Optimal Day-Ahead Scheduling and Bidding Strategy of Risk-Averse Electric Vehicle Aggregator

A Case Study of the Nordic Energy and Frequency Containment Reserve Markets

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Master's Thesis at School of Electrical Engineering & Computer Science
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Date: Aug 2018

TRITA-EECS-EX-2018:313
Abstract

The Nordic synchronous grid is facing a number of challenges. The ongoing phaseout of synchronous generation coupled with increased penetration of intermittent renewable generation is leading to reduced system inertia. Additionally, the electrification of sectors of the economy such as transport will result in the addition of significant new electrical loads. All these factors are contributing to increased complexities in maintaining the power balance. As such, it is imperative that every resource potentially capable of providing flexibility, on both sides of the balancing equation, must be closely examined.

The electrification of private transport is a technology of growing interest that can provide flexibility to the power system if adequately utilized. Electric vehicles (EV) can be considered as temporary energy storages with availability, energy and capacity constraints. If aggregated in sufficient numbers or combined with other assets they can fulfill the minimum bid size of specific markets. Numerous previous references have studied the potential in aggregating the increasingly important EV charging load. However, they are based on synthetic driving behavior and vehicle characteristics and commonly investigate only energy arbitrage. Furthermore, no studies have examined an EV aggregator entering Nordic energy and primary reserve markets to the authors’ best knowledge.

In this study, we use first hand data of a real EV fleet of 806 Tesla vehicles and their historical driving patterns to develop a two-stage stochastic optimization problem. Based on a scenario selection method, this research provides an optimal risk-averse bidding strategy for an aggregator of EVs that places bids in both the day ahead energy and primary reserve markets in the Nordics through the use of GAMS/Matlab software. Only uni-directional charging is examined, while we consider two sources of uncertainty from prices and vehicle utilization and model a risk averse aggregator that aims to maximize its profits. A case study is carried out modelling individual vehicles and their real world characteristics and driving behavior in the price areas NO5 & SE3 in Norway & Sweden across a 24hr weekday period for winter and summer. Results show strong alignment of EV availability and periods of high primary reserve market prices, with consumption being shifted largely towards early hours of the morning. In Norway, 342 NOK can be expected as revenue from combined energy arbitrage and FCR-N per vehicle per year, while in Sweden the value is 1470 SEK. When compared to a reference “cost of charging case”, up to 50% of the cost of charging can be covered in Norway, while the entire cost is essentially met in Sweden; resulting in the value proposition of “free charging” to the end user.
Sammanfattning

Det nordiska synkroniserade elnätet står inför ett antal utmaningar. Uthyttet av synkron generation i kombination med ökad penetration av intermittent förnybar generation leder till minskad svängmassa i systemet. Dessutom kommer elektrifiering av flera sektorer av ekonomin som transport resultera i en ökad belastning av systemet. Alla dessa faktorer bidrar till ökad komplexitet att upprätthålla kraftbalansen. Som sådan är det nödvändigt att varje resurs som potentiellt är kapabel att tillhandahålla flexibilitet, på båda sidor av balancersekvationen, måste undersökas noggrant.

Elektrifiering av privat transport är en teknik av växande intresse som kan ge flexibilitet till elsystemet om det används tillfredsställande. Elektriska fordon (EV) kan betraktas som tillfälliga energilager. Om de aggregeras i tillräckliga antal eller i kombination med andra tillgångar kan de uppfylla minsta budstorlek för specifika marknader. Tidigare studier har studerat potentielen för att aggregera den allt viktigare EV laddningsbelastningen. De är dock baserade på syntetiskt körbeteende och fordonssegenskaper och undersöker vanligtvis bara energiabitrage. Å andra sidan har inga undersökningar granskat en EV-aggregat som en del på den nordiska spotmarknaden och primärregleringen till författarens bästa kunskaper.

I den här studien använder vi förstahandsuppgifter av en verklig EV-flotta med 806 Tesla-fordon och deras historiska körmönster för att utveckla ett stegvis optimeringsproblem i två steg. Baserat på en scenariosvalsmetod ger denna forskning en optimal riskavvikande budstrategi för ett aggregat av EV som placerar bud på både den dagliga spotmarknaden och primära reservmarknaden i Norden genom användningen av GAMS / Matlab. Endast enriktad laddning undersöks, medan vi betraktar två källor till osäkerhet från priser och fordonsutnyttjande och modellerar en riskavvikande aggregator som syftar till att maximera vinsten. En fallstudie genomfördes modellering enskilda fordon och deras verkliga världskaraktäristika och körbeteende i prisområdena NO5 & SE3 i Norge & Sverige under en 24-timmars veckodag under vinter och sommar. Resultatet visar starkt anpassning av EV-tilgängligheten och perioder med höga primära reservmarknadspriser, där konsumtionen förskjuts i stor utsträckning mot tidigt på morgonen. I Norge kan 342 kronor förväntas som intäkter från energi arebitrage + FCR-N per fordon per år, medan i Sverige värdet är 1470 SEK. Jämfört med en referens kostnad för laddning kan upp till 50% av laddningskostnaden täckas i Norge, medan hela kostnaden i huvudsak möts i Sverige.
Acknowledgements

First and foremost, my thanks must be passed to my academic supervisor Lars Herre at KTH and my industry supervisor Jakob Jönsson at Tibber. You generously provided me with constant support, guidance and most importantly your precious time. We worked through the good and the bad of this process, struggled, laughed and learnt together. I thoroughly enjoyed every minute of it and I cannot imagine having a better pair of supervisors. I thank the entire Tibber team and particularly Daniel Linden for having an open mindset, immediately seeing the potential value in this work and providing me with the opportunity in the first place.

Next, to my "game-changing" SELECT masters colleagues: thank you for these indescribable past two years. We’ve done some beautiful things together and I know this is only the beginning. Lets prove the title right and drive this clean-energy transition forward.

