters to be able to approximate the data to a normal distribution. The majority of the $k$- and $s$-values does not satisfy the $k = 3 \pm 2$ and $s = 0 \pm 1$.

### 5.1.1.2 Descriptive statistics

Additionally to the calculation of $k$ and $s$, inspection of the histograms and QQ-plots were made to evaluate if a normal approximation is reasonable. An example of a histogram of a flagged company can be seen in Figure 5.1.

Figure 5.1: Histograms of the up regulation winter and summer bid prices for company C in aFRR.

Figure 5.2 shows examples of the QQ-plots of an up regulation data set made with their corresponding kurtosis and skewness in Table 5.1.
5.1.2 Balancing energy market

The results for testing the plausibility of approximating the data to normal distribution in the market is presented below for the mFRR market.

5.1.2.1 Normality tests

The kurtosis and skewness for three randomly selected flagged ROs can be seen in Table 5.2.

Table 5.2: Kurtosis and skewness of the seasonal historic up regulation data for three flagged ROs in mFRR.

<table>
<thead>
<tr>
<th>RO</th>
<th>Winter</th>
<th>Spring</th>
<th>Summer</th>
<th>Autumn</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>k 3.03</td>
<td>s 0.73</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>5.60</td>
<td>3.12</td>
</tr>
<tr>
<td>B</td>
<td>k 5.17</td>
<td>s -2.04</td>
<td>2.52</td>
<td>2.87</td>
</tr>
<tr>
<td>C</td>
<td>k 3.76</td>
<td>s 0.52</td>
<td>67.33</td>
<td>3.94</td>
</tr>
</tbody>
</table>

Although some of the $k$ and $s$ of the data sets fall into the intervals of being able to approximate to normal distribution, as mentioned in Section 4.3.1.1, the majority of them do not.
5.1.2.2 Descriptive statistics

The histograms for a flagged RO during the winter and the summer in up regulation are shown in Figure 5.3.

![Histograms](image)

(a) Winter up regulation bid prices.  
(b) Summer up regulation bid prices.

Figure 5.3: Histogram of the winter and summer up regulation bid prices for flagged RO 13 in mFRR.

It can be seen that from Figure 5.3a or Figure 5.3b that the histograms do not follow the typical bell shaped histogram that could imply a normal distribution.

The QQ-plots for the winter and the summer are shown for flagged RO 13 in Figure 5.4.

![QQ-plots](image)

(a) Winter up regulation bid prices.  
(b) Summer up regulation bid prices.

Figure 5.4: QQ-plots of the summer bid prices for flagged RO 13 in mFRR.

The QQ-plots show that the data sets have various distribution shapes. Some values align with the reference line but the majority tend to deviate. The tails especially deviate from the reference line.
5.2 Screening analysis

The flagged bids from normal approximation and bootstrap are presented here for comparison for each of the four markets.

5.2.1 FCR-N

The number of flagged bids in FCR-N in D-1 and D-2 during a arbitrary selected week during autumn 2019 are shown in Table 5.3.

Table 5.3: Number of flagged bids during a week in FCR-N during D-1 and D-2, $N_{FCRN-D_1}^f$ and $N_{FCRN-D_2}^f$ respectively, after running screening analysis with normal approximation and bootstrap.

<table>
<thead>
<tr>
<th></th>
<th>Normal approximation</th>
<th>Bootstrap</th>
</tr>
</thead>
<tbody>
<tr>
<td>$N_{FCRN-D_1}^f$</td>
<td>15</td>
<td>111</td>
</tr>
<tr>
<td>$N_{FCRN-D_2}^f$</td>
<td>235</td>
<td>485</td>
</tr>
</tbody>
</table>

5.2.2 FCR-D

The number of flagged bids in FCR-D in D-1 and D-2 during a arbitrary selected week during autumn 2019 are shown in Table 5.4.

Table 5.4: Number of flagged bids during a week in FCR-D during D-1 and D-2, $N_{FCRD-D_1}^f$ and $N_{FCRD-D_2}^f$ respectively, after running screening analysis with normal approximation and bootstrap.