Finally, to my wonderful family; if I had to name one thing that has made this journey possible, albeit from tens of thousands of kilometres distance, it would have to be your endless love and support. Thank you.
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Chapter 1

Introduction

1.1. Background

The Nordic Synchronous grid is facing a number of challenges including the phase out of synchronous generation, increased HVDC connections and an increasing penetration of distributed & intermittent renewable generation; all amounting to reduced system inertia. It is estimated that more than a 20% reduction in annual mean inertia will occur between 2020 and 2040. Additionally, economy wide electrification, particularly in the transport, steel & cement manufacturing industries will see the introduction of new electrical loads with potentially greater demand peaks [2]. There exists the obvious introduction of electric vehicle loads in the transport sector, while the shift to hydrogen (from electrolysis) as a reducing agent in the steel production process is predicted to require an additional 15 TWh/year, amounting to 30% of current Swedish industrial demand [3].

Due to these challenges, the traditional focus on the supply side of the equation is becoming increasingly insufficient for ensuring system stability. Concurrently, the concept of demand side management is now widely recognised as an essential element whose importance is only going to continue to grow. Already worldwide, significant demand flexibility is being untapped in industry and commerce. In more advanced markets such as France for instance, large industrial players have been taking part in the balancing mechanism since 2003 [4], while the potential flexibility in the immense German industrial sector is estimated to be as large as 4.5 GW in the medium-term [5]. However, the sectors of commerce and industry only present one half of total economy wide electricity demand [6] and the enormous potential of residential demand flexibility has not, as of yet, been extracted at scale. Despite this, due to the challenges outlined above, it is imperative that the resource of residential flexibility is mobilised and the value extracted in the near future.

To this end, electric vehicles immediately stand out as a critical load in the context of residential demand side management. Firstly, a single full electric vehicle’s energy demand is comparable to that of a single family dwelling [7]. Hence, their exponentially increasing market penetration is set to inject a considerable
additional load into the system. In the International Energy Agency’s 2-Degrees Scenario (50% chance of limiting warming to 2°C), the plug-in passenger vehicles stock exceeds 150 million with a market share of 10% by 2030 worldwide. By 2060, this share increases to 60% with 1.2 billion electric vehicles in circulation \[8\]. For the Nordics, this penetration is far more dramatic, with a 15 times increase of EV units from 2017 to 2030, with 4 million vehicles predicted on the road. This would reflect a charging energy demand of 9 TWh or 2-3% of total demand for the region, up from less that 0.2% today \[9\]. Additionally, EVs and their chargers pose as the quintessential ’low hanging fruit’, when speaking in terms of aggregation, as a virtue of being a relatively new technology and often already possessing a high level of connectivity. All Tesla vehicles for instance, are mobile data connected.

1.2. Literature Review

Due to the inherent, but as of yet imperfectly harnessed value in residential demand side management, there has been a wealth of research carried out in this field. Of particular interest has been the aggregation of flexible EV loads. Most studies publish results of lower charging costs and increased aggregator profits through the extraction of value in EV flexibility. Literature can be divided into bi-directional charging, also referred to as vehicle-to-grid, and uni-direction charging; where a only a time-shift in charging occurs.

In \[10\] the authors derive an optimal bidding strategy for electric vehicle aggregators in the day-ahead, real-time and regulation markets. The objective function comprises day-ahead energy cost, real-time energy cost, revenue from the day-ahead bid and finally a penalty term for the deviation of real-time consumption from the day-ahead energy bid. Deviations were split into instructed and un-instructed volumes, related to the stochastic dispatch to contract ratio accounting for the activation of reserves. Synthetic EV parameters and driver behaviour are also used to stochastically model time of arrival, departure and SOC at arrival. The results showed the heavy influence of the size of the penalty on the aggregators bidding strategy and resulting profit. Perfect price information is assumed in all day-ahead and regulation markets. For a case study of a 1000 vehicle fleet in a region in the Eastern USA, with a penalty of 2.98USD/MWh deviation, the aggregator’s charging cost turns into a profit of 427.7USD per day.

Three different optimization problems of independent aggregators making day-ahead decisions in the wholesale and secondary reserve markets are presented in \[11\]. Synthetic EV data was created in order to determine so called ”flexible periods” while the impact of forecast errors & uncertainty was considered through the comparison of results of perfect forecasts with a naive forecasting method. The authors build upon this previous study in \[12\] by developing an operational management & control model to minimize the difference between contracted and actual charging schedules. They find that adding this operational layer provides even more value with a 30-35% decrease in charging cost as opposed to purely optimizing the day-ahead energy bid.
One pertinent aspect examined within previous literature is the consideration of risk. As with any process involving uncertainty, an element of risk is present in the aggregator problem. For instance, the expected price scenario may not eventuate and a decision an aggregator has committed to may result in a greater cost or a loss. The optimal scheduling behaviour of a risk-averse aggregator is stochastically modelled in [13]. A comparison between two scenarios; one where the aggregator has no control and another where dynamic load control is exercised, is used to evaluate the value of EV flexibility in the day-ahead and real-time markets. Additionally, the expected value of aggregation is determined by comparing the aggregator profits with varying EV fleet size. The risk term; conditional value at risk (CVaR), described in detail in [14], is included while the authors also deduce the optimal risk-aversion factor $\beta$. Results show a shift away from day-ahead bids with increasing risk aversion. Meanwhile, the authors use a methodology to determine the required number of scenarios necessary to sufficiently model inherent uncertainty. This methodology is also utilized in this study and is outlined in section 3.3. A different method is exploited in [15], where chance constraints and the Markov inequality are used to create an efficient algorithm whose performance was evaluated against existing algorithms. Two thousand data points collected from smart chargers in British Columbia were extrapolated to mimic the charging sessions of a 1000 vehicle fleet. The algorithm developed was found to deliver higher returns to the EV aggregator.

1.3. Research Gap

Although there have been a large number of past studies examining the bidding behaviour of EV aggregators, all are reliant on the creation of synthetic driving behaviour and EV fleet data [16],[12],[11],[17], [18],[13],[20],[21] or utilize a small first hand data sample and extrapolate to a larger synthetic sample [15], [22]. Furthermore, none of those looked at the self-scheduling problem for combined bids in energy and balancing markets. Lastly, few studies have been carried out in detail specifically for the Nordic context. Therefore, the research question of this masters thesis revolves around determining an explicit value of the inherent flexibility of EV charging.

1.4. Contribution

Through a collaboration with the Norwegian/Swedish energy company Tibber [23], this study has access to first hand driving behaviour and vehicle fleet data. Tibber is a start-up that operates as an electricity retailer servicing customers in Norway and Sweden with 100% renewable energy. Additionally, the company offers smart home services such as optimizing comfort, control and cost through artificial intelligence as well as acting as a reseller of intelligent hardware such as smart-thermostats. With respect to electric vehicles, smart charging is carried out to minimize the charging cost against the day-ahead prices. Tibber currently offers smart charging...
to Tesla, Volkswagen and BMW electric vehicle owners who are their contracted customers. As such, a case study was carried out for the real fleet of 806 of Tibber’s contracted Tesla vehicles to determine the expected profit from operating in the day-ahead, real-time and primary regulation markets. Through such case studies, an explicit value of flexibility stemming from EV charging can be determined.

1.5. Thesis Structure

The rest of this thesis will possess the following structure; Chapter 2 will provide an overview of the relevant energy markets for the Nordics, followed by Chapter 3 describing the methodology of this study. The mathematical formulation is presented in Section 3.1, while the case studies are outlined in Chapter 4. The results are presented in Chapter 5 followed by Chapters 6 and 7 that contain the discussion and conclusion respectively.
Chapter 2

Overview of Relevant Markets

The entire electricity system must maintain a constant balance between the consumption and supply of electrical power. A balanced system results in the maintenance of a frequency of 50Hz for the alternating current within the grid and represents the "quality" of power delivered since large deviations from this frequency can harm important equipment or disturb loads and eventually cause a system black event. A downward deviation from 50Hz would signify consumption being greater than supply, while an upwards deviation stems from supply being greater than consumption.

Therefore, electricity markets have been formulated in such a way so as to facilitate this balance and can be broken down according to how long they are cleared prior to the operational hour. The Nord Pool power market includes the Nordics, Baltic states, Germany and the UK and includes both intra-day and day-ahead markets, while Nasdaq operates the futures or financial markets and the respective TSOs (Transmission System Operators) operate the short-term markets.

2.1. Day-ahead - Elspot

The day-ahead market is also known as the wholesale spot market and is where the vast majority of volume is traded (roughly 1.3 TWh is traded on Nordpool per day). Here, energy traders offer bids for purchasing and selling energy according to hourly blocks in the day-ahead. The spot price and volume of energy is determined at the point at which the cumulative curves of demand and supply intersect. This method is also known as marginal pricing; since all accepted bids receive the spot price which corresponds to the marginal cost of the most expensive producer.

2.2. Intra-day - Elbas

Trades within the day-ahead market are based on forecasts of demand and supply and these inevitably change closer to the delivery hour due to effects such as variations in weather. As a result, the intra-day market acts largely as a plat-
form for Balance Responsible Parties (BRPs) to compensate for variations from the consumption or production volumes calculated for trade in the day-ahead market.

### 2.3. Nordic Balancing Markets

Here, an important distinction must be made between the responsibility of balancing borne by BRPs and TSOs. BRPs are expected to balance their portfolio per hour, up until the operational hour, through trading within the day-ahead market, intra-day market and bilateral trades; this is also referred to as the planning phase. Following the gate-closure of the intra-day market, the responsibility for balancing is shifted to the TSO through the operation of the Nordic balancing markets; aided with the final production & consumption plans sent to them by the BRPs 45 minutes prior to the operational hour[26].

The Nordic Balancing markets exist at an even more granular level to the intra-day market and can be broken down further into the tertiary, secondary and primary reserves depending on the purpose of the reserve in relation to frequency deviation and the necessary speed of their reactions.

**Manual Frequency Restoration Reserve (mFRR) - Tertiary Reserve**

The tertiary reserve of mFRR is widely known as the common Nordic Regulating Power Market (RPM) where activation comprises a manual order from the system operators.

BRPs can voluntarily submit hourly bids up until 45 minutes prior to the operating hour, while the minimum bid size is 10MW throughout Sweden apart from SE4 (price area no.4) where the minimum bid is 5MW. Bids must include capacity (MW), price (SEK/MWh), direction, activation time and regulation object (RO) and are prioritized for the entire Nordic system while accounting for any congestion restraints. The formation of these bids through marginal pricing determines the regulating price displayed on Nordpool. real-time measurement and reporting is required to Svenska kraftnät[27].

Additionally, Svenska kraftnät procures mFRR as so called ‘disruption reserves’. These are multi-year contracted reserves that do not participate in the RPM and are designed to restore FCR-D after a fault and can be manually activated slower than 15 minutes. Once again, the required disturbance capacity is related to the N-1 incident and is equal to 1450MW.

---

1The Nordic countries are split into so called 'price areas'. For instance; three horizontal borders split Sweden into 4 price areas. Within an area, market prices are constant but can vary between other price areas for reasons such as congestion in transmission lines.
Automatic Frequency Restoration Reserve (aFRR) - Secondary Reserve

The Nordic electricity grid has been experiencing continually worsening 'quality' of electricity, with the minutes outside the normal frequency band (MoNB) of 49.9Hz-50.1Hz increasing throughout the years of 2001 to 2016 [1].

![Figure 2.1: Minutes of frequency outside normal band (MoNB)](image)

The stated goal is to restrict MoNB to less than 6000 minutes per year or 115 minutes per week. Despite this, 2016 saw 13 862 MoNB for the year or 267 per week as observed within Figure 2.1. Consequently, the automatic Frequency Restoration Reserve (aFRR) was introduced in 2013 in a bid to reduce the MoNB and an agreement was signed in 2016 to have a common Nordic market for aFRR commence operation in the first half of 2018 [28]. It is designed to operate alongside FCR-N (see section FCR-N Normal Operation 2.3) within the normal operating band of 50±0.1Hz by restoring the frequency once it has been contained by the primary reserves. It is capable of reacting much faster than mFRR since it is automatically activated with a control signal sent from the TSO following a central measurement of frequency. The reserves must react within 30 seconds and be fully activated by 120 seconds. Currently, a total of 300MW of aFRR is being traded on a common Nordic auction, 130MW of which is based in Sweden [29].