<table>
<thead>
<tr>
<th></th>
<th>Normal approximation</th>
<th>Bootstrap</th>
</tr>
</thead>
<tbody>
<tr>
<td>$N_{FCRD-D_1}^f$</td>
<td>390</td>
<td>53</td>
</tr>
<tr>
<td>$N_{FCRD-D_2}^f$</td>
<td>456</td>
<td>75</td>
</tr>
</tbody>
</table>

5.2.3 aFRR

The number of flagged bids in aFRR during a arbitrary selected week during autumn 2019 are shown in Table 5.5.
Table 5.5: Number of flagged bids, $N_{aFRR}^f$, during a week in aFRR after running screening analysis with normal approximation and bootstrap.

<table>
<thead>
<tr>
<th>Normal approximation</th>
<th>Bootstrap</th>
</tr>
</thead>
<tbody>
<tr>
<td>$N_{aFRR}^f$</td>
<td>284</td>
</tr>
</tbody>
</table>

5.2.4 mFRR

The number of flagged bids in mFRR during an arbitrary selected week during autumn 2019 are shown in Table 5.6.

Table 5.6: Number of flagged bids, $N_{mFRR}^f$, during a week in mFRR after running screening analysis with normal approximation and bootstrap.

<table>
<thead>
<tr>
<th>Normal approximation</th>
<th>Bootstrap</th>
</tr>
</thead>
<tbody>
<tr>
<td>$N_{mFRR}^f$</td>
<td>1614</td>
</tr>
</tbody>
</table>

5.3 Regression analysis

The validation of the regression presents the amount of discarded bids, the $R^2$ value from the regressions and the statistical parameters of the coefficients for the regression with the highest $R^2$ value.

The amount of bids discarded by the regression is presented in Table 5.7 together with the amount of flagged bids from the bootstrap.

Table 5.7: Number of flagged bids from bootstrap and discarded bids after the regression.

<table>
<thead>
<tr>
<th>Bootstrap</th>
<th>Regression bids discarded</th>
</tr>
</thead>
<tbody>
<tr>
<td>$N_{FCRN-D1}^f$</td>
<td>111</td>
</tr>
<tr>
<td>$N_{FCRN-D2}^f$</td>
<td>485</td>
</tr>
<tr>
<td>$N_{FCRD-D1}^f$</td>
<td>53</td>
</tr>
<tr>
<td>$N_{FCRD-D2}^f$</td>
<td>75</td>
</tr>
<tr>
<td>$N_{aFRR}^f$</td>
<td>180</td>
</tr>
<tr>
<td>$N_{mFRR}^f$</td>
<td>797</td>
</tr>
</tbody>
</table>

The difference between the amount of flagged bids from the bootstrap method and the amount of discarded bids from the regression are the number of bids that could be explained by the external factors. The only market
where flagged bids and discarded bids differed was in mFRR.

The $R^2$ values and regression coefficients are presented below for each market.

### 5.3.1 FCR-N

The $R^2$ values of the flagged company regressions in FCR-N are presented in Table 5.8 for the bids in D-1 and in Table 5.9 for D-2.

Table 5.8: $R^2$ values from the multiple linear and polynomial regression as well as multiple regression with an interaction term for each flagged company in FCR-N in D-1.

<table>
<thead>
<tr>
<th>Company</th>
<th>Linear</th>
<th>Polynomial</th>
<th>Interaction</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>0.1299</td>
<td>0.1635</td>
<td>0.1691</td>
</tr>
<tr>
<td>B</td>
<td>0.3413</td>
<td>0.4200</td>
<td>0.4379</td>
</tr>
<tr>
<td>C</td>
<td>0.0593</td>
<td>0.1464</td>
<td>0.1465</td>
</tr>
</tbody>
</table>

Table 5.9: $R^2$ values from the multiple linear and polynomial regression for three flagged company in FCR-N in D-2.

<table>
<thead>
<tr>
<th>Company</th>
<th>Linear</th>
<th>Polynomial</th>
<th>Interaction</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>0.1389</td>
<td>0.1861</td>
<td>0.1906</td>
</tr>
<tr>
<td>B</td>
<td>0.193</td>
<td>0.2283</td>
<td>0.2303</td>
</tr>
<tr>
<td>C</td>
<td>0.2457</td>
<td>0.3337</td>
<td>0.3356</td>
</tr>
</tbody>
</table>

Table 5.10 shows the regression coefficients for company B in Table 5.8 with polynomial regression and an interaction term. The regression with interaction of company B was chosen as it had the highest $R^2$ value.