Similarly to FCR, market players must be pre-qualified with bids currently submitted on a weekly basis for specific hours of the day for the following week. However, with the common aFRR Nordic market soon to come into effect, the following procurement procedures will take place [30]:

- Daily auction with hourly products, gate closure D-2 at 20:00
- Minimum bid: 5MW and in multiples of 5MW
- Total volume & time period dependent on system needs
- Total demand is distributed over all eleven bidding areas forming local demand
No requirement for symmetrical bids (can be submitted in one direction)

The aFRR capacity market will be defined by: 1) it Geographical scope, 2) a Pre-determined set of Imbalance Settlement Periods (ISPs) when capacity is procured and 3) a Pre-determined volume to be procured per ISP (separate for up and down regulation). The Nordic TSOs will review these three factors annually[31].

A capacity payment is made for accepted bids according to a pay-as-bid system, while currently an energy compensation comes in the form of payment on the gross volume of activated up and down regulation. In the second half of 2018 however, the Nordic aFRR capacity market will be expanded to include a Nordic energy activation market, with pricing according to a common merit order list and integrated real-time congestion management[30].

**Frequency Containment Reserve (FCR) - Primary Reserve**

The frequency containment reserve (otherwise known as the primary reserve) is designed to automatically and continuously stabilise the frequency at a level of 50Hz and can be further broken down into 'FCR-N' for 'normal operation' and 'FCR-D' for 'disturbed operation'.

**FCR-N - Normal Operation**

For FCR-N, the frequency is measured on-site and therefore the automatic activation does not require a control signal from the TSO. As such, FCR-N is activated continuously 24hrs per day within the "normal operating band" of 50Hz ±0.1Hz. FCR-N is symmetrical and increases with a linear relationship to the deviation of the frequency from 50Hz. In other words, as the frequency deviates further, up or down from 50Hz, the automatic activation of FCR-N similarly increases, until it is fully activated at 50±0.1Hz. Within 60 seconds, 63% of the reserve should be activated while 100% must be activated within 180 seconds if required. The Standard Operating Agreement (SOA) between the TSOs requires capacity for FCR-N throughout the Nordics to be 600MW, of which Sweden must contribute 230MW[32].

The reserves must be capable of being maintained for 15 minutes[33].

**FCR-D - Disturbed Operation**

Similarly to FCR-N the Frequency Containment Reserve for disturbed operation (FCR-D) is automatically activated following on-site frequency measurement. However, the difference exists where FCR-D is only activated when the frequency drops further than 49.9Hz and must be fully activated at 49.5Hz. Therefore, FCR-D is asymmetrical and only provides up-regulation. Since it is a reserve designed for disturbed operation, FCR-D is required to react faster; requiring 50% to be activated within 5 seconds, while 100% must be made available within 100 seconds.
The SOA requires FCR-D to be capable of responding to the N-1 criterion and hence has a volume of 1160MW for the Nordics. The requirements of each control area is based on the ratio of the energy generated in that control area compared to the energy generated in the entire synchronous region. Therefore Sweden must contribute 400MW to the FCR-D operating reserve.

**Pre-qualification, Bidding, Procurement & Reporting of FCR**

Prior to any bids being submitted, balance responsible parties must undergo a series of checks and tests that make up a pre-qualification procedure. Provided the service passes the tests by delivering FCR as per the requirements stated above, the system operator will approve entry and the provision of FCR will be included in the balance responsibility agreement. Currently, FCR pre-qualification specifications are designed purely for hydro-power resources with the first pre-qualification for demand-side reserves being carried out during the Svenska Krafnt & Fortum pilot project for FCR-N carried out in 2017.

The minimum bid size for FCR-N is 0.1MW and bids can be submitted for a minimum of one hour blocks, one day (D-1) or two days (D-2), prior to the delivery day. The maximum block sizes are three hours and six hours for D-1 and D-2 respectively while bidding opens at 12:00 noon and closes at 18:00 and 15:00 respectively for D-1 and D-2. Following the assessment of the electricity system and the submitted bids, the TSOs will complete procurement by 21:00 for D-1 the day before operation day and 16:00 for D-2 two days prior to the operational day.

Once bids are drafted, Balance Providers are required to submit FCR plans per constraint area to the TSOs. Similarly, every 3-minutes, the volume of activated FCR-N & FCR-D and the time constant must be submitted to the TSO. All information flows are carried out electronically via "Ediel" - the Nordic electronic information exchange system.

For FCR-N; accepted bids are compensated for their capacity according to a pay as bid system, while activated bids are compensated with a net energy payment where the price is determined from the regulating power market. Contrastingly, FCR-D is only remunerated with a capacity payment for accepted bids. If there is a failure to deliver, the responsible balance service provider is to notify the system operator who procures additional reserves - the cost of which is then passed onto the responsible service provider.

Bids to FCR must be based on actual costs for regulation as outlined within balance agreements. Currently, all pricing schemes for FCR are based entirely on hydro-power resources and are related to the loss of efficiency suffered by the turbines from providing primary reserves, together with the volume of water used that could have otherwise been utilized to produce energy sold in the wholesale markets.

---

2 Level of system security ensuring that power system can withstand the loss of the largest individual system component - Oskarshamn 3 with 1450MW minus 200MW.