Table 5.10: Statistical parameters of the coefficients from the multiple polynomial regression with an interaction term for company B in FCR-N in D-1 (‘***’ 0.001, ‘*’ 0.05).

<table>
<thead>
<tr>
<th></th>
<th>Standard Error</th>
<th>$t$-value</th>
<th>$p$-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>4.777e-02</td>
<td>129.500</td>
<td>&lt; 2e-16 ***</td>
</tr>
<tr>
<td>Capacity</td>
<td>2.615e-01</td>
<td>-2.545</td>
<td>0.0110 *</td>
</tr>
<tr>
<td>Capacity$^2$</td>
<td>2.957e-01</td>
<td>7.109</td>
<td>1.31e-12 ***</td>
</tr>
<tr>
<td>Spot Price</td>
<td>1.978e-01</td>
<td>15.387</td>
<td>&lt; 2e-16 ***</td>
</tr>
<tr>
<td>Spot Price$^2$</td>
<td>2.091e-01</td>
<td>2.388</td>
<td>0.0170 *</td>
</tr>
<tr>
<td>Storage</td>
<td>1.411e+00</td>
<td>-14.256</td>
<td>&lt; 2e-16 ***</td>
</tr>
</tbody>
</table>
Table 5.10: Statistical parameters of the coefficients from the multiple polynomial regression with an interaction term for company B in FCR-N in D-1 (‘***’ 0.001, ‘*’ 0.05).

<table>
<thead>
<tr>
<th></th>
<th>Standard Error</th>
<th>t-value</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Storage</td>
<td>4.295e-01</td>
<td>-5.538</td>
<td>3.20e-08 ***</td>
</tr>
<tr>
<td>Inflows</td>
<td>1.435e+01</td>
<td>-13.313</td>
<td>&lt; 2e-16 ***</td>
</tr>
<tr>
<td>Inflows²</td>
<td>2.860e-01</td>
<td>2.162</td>
<td>0.0306 *</td>
</tr>
<tr>
<td>Storage*Inflow</td>
<td>4.375e-05</td>
<td>13.914</td>
<td>&lt; 2e-16 ***</td>
</tr>
<tr>
<td>Winter</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Spring</td>
<td>4.045e-02</td>
<td>-5.889</td>
<td>4.11e-09 ***</td>
</tr>
<tr>
<td>Summer</td>
<td>8.317e-03</td>
<td>-9.046</td>
<td>&lt; 2e-16 ***</td>
</tr>
</tbody>
</table>

The reason for the missing values in the row "Winter" in Table 5.10 is that there are no bids during this period for company B.

5.3.2 FCR-D

The $R^2$ values of the flagged company regressions in FCR-D are presented in Table 5.11 for the bids in D-1 and in Table 5.12 for D-2.

Table 5.11: $R^2$ values from the multiple linear and polynomial regression for each company from the flagged bids in $N_{FCRD-D1}^f$.

<table>
<thead>
<tr>
<th></th>
<th>Linear</th>
<th>Polynomial</th>
<th>Interaction</th>
</tr>
</thead>
<tbody>
<tr>
<td>Company A</td>
<td>0.2309</td>
<td>0.2361</td>
<td>0.2362</td>
</tr>
<tr>
<td>Company B</td>
<td>0.1226</td>
<td>0.1444</td>
<td>0.1554</td>
</tr>
</tbody>
</table>

Table 5.12: $R^2$ values from the multiple linear and polynomial regression for each company from the flagged bids in $N_{FCRD-D2}^f$.

<table>
<thead>
<tr>
<th></th>
<th>Linear</th>
<th>Polynomial</th>
<th>Interaction</th>
</tr>
</thead>
<tbody>
<tr>
<td>Company A</td>
<td>0.2488</td>
<td>0.2656</td>
<td>0.2703</td>
</tr>
<tr>
<td>Company B</td>
<td>0.2458</td>
<td>0.2649</td>
<td>0.2715</td>
</tr>
</tbody>
</table>

Table 5.13 shows the regression coefficients for company B in D-2 from Table 5.12 with polynomial regression and an interaction term.
Table 5.13: Statistical parameters of the coefficients from the multiple polynomial regression with an interaction term for company B in FCR-D in D-2 (‘***’ 0.001, ‘*’ 0.05).

<table>
<thead>
<tr>
<th></th>
<th>Standard Error</th>
<th>t-value</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>1.121e+00</td>
<td>-8.342</td>
<td>&lt; 2e-16***</td>
</tr>
<tr>
<td>Capacity</td>
<td>1.316e+02</td>
<td>-263.179</td>
<td>&lt;2e-16***</td>
</tr>
<tr>
<td>Capacity(^2)</td>
<td>1.267e+02</td>
<td>108.661</td>
<td>&lt;2e-16***</td>
</tr>
<tr>
<td>Spot Price</td>
<td>1.435e+02</td>
<td>192.765</td>
<td>&lt;2e-16***</td>
</tr>
<tr>
<td>Spot Price(^2)</td>
<td>1.281e+02</td>
<td>-77.580</td>
<td>&lt;2e-16***</td>
</tr>
<tr>
<td>Storage 2.047e-02</td>
<td>81.822</td>
<td></td>
<td>&lt;2e-16***</td>
</tr>
<tr>
<td>Storage(^2)</td>
<td>1.658e+02</td>
<td>-34.018</td>
<td>&lt;2e-16***</td>
</tr>
<tr>
<td>Inflows 5.182e-04</td>
<td>-22.822</td>
<td></td>
<td>&lt;2e-16***</td>
</tr>
<tr>
<td>Inflows(^2)</td>
<td>1.428e+02</td>
<td>-0.700</td>
<td>0.484*</td>
</tr>
<tr>
<td>Storage*Inflow</td>
<td>1.027e-05</td>
<td>76.855</td>
<td>&lt;2e-16***</td>
</tr>
<tr>
<td>Spring</td>
<td>7.863e-01</td>
<td>115.502</td>
<td>&lt;2e-16***</td>
</tr>
<tr>
<td>Summer</td>
<td>5.822e-01</td>
<td>26.997</td>
<td>&lt;2e-16***</td>
</tr>
<tr>
<td>Autumn</td>
<td>6.063e-01</td>
<td>-80.209</td>
<td>&lt;2e-16***</td>
</tr>
</tbody>
</table>

5.3.3 aFRR

Running a regression on the flagged companies gives the \(R^2\) values shown in Table 5.14 and the statistical parameters of the independent variable coefficients for a flagged company in Table 5.15.

Table 5.14: \(R^2\) values from the multiple linear and polynomial regression for three flagged companies in aFRR in up regulation.

<table>
<thead>
<tr>
<th></th>
<th>Linear</th>
<th>Polynomial</th>
<th>Interaction</th>
</tr>
</thead>
<tbody>
<tr>
<td>Company A</td>
<td>0.1843</td>
<td>0.226</td>
<td>0.2264</td>
</tr>
<tr>
<td>Company B</td>
<td>0.0999</td>
<td>0.1401</td>
<td>0.1561</td>
</tr>
<tr>
<td>Company C</td>
<td>2626</td>
<td>0.325</td>
<td>0.352</td>
</tr>
</tbody>
</table>

Table 5.15: Statistical parameters of the coefficients from the multiple polynomial regression with an interaction term for company C in aFRR (‘***’ 0.001, ‘**’ 0.01).

<table>
<thead>
<tr>
<th></th>
<th>Standard Error</th>
<th>t-value</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>3.729e-02</td>
<td>172.018</td>
<td>&lt; 2e-16***</td>
</tr>
<tr>
<td>Capacity</td>
<td>7.926e-03</td>
<td>5.686</td>
<td>1.31e-08***</td>
</tr>
</tbody>
</table>
Table 5.15: Statistical parameters of the coefficients from the multiple polynomial regression with an interaction term for company C in aFRR (‘***’ 0.001, ‘**’ 0.01).