3 A net energy volume between up & down delivered regulation is calculated
2.4. Imbalance Settlement and Pricing

The independent service company eSett is responsible for Nordic imbalance settlements. It collects, validates and manages imbalance data and sends the weekly imbalance invoices to respective BRPs. Nordic imbalance settlement is based on the calculation of two imbalance volumes; the production imbalance (2.1) and consumption imbalance (2.2). The imbalance adjustment accounts for any balancing market products the BRP has provided (FCR, aFRR, mFRR, RR) [37].

\[
\text{Prod. Imbalance} = \text{Prod.} - \text{Prod. Plan} \pm \text{Imbalance Adj.} \quad (2.1)
\]

\[
\text{Cons. Imbalance} = \text{Cons.} + \text{Prod. Plan} \pm \text{Trade} \pm \text{Imbalance Adj.} \quad (2.2)
\]

If a BRP produces less than it planned to produce, there is a deficit in the production imbalance and the BRP must "buy" imbalance energy from eSett. Similarly, if a BRP consumes more electricity than the combined sum of what it planned to produce as well as what it purchased in trades, then there is a deficit in the consumption imbalance and it too must purchase imbalance energy from eSett.

Table 2.1: Two-price model: Production Imbalance Settlement

<table>
<thead>
<tr>
<th>Regulation Direction</th>
<th>+’ve Production Imbalance (must sell)</th>
<th>−’ve Production Imbalance (must buy)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Up-Regulation</td>
<td>Get spot price (lower than RPM price)</td>
<td>Pay RPM price (higher than spot price)</td>
</tr>
<tr>
<td>Down-Regulation</td>
<td>Get RPM price (lower than spot price)</td>
<td>Pay spot price (higher than RPM price)</td>
</tr>
</tbody>
</table>

Table 2.2: One-price model: Consumption Imbalance Settlement

<table>
<thead>
<tr>
<th>Regulation Direction</th>
<th>+’ve Consumption Imbalance (must purchase)</th>
<th>−’ve Consumption Imbalance (must sell)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Up-Regulation</td>
<td>Pay RPM price (higher than spot price)</td>
<td>Get RPM price (higher than spot price)</td>
</tr>
<tr>
<td>Down-Regulation</td>
<td>Pay RPM price (lower than spot price)</td>
<td>Get RPM price (lower than spot price)</td>
</tr>
</tbody>
</table>

In the common Nordic market, there exists a "two-price system" for production imbalances; whereby the price of imbalance energy depends on the direction of regulation during the hour and the sign of the production imbalance for each BRP. This is organised in such a way that the price the BRP receives for production imbalances is never advantageous. For example; during up regulation (where there is insufficient energy in the system) the price of a negative production imbalance (where BRP must purchase energy) is the up-regulation price, while the price of
positive production imbalances (BRP must sell energy) is the spot price. In peri-
ods of up-regulation, the up-regulating price is always higher than the spot price
since energy is under greater demand and therefore the BRP will always receive
the "worse" price \cite{37}. The two-price model for the production imbalance price is
summarised in Table 2.1.

In contrast, the consumption imbalance price follows a "one-price model"; whereby
it is always the regulating market price in the main direction of regulation for that
price area. Here, it is possible for BRPs to receive a favourable price and in-fact
profit from a consumption imbalance. For example; if a BRP consumes more than
it purchased and the system is in down regulation, then the BRP is forced to pur-
chased imbalance energy at the price of RPM, which would be lower than what they
would have had to pay as a spot price.
Chapter 3

Methodology

The methodology for this study will be outlined below. The explicit value of this flexibility was determined through the creation of a two-stage stochastic optimization model, maximising the aggregator’s expected profit through developing a risk-averse optimal bidding strategy when entering the Nordic energy and frequency containment reserve markets. Once again, this work only considers uni-directional charging and does not examine vehicle-to-grid (bi-directional) arrangements. The flow of data can be visualised in Figure 3.1. Two vehicle parameters and four driving behaviour parameters are determined from Tibber’s data. Meanwhile, prices from three different markets are taken from the TSOs and Nord Pool. Matlab is then used to compile these parameters into a file format readable by the General Algebraic Modeling System (GAMS) used to carry out the optimization. Finally, an output file is read by Matlab to plot and visualise the results.

Figure 3.1: Data Flowchart Diagram
3.1. Description of Stochastic Optimization Model

In the following nomenclature the sets, parameters and variables of the mathematical formulation are listed. Four different models will be referred to throughout this work and are outlined below:

- **Model A**: Energy arbitrage between day-ahead and real-time only.
- **Model N**: Energy arbitrage & FCR-N provision.
- **Model D**: Energy arbitrage & FCR-D provision.
- **Model R**: Reference model, uncontrolled (dumb) charging.

**Formulation of Model A**

**Sets:**
- $\mathcal{I}$ (Index) of electric vehicles
- $\mathcal{T}$ (Index) of hourly time intervals
- $\mathcal{K}$ (Index) of 15 minute sub-hourly time intervals
- $\mathcal{K}_t$ (Set) of sub-hourly time intervals within hour $T$
- $\mathcal{\Omega}$ (Index) of scenarios

**Parameters:**
- $\lambda_{DA,E}^t$ Day-ahead electricity price, in NOK/kWh or SEK/kWh.
- $\lambda_{DA,R}^t$ Day-ahead regulation price, in NOK/kWh or SEK/kWh.
- $\lambda_{RT,E}^{k,t,\omega}$ Real-time electricity price = Imbalance settlement price in (NOK or SEK)/kWh.
- $\Delta T$ Sub hourly time interval in hours, 15 minutes = 0.25.
- $\pi_\omega$ Probability of scenario $\omega$, $[0,1]$.
- $\eta_i$ Efficiency of charger = 0.8 $\forall i$.
- $u_{k,i,\omega}$ Binary parameter equal to 1 when $i$th veh is home.
- $E_{i,bat,max}$ Battery capacity of $i$th vehicle, in kWh.
- $P_{i,chrg}$ Power of charge of $i$th vehicle, in kW.
- $T_{i,arr/dep}$ Arrival/departure time of $i$th vehicle.
- $SOC_{i,dep}$ SOC at departure of $i$th vehicle, $[0,1]$. 
CHAPTER 3. METHODOLOGY

$SOC_{i,ω}^{arr}$  SOC at arrival of $i$th vehicle, $[0,1]$.