<table>
<thead>
<tr>
<th></th>
<th>Standard Error</th>
<th>t-value</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Capacity(^2)</td>
<td>3.510e-04</td>
<td>-10.192</td>
<td>&lt; 2e-16 ***</td>
</tr>
<tr>
<td>Spot Price</td>
<td>7.623e-01</td>
<td>-4.425</td>
<td>9.67e-06 ***</td>
</tr>
<tr>
<td>Spot Price(^2)</td>
<td>6.367e-01</td>
<td>-0.732</td>
<td>0.46438</td>
</tr>
<tr>
<td>Storage</td>
<td>1.572e+00</td>
<td>-16.778</td>
<td>&lt; 2e-16 ***</td>
</tr>
<tr>
<td>Storage(^2)</td>
<td>8.348e-01</td>
<td>-43.024</td>
<td>&lt; 2e-16 ***</td>
</tr>
<tr>
<td>Inflows</td>
<td>1.896e+00</td>
<td>25.394</td>
<td>&lt; 2e-16 ***</td>
</tr>
<tr>
<td>Inflows(^2)</td>
<td>8.062e-01</td>
<td>-1.295</td>
<td>0.19536</td>
</tr>
<tr>
<td>Storage*Inflows</td>
<td>4.375e-05</td>
<td>13.914</td>
<td>&lt; 2e-16 ***</td>
</tr>
<tr>
<td>Winter</td>
<td>1.805e-02</td>
<td>-38.561</td>
<td>&lt; 2e-16</td>
</tr>
<tr>
<td>Spring</td>
<td>1.237e-02</td>
<td>42.874</td>
<td>0.00677 **</td>
</tr>
<tr>
<td>Summer</td>
<td>3.055e-07</td>
<td>-31.407</td>
<td>&lt; 2e-16 ***</td>
</tr>
</tbody>
</table>

### 5.3.4 mFRR

A regression was performed for all the RO’s that were flagged. The $R^2$ values for the polynomial regression are presented in Table 5.16.

Table 5.16: $R^2$ values from the multiple linear and polynomial regression as well as multiple regression with an interaction term for three flagged ROs in mFRR in up regulation.

<table>
<thead>
<tr>
<th></th>
<th>Linear</th>
<th>Polynomial</th>
<th>Interaction</th>
</tr>
</thead>
<tbody>
<tr>
<td>Company A</td>
<td>0.8030</td>
<td>0.8298</td>
<td>0.8314</td>
</tr>
<tr>
<td>Company B</td>
<td>0.9999</td>
<td>0.9999</td>
<td>0.9999</td>
</tr>
<tr>
<td>Company C</td>
<td>0.6016</td>
<td>0.6763</td>
<td>0.6765</td>
</tr>
</tbody>
</table>

The statistical parameters of the coefficients of the best RO in terms of the highest $R^2$ value is presented in Table 5.17.

Table 5.17: Statistical parameters of the coefficients from the multiple polynomial regression with one interaction term for the best $R^2$ value (flagged company 13) in mFRR (‘***’ 0.001).

<table>
<thead>
<tr>
<th></th>
<th>Standard Error</th>
<th>t-value</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>1.063e-01</td>
<td>40.602</td>
<td>&lt; 2e-16 ***</td>
</tr>
<tr>
<td>Capacity</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>
Table 5.17: Statistical parameters of the coefficients from the multiple polynomial regression with one interaction term for the best $R^2$ value (flagged company 13) in mFRR (‘***’ 0.001).

<table>
<thead>
<tr>
<th></th>
<th>Standard Error</th>
<th>t-value</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Capacity$^2$</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Spot Price</td>
<td>1.849e-04</td>
<td>5417.984</td>
<td>&lt; 2e-16 ***</td>
</tr>
<tr>
<td>Spot Price$^2$</td>
<td>1.654e-07</td>
<td>-4.140</td>
<td>3.49e-05 ***</td>
</tr>
<tr>
<td>Storage</td>
<td>3.730e-03</td>
<td>4.997</td>
<td>5.88e-07 ***</td>
</tr>
<tr>
<td>Storage$^2$</td>
<td>3.671e-05</td>
<td>-6.610</td>
<td>3.96e-11 ***</td>
</tr>
<tr>
<td>Inflows</td>
<td>3.702e-05</td>
<td>4.630</td>
<td>3.67e-06 ***</td>
</tr>
<tr>
<td>Inflows$^2$</td>
<td>3.833e-09</td>
<td>-6.097</td>
<td>1.10e-09 ***</td>
</tr>
<tr>
<td>Storage*Inflow</td>
<td>5.128e-07</td>
<td>1.777</td>
<td>0.0756 *</td>
</tr>
<tr>
<td>Weekend</td>
<td>1.988e-02</td>
<td>8.501</td>
<td>&lt; 2e-16 ***</td>
</tr>
<tr>
<td>Winter</td>
<td>3.723e-02</td>
<td>0.730</td>
<td>0.4652 *</td>
</tr>
<tr>
<td>Spring</td>
<td>5.079e-02</td>
<td>0.454</td>
<td>0.6499 *</td>
</tr>
<tr>
<td>Summer</td>
<td>2.545e-02</td>
<td>5.916</td>
<td>3.35e-09 ***</td>
</tr>
</tbody>
</table>
Chapter 6