$α$  Confidence level for risk evaluation, $[0,1]$.

$β$  Risk aversion factor, $[0,1]$.

$M$  Consumption Imbalance Price, in NOK/MWh or SEK/MWh.

Variables:

$E(Π^A)$  Expected Profit, in NOK or SEK.

$Π_ω$  Profit for scenario $ω$, in NOK or SEK.

$E_{t}^{DA}$  Day-ahead energy bid, in kWh.

$R_{t}^{DA}$  Day-ahead regulation bid, in kWh.

$ΔE_{t,ω}$  Real-time energy bid; in kWh.

$E_{t,ω}^{RT}$  Total real-time energy consumption, in kWh.

$E_{k,ω}^{RT}$  Total sub-hourly real-time energy consumption, in kWh·$ΔT$.

$E_{k,i,ω}^{RT}$  Real-time energy consumption of $i$th vehicle, in kWh·$ΔT$.

$P_{k,i,ω}^{RTmax}$  Maximum real-time power consumption of $i$th vehicle, in kW.

$SOC_{k,i,ω}$  State of Charge of $i$th vehicle, $[0,1]$.

$CVaR$  Conditional Value at Risk, in NOK or SEK.

$ζ$  Auxiliary variable for CVaR.

$ι$  Scenario dependent auxiliary for CVaR.
3.1. DESCRIPTION OF STOCHASTIC OPTIMIZATION MODEL

The objective of the risk-averse aggregator is to maximise the expected profit considering the Conditional Value at Risk (CVaR) as per Equation 3.1, while the level of risk aversion is determined by the parameter \( \beta \). These risk terms are described further in sections 3.4 and 3.5.

\[
\max \left[ (1 - \beta) \cdot \mathbb{E}(\Pi^A) + \beta \cdot CVaR \right] \quad (3.1)
\]

subject to:

Expected Profit, \( \mathbb{E}(\Pi^A) = -\Pi^{DA} - \Pi^{RT} - \Pi^P \) \quad (3.2)

Day-ahead Cost, \( \Pi^{DA} = \sum_t [\lambda_{t}^{DA,E} \cdot E^{DA}_t] \quad \forall t \) \quad (3.3)

Real-Time Cost, \( \Pi^{RT} = \sum_\omega \pi_\omega \sum_t [\lambda_{t}^{RT,E} \cdot \Delta E_{t,\omega}] \quad \forall t, \omega \) \quad (3.4)

Positive Cons. Imbalance Penalty, \( \Pi^P \geq \sum_\omega \pi_\omega \sum_t [M \cdot \Delta E_{t,\omega}] \quad \forall t, \omega \) \quad (3.5)

Negative Cons. Imbalance Penalty, \( \Pi^P \geq \sum_\omega \pi_\omega \sum_t [-M \cdot \Delta E_{t,\omega}] \quad \forall t, \omega \) \quad (3.6)

\( \Delta E_{t,\omega} = E_{RT_{t,\omega}} - E_{DA_t} \quad \forall t, \omega \) \quad (3.7)

\( E_{RT_{t,\omega}} = \sum_k E_{RT_{k,\omega}} \quad \forall t, \omega, k \in K_t \) \quad (3.8)

\( E_{RT_{k,\omega}} = \sum_i E_{RT_{k,i,\omega}} \quad \forall k, \omega \) \quad (3.9)

\( E_{RT_{k,i,\omega}} \leq \frac{\left( P_{k,i,\omega}^{\text{max}} + P_{k+1,i,\omega}^{\text{max}} \right)}{2} \cdot \Delta T \quad \forall k, \omega \) \quad (3.10)

\( P_{k,i,\omega}^{\text{max}} \leq u_{k,i,\omega} \cdot P_{chrg}^i \quad \forall k, i, \omega \) \quad (3.11)

\( SOC_{k+1,i,\omega} = SOC_{k,i,\omega} + \frac{\eta}{E^{RT}_{\omega, \text{max}}} E_{RT_{k,i,\omega}} \quad \forall k, i, \omega \) \quad (3.12)

\( 0 \leq SOC_{k,i,\omega} \leq 1 \quad \forall k, i, \omega \) \quad (3.13)

\( SOC_{T_{\omega, \text{dep}}} = SOC_{T_{\omega, \text{dep}}}^\text{dep} \quad \forall i, \omega \) \quad (3.14)

\( SOC_{T_{\omega, \text{arr}}} = SOC_{T_{\omega, \text{arr}}}^\text{arr} \quad \forall i, \omega \) \quad (3.15)

\( R_{t,\omega}^{DA} \leq E_{RT_{t,\omega}} \quad \forall t, \omega \) \quad (3.16)

\( R_{t,\omega}^{DA} \leq \sum_i [u_{k,i,\omega} \cdot P_{chrg}^i] - E_{RT_{t,\omega}} \quad \forall t, \omega, k \in K_t \) \quad (3.17)

\( CVaR = \zeta - \frac{1}{(1 - \alpha)} \sum_\omega \pi_\omega t_\omega \quad \forall \omega \) \quad (3.18)

\( \zeta - \Pi_\omega \leq t_\omega \quad \forall \omega \) \quad (3.19)

\( t_\omega \geq 0 \quad \forall \omega \) \quad (3.20)

The expected profit [3.2] is calculated as the sum of the day-ahead cost of energy in the first term [3.3], the expected cost (or revenue) from the purchase
(or sale) of energy in the real-time, represented by the second term (3.4), and finally the penalty due to deviation, in the form of a consumption imbalance fee, in the last term. This fee is calculated for positive deviation in Equation (3.5) and negative deviation in (3.6). It must be noted that in this work, the term "real-time" refers to the imbalance settlement and therefore is associated with the RPM price. Equation (3.7) gives the volume of energy that is purchased or sold in the real-time and is equivalent to the deviation between the real-time energy consumption and the day-ahead bid. (3.8) and (3.9) outline the aggregated hourly real-time consumption as the sum of all sub hourly \((k)\) real-time consumptions of vehicles in set \(I\). Equation (3.10) gives an approximation of real-time energy consumption through the trapezoidal rule of \(P_{\text{max}}\) at \(k\) and \(k+1\), while (3.11) constrains \(P_{\text{max}}\) to be less than or equal to the rated charge power when the vehicle is connected and at home. The \(SOC\) between time steps is calculated by (3.12) and constrained in (3.13). Equations (3.14) and (3.15) define the \(SOC_{\text{arr}}\) and \(SOC_{\text{dep}}\) at \(T_{\text{arr}}\) and \(T_{\text{dep}}\) respectively. The maximum up-regulation is determined by (3.16), while the maximum down-regulation is calculated in (3.17). Finally, conditional value at risk is reflected in (3.18) with auxiliary variables constrained in (3.19) and (3.20).