Results

This chapter explains the validation results from Chapter 5. The validation is analysed and the performance of the proposed method is determined.

6.1 Manipulation

From the interviews it was clear that cartels could be a potential manipulation risk, especially with the increased transparency if the bids would become public. It was the manipulation type that would be most considerable in the balancing power market.

From the ACER’s guidelines on REMIT it could be concluded that many of the manipulation types could be discarded due to the market configuration described in Section 2.3.5. However, it could be identified that abusive squeeze or market cornering could be a potential risk in the balancing power market due to the fact that there are a few market participants.

6.2 Screening Analysis

By looking at the validation of the data in Section 5.1 to determine if it is possible to approximate the data to normal distribution we see that there are numerous data sets that are unsatisfactory. An ideal QQ-plot would have all the sample quantiles equal to the corresponding reference line. All of them have tails that deviate from the reference line. This goes for both market designs. Therefore, the use of a method in which we assume normal distribution is not a preferable choice. A method that can handle different distributions is more satisfactory.
The validation of the bootstrap method in Section 5.2 gave promising results in terms of the number of flagged bids. From a statistical standpoint the number of flagged bids in the bootstrap analysis was more in line with the significance level used in the validation of the method. To approximate the data to a normal distribution is not recommended in future studies which the normality tests showed. An attempt to approximate the data to normal distribution was made and it resulted in the amount of flagged bids as in Section 5.2. The amount of flagged bids did not reflect the value of the significance level and the bootstrap method was concluded to be the method of choice.

6.3 Regression Analysis

The regression analysis is more adaptable in the balancing energy market than in the balancing capacity market. The bid prices in the capacity market spans over a large interval, much likely due to being bids for different regulation objects in the company, which the regression cannot handle as much as in the balancing energy market where the bid prices spans over a smaller interval. This could be concluded from the low $R^2$-values in the regression of the balancing capacity market. As can be seen in Table 5.7, the regression model could not predict any bids with the external variables in the balancing capacity market. The balancing energy market had some bids that were explained but 90% of the flagged bids were still discarded.

So the specific regression model conducted in this study is not recommended to use in the balancing capacity market. However, for some of ROs in the balancing energy market, the regression model is an acceptable model in explaining the variations in the predictive variable. But since this is not a generic validation of all the ROs in the balancing energy market, the regression model is not recommended to use for prediction.
Chapter 7

Discussion

In this chapter, a discussion of the results will be provided as well as a discussion about the potential market manipulation in the balancing power market.

In the initiation of the project a limitation was made on the historical data. It was mentioned that there is no certainty that the provided historical data are without market violations. There would not be an investigation of the data as it was not the scope to find potential abuse in those. For all we know, there could be potential market violations in the historical data that would affect the results. If there were to be any market violations in the historical bids it would cause the model to get inaccurate benchmark prices. Those inaccurate benchmark prices could potentially cause bids that are anomalous to slip through.

7.1 Assessing Manipulation Types

It can be argued whether or not all the manipulation types mentioned in Section 3.2 are adaptable in the balancing market. The design of the balancing market differs from the other wholesale electricity markets in the aspect that there is only a one-way trade as mentioned in Section 2.3.5. The trade is strictly between the BRP and SvK, SvK is the only buyer during up-regulation and the only seller during down-regulation. It does not allow trading between two BRP’s. Furthermore, there is only one trade made for the available energy. The capacity that has been traded once will not be traded again. It eliminates the possibility of influencing the price by trading power with another BRP, trading with yourself, by bidding near the close of the market or by.