**Formulation of Model N**

The mathematical formulation for Model N; the combination of energy arbitrage and the provision of FCR-N, is summarised below and is precisely the same as Model A, except for the addition of the return from regulation term \(\Pi^R\) (3.22).

\[
\max \left[(1 - \beta) \cdot \mathbb{E}(\Pi^N) + \beta \cdot CVaR\right]
\]

subject to:

Equations 3.3 - 3.20

\[
\mathbb{E}(\Pi^N) = \Pi^R - \Pi^{DA} - \Pi^{RT} - \Pi^P
\]  

(3.21)  

Return from Regulation, \(\Pi^R = \sum_t [\lambda_{t,DA,FCR-N} R^{DA}_t] \quad \forall t\)  

(3.22)

**Formulation of Model D**

Model D represents a combination of energy arbitrage and FCR-D provision. Its formulation is closely related to the FCR-N model, with the inclusion of two additional parameters and two additional variables as outlined below.

**Parameters:**

\(\lambda_{t,DA,FCR-D}\)  
Day ahead regulation price - FCR-D

\(R^{dc}_t\)  
Dispatch to contract ratio (activation)
3.2. Assumptions

Variables:

\( \Delta E \cdot I_{t,\omega} \)  Instructed deviation of real-time energy consumption from day-ahead bid

\( \Delta E \cdot U_{t,\omega} \)  Uninstructed deviation of real-time energy consumption from day-ahead bid

Equations:

\[
\begin{align*}
\max & \left[ (1 - \beta) \cdot E \left( \Pi^D \right) + \beta \cdot CVaR \right] \\
\text{subject to:} \\
\text{Equations 3.3 to 3.22} \\
\Delta E_{t,\omega} &= \Delta E \cdot I_{t,\omega} + \Delta E \cdot U_{t,\omega} \quad \forall t, \omega \quad (3.23) \\
\Delta E \cdot I_{t,\omega} &= R_{dc} \cdot R_{DA} \quad \forall t, \omega \quad (3.24)
\end{align*}
\]

The variation between the FCR-N and FCR-D formulations stems from the fact that FCR-D is not symmetrical in nature and is only up regulating. Therefore, as occurs in \[19\], the activation of bids must be considered via a "dispatch to contract ratio" \((R_{dc}^t)\). This parameter provides the proportion of submitted FCR-D bids that must be activated \((3.24)\) and is directly related to the frequency in the Nordic synchronous grid, as outlined in greater detail in Section 4.3. Since the activation of a bid would, in itself, result in a deviation from the day-ahead energy bid, \( \Delta E_{t,\omega} \) is split into instructed \((\Delta E \cdot I_{t,\omega})\) and uninstructed deviation \((\Delta E \cdot U_{t,\omega})\) as outlined in Equation \((3.23)\).

Formulation of Model R

Model R represents the reference case of uncontrolled charging, often referred to as dumb charging. Its formulation is exactly the same as Model A, the only difference being that the binary-parameter \( u \) in Model R is pre-treated so as to force the charging to commence when the vehicle is first home until full. Thereby replicating the behaviour of so called "dumb-charging".

3.2. Assumptions

It is assumed that the aggregator has perfect price information for day-ahead energy and primary regulation markets. Secondly, the aggregator is a price taker who has no effect on market prices. Thirdly, it is assumed that the aggregator is capable of dynamic load control (DLC), in other words it has the capability to remotely switch on/off individual EV charging. However, each vehicle is assumed to only have one charging cycle per day available for control by the aggregator, and this occurs while the vehicle is at home only. Next, it is assumed that the minimum bid size is always met. This is a reasonable assumption in the Nordic context since BRPs are known to be permitted to consolidate bids from various resources to meet minimum bids.
Lastly, it is assumed that the activation of primary FCR-N regulation has a zero mean character. This final assumption is based on the fact that FCR-N is a symmetric product, maintaining the frequency average at 50Hz and thereby having equal up & down regulation.

This model isolates the profits of the aggregator gained from participation in the wholesale electricity and reserve markets, from the income generated via retail contracts with end consumers. The objective is to maximize the profits in the energy and frequency containment reserve markets. The contract offered to end consumers could include incentives such as a price reduction that remunerates the end consumer for transferring the control of the vehicle charging to the aggregator. The operational business and contractual details of the EV aggregator with its end consumers is however outside of the scope of this work. The details of the end-consumer contract might influence the charging patterns and behavior of the consumer. With the presented problem formulation, the profits of the aggregator under uncertain price and charging profiles can be analysed irrespective of the business model of the aggregator and without the impacts that a specific customer contract type might have on the charging patterns.

3.3. Selection of Scenarios

It was determined that there exist two critical sources of uncertainty when modelling the optimal bidding strategy of an aggregator, namely; driving behaviour uncertainty and price uncertainty. In this study, perfect price information was assumed for day-ahead ($\lambda_{DA,E}^t$) and primary regulation prices ($\lambda_{DA,R}^t$) which is in line with the literature [10], [18], [38].