One way to influence the price is to create a false demand. The false demand can be acquired by buying and selling repeatedly. That is not possible in the balancing power market as the demand is known. The automatic reserves
has requirements on how much capacity should be available and SvK procures enough to fulfil the requirement. The energy for the manual reserves is bought or sold to saturate the deviation in energy in real time and the actual demand is known when the trade occurs.

With this said, most of the manipulations types in Section 3.2 can be excluded from analysis of balancing power market. The interviews in Section 3.2.2 mention cartel to be a possible manipulation type no one considered any other manipulation type in the balancing power market.

### 7.2 Preferable Screening Approach

The question in being able to compare the two different approaches used in the screening analysis is whether the data could be approximated to normal distribution or not. By utilising the techniques of descriptive statistics and normality tests described in Section 4.3.1.1.1 and 4.3.1.1.2, results showed to not be promising for most of the data sets. Although a part of the data sets were within acceptable intervals of being able to approximate it to normal distribution, most of them were vague and skewed to a limit that an attempt of approximating it to normal distribution would be beyond acceptable. Approximating the data sets to normal distribution and using the corresponding z-values would be deemed theoretically incorrect. Considering that the distribution of the data sets differ, using a non-parametric solution such as bootstrap proved to be more accurate.

With the significance level $\alpha$ that was chosen, the bootstrap approach gave more satisfactory results in the screening analysis. The amount of flagged bids in the screening analysis with normal approximation constituted a larger proportion of the total number of bids during the analysed week than in the bootstrap approach. This in itself would not necessarily mean that the results from the normal approximation is less better than the bootstrap. Although, looking at the significance level chosen, the amount of flagged bids should reasonably be the same or approximately the same percentage of the total amount of bids during the analysed week as the $\alpha$ chosen. The reason was due to the fact that all data sets could not be approximated to normal distribution leading to benchmark prices that were not ideal. Therefore, the bootstrap was chosen as the preferable screening approach to flag bids that would be used in the regression analysis.
7.3 Market Design

When inspecting the histogram of the company’s bid prices in the capacity markets it can be seen that they have a heavy-tail distribution. Because of the market design of the capacity market, each bid is not assigned to a specific generator, it is assigned to a company as mentioned in Section 2.3. A company might have several generators with the capability to reserve capacity to the market during a specific hour. This is most likely the reason for why a company places several bids with different bid prices at a specific hour. From the BRP point of view, the company probably has a complex optimisation problem consisting of all the RO that they own and variables such as production and price prognoses. The solution of the optimisation problem is a forecast of the which market each RO should be dispatched to what capacity and to which price. That is why the bids for the same company at the given hour could be so variate. Having several unique bids from the same company at the same hour makes the analysis a bit more complex since it is not capable to identify one bid from one hour to another. It is difficult if not impossible to identify which bidding zone the power would be dispatched in. Thus, variables that vary substantially between price areas would be difficult to use, such as ambient conditional variables. To have price variation in a company’s bid at the same hour might make the screening analysis a bit biased. Biased in that sense that the lower bids affect the benchmark level more than the higher priced bids or vice versa.

A statistical analysis could therefore be considered as faulty when the market design does not reflect the way the companies are actually bidding, by placing bids indirectly linked to an RO. Comparing with the results acquired from mFRR where the bids can actually be connected to an RO, the results were more statistically correct since the bids reflected the behaviour of that RO. It is therefore considered reasonable to believe that applying a statistical analysis to a market, where the bids are not connected to a special RO or does not reflect the way the company is bidding, would cause it to fail at obtaining sensible results. This because the behaviour of the bids most likely varies as it is not known which RO the company are meaning to dispatch with a specific bid. If the market design were to change and the bids would include which RO that would be dispatched, the analysis would be more accurate to determine a behaviour and to identify anomalies.
7.4 Regression Analysis

The results from the regression shows low $R^2$-values, especially in the capacity market. With low $R^2$-values, the regression model cannot capture the variations in the response variable as much as if the regression would show higher $R^2$-values. However, the predictive variables in the regression model shows statistical significance with $p$-values less than 0.05 which means that the variables are statistically significant on a 95% confidence level. The low $p$-value indicates that the coefficients for the predictive variables cannot be neglected. Although the model in a whole have a low $R^2$ and cannot explain the variations in the response variable, a valuable conclusion can be drawn from the independent variables in the sense that they are of some importance.

A reason for the general higher values of $R^2$ in the energy market can be that the bids are laid per RO. The regression model can better reflect the variations of the response variable with higher $R^2$-values. Since the price of the bids aren’t as spread out as in the capacity market the regression model can better explain the variations in the data. In the capacity market where the bids are laid per company it is harder to distinguish the reason for the variations in the bid price. The companies in the capacity markets most likely bids according to ROs but this is not shown in today’s market design of the capacity market as discussed above.

A reason for why not more bids were explained in the balancing energy market could be a lack of data. The data used in the balancing energy market spanned from Sep 2017 to Sep 2019. As 2018 was an unlikely expensive year it surely affected the validation of the regression.

The regression did not give satisfactory results for the balancing power market and an interesting thing to test would be to try a non linear regression to see if it could fit the varying data better unless the market design is changed such that bids are connected to RO’s.
Chapter 8

Closure

This chapter will give a conclusion about the findings in this study as well as some recommendations of possible future works.

8.1 Conclusion

Market manipulation is a trading behaviour with the intent to artificially increase or decrease the price of an asset. In the balancing power market, it can be concluded from the interviews that this market can be exposed to companies forming cartels.

From the results of the screening analysis it can be concluded that the bootstrap method is to prefer since the data to be analysed cannot be approximated to a normal distribution. Also the low variance of the benchmarks from the bootstrap in the balancing energy market showed that the bootstrap method worked better for that market where the distributions are not as heavy-tailed as in the capacity market.

It is not appropriate to use the specific regression model developed in this study to analyse the bidding outcome in the capacity market. In the balancing energy market however, the regression model could be a possible approach for some of the RO’s where the regression model have proven to be a good fit of the bid price variations. Nevertheless, the explanatory variables had statistical significance in all markets which is a first step in analysing the bid price variations in the capacity market as well.
8.2 Future work

More work needs to be done in the screening analysis for heavy-tailed distributions. Modifications of the bootstrap can be made or some other non-parametric approach could be used to better replicate the underlying distribution in order to find the statistical parameters of interest. Also, test other methods that can handle large variations in the data to be analysed to make better estimates of a reasonable bid price.

As discussed in Chapter 7, there is no certainty that the historical bids are free of violations. Investigation of that data was not performed since the scope of the project was to identify anomalies in the weekly data. It should therefore be considered to analyse the historical bids to investigate whether the data contain violations or not.

A method that was proposed during the interview with [21] was a bid/cost markup estimation. The idea was to estimate the cost of a specific RO with exogenous variables to get the price markup on their bids. If the markup increased over time, their would be a reason to believe that the RO would be violating the market. The bid/cost markup would be interesting to investigate on a market where the bids are submitted for a RO so that exogenous variables such as weather and local inflow could be used. The method would then phase the difficulties of estimating the cost of the parties.

Many of the interviewees mentioned that one possible risk with publication of bid data is that the market is more exposed to companies colluding. In the near future when the bid data will be published a study in analysing the potential risks of colluding companies and/or any signs of colluding companies in the balancing power market could be important to consider.

The interview part only consisted as a small part of this study and was initiated in the beginning. The interviews gave a lot of insight in market manipulation and especially how market manipulation could be applied in the balancing power market. It would be interesting to conduct more interviews with relevant people and conduct more in depth and a more organised interview study to further assess what manipulation types can be applied and perhaps even more interesting, how they can be applied in the balancing power market.

One consideration in analysing market manipulation in the balancing power market is to measure the level of market power. If a company or companies has a high influence over a market there is a risk of them being abusive of the market power they have. This is related to the abusive squeeze or market cornering listed in Section 3.2. Further studies could be conducted to analyse if it exists market power in the Swedish balancing power market and also if there
exists evidence of someone abusing their market power.

The bidding in the balancing power market is the last step in the electricity trade. Players who participate in the balancing power market do also have the possibility to trade in other energy wholesale markets other than the balancing power market. A player can be strategic between markets to maximise profit and an interesting subject to investigate is to analyse the possible correlation with a player’s behaviour in one market and on another. For example, analysing a market participant’s trading in the spot market and the same participant’s trading in the balancing power market to see if the behaviour between the markets could have an impact. An action in one market might not constitute market manipulation on its own but the combination of the trading pattern between markets might be considered as potential market manipulation.
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