Meanwhile, uncertainty is reflected via real-time ($\lambda_{RT,E}^{t,w}$) price scenarios based on historical market data; with one day of historical prices representing one scenario. Similarly, driving behaviour scenarios were created via random sampling of the pool of trips developed per vehicle from first-hand Tibber data. These two factors represent independent sources of uncertainty and it was necessary to utilize the following methodology to correctly combine the two sources and determine the number of scenarios necessary to accurately reflect the uncertainty inherent in the problem. Arbitrarily choosing a high number of scenarios may cause unnecessary computational complexity, while selecting too low a number of scenarios would not sufficiently model the stochastic nature of the problem.

Firstly, the number of vehicle scenarios ($N^\omega_v$) is fixed at one, while the number of price scenarios ($N^\omega_\lambda$) are set at an arbitrarily low number, for example 5. The model is run in GAMS with the expected profit ($E(\Pi)$) recorded. Next, $N^\omega_\lambda$ is increased while $N^\omega_v$ remains fixed and once again the model is run with $E(\Pi)$ recorded. The process is continued with increasing $N^\omega_\lambda$ and a fixed $N^\omega_v$ until the $E(\Pi)$ stabilises. It is at point, as indicated by Figure 3.2, with $N^\omega_\lambda$ real-time price scenarios, that the inherent uncertainty in the stochastic nature of real-time prices is being adequately represented in the model. Similarly, the process is repeated when accounting for
driving behaviour uncertainty. Swapping the sources of uncertainty, \( N_\lambda \) is fixed to one while \( N_\omega \) is increased until once more, the \( \mathbb{E}(\Pi) \) stabilises. Finally, the two sources of uncertainty are combined by creating unique scenarios from all the possible combinations of driving behaviour and real-time price scenarios. The final number of scenarios is then \( N_\omega \times N_\lambda \).

Following the above procedure, it was determined that \( N_\lambda = 15 \) as indicated in Figure 3.2, while \( N_\omega = 5 \). Therefore, the total number resulting from all possible combinations of these scenarios and the final number of scenarios used is 75.

3.4. **Conditional Value at Risk - CVaR**

The mathematical formulation described above accounts for risk adversity through the risk term CVaR. If the objective function was to simply include the expected profit (\( \mathbb{E}(\Pi) \)), this would be considered a risk-neutral formulation whereby all the probabilities of the possible scenarios are consolidated into one expected profit. There is a possibility that a number of scenarios will result in a considerable loss while others will result in a considerably high expected profit, however this risk-neutral formulation will optimize decisions so as to purely maximise the final \( \mathbb{E}(\Pi) \) accounting for all these possibilities.

The risk term CVaR is described in [14] as "the expected value of profit of the \((1 - \alpha)\)-quantile of the profit distribution." In other words, given a confidence interval \( \alpha \), of for example 90%, the CVaR would return the average of all the bottom 10% of expected profits from the profit distribution. Therefore, by including the CVaR term in the objective function, the model is being shifted from a risk-neutral to a risk-averse formulation whereby not only is the \( \mathbb{E}(\Pi) \) maximised, but so too is the bottom \((1 - \alpha)\)% of profits. In this work, a confidence interval of \( \alpha = 90\% \) is used.
3.5. Finding an Optimal $\beta$

As was described in [13], there exists a methodology to determine the optimal risk adversity parameter $\beta$. Since $\beta$ essentially functions as a weighting parameter that forces the optimization of the objective function towards the purely risk neutral expected profit ($E(\Pi)$) term or towards the CVaR term. Therefore, as the adversity to risk is increased by raising the $\beta$, CVaR (the average of the lowest possible profits) will be increased. Simultaneously however, the expected profit is reduced. Hereby exists the compromise between hedging for risk by reducing exposure to lower profits, and coincidently conceding lower overall expected profit.

This trade-off can be visualised by plotting both the CVaR and expected profit for corresponding $\beta$s. An optimal level of risk adversity becomes evident, beyond which the marginal increase in CVaR does not warrant the marginal decrease in expected profit. For example, Figure 5.4 clearly illustrates the optimal point at $\beta=0.45$. Increasing risk adversity beyond this point results in steep reductions in expected profit with only incremental increases in CVaR, as shown by the plots of $\beta=0.5, 0.6$ and $0.7$.

3.6. Determining the Value of Flexibility

Numerous studies such as [13] and [16] have attempted to determine the value of flexibility by comparing the resulting expected profit where the EV aggregator is capable of carrying out dynamic load control $E(\Pi^{A,N,D,R})$, to the expected profit from a reference case where no control is possible, denoted as $E(\Pi^{R})$. Essentially, in this reference case zero flexibility is utilized and is thus often referred to in literature as "uncontrolled charging" or "dumb-charging" [11, 39] - the opposite of smart charging. Here, the vehicles simply charge when first connected, until full. Therefore the value of flexibility can be described as $E(\Pi) - E(\Pi^{R})$.

$E(\Pi^{R})$ was determined by pre-treating the binary parameter $u_{k,i,\omega}$ to force charging to start immediately when vehicles arrived home and to remain charging until $SOC_{dep}$ is reached. Finally, in an attempt to isolate the value extracted from various use cases of an EVs flexibility; an energy arbitrage-only model was also created. In this case, FCR regulation was not considered; thereby value could only be gained from optimizing the charging and carrying out energy arbitrage. The expected profit in this scenario is referred to as $E(\Pi^{A})$ and the mathematical formulation of this arrangement can be found in Section 3.1.
Chapter 4

Case Studies

In order to analyse the business case for the aggregation of flexible residential loads in the form of EV charging, case studies were carried out as outlined below with specific driving behaviour, vehicle and price parameters.

4.1. Scope of Case Studies

The two-stage stochastic optimization problem previously described is initially formulated for the day-ahead wholesale, real-time (imbalance settlement) and FCR-N markets in the price area NO5 of Norway. This context was selected since the vast majority of Tibber’s contracted electric vehicles reside in Norway. Additionally, Tibber is in the early stages of a pilot project in collaboration with the Norwegian TSO Statnett; therefore this study was deemed valuable if results could be drawn for this setting. On a temporal level, the model considers only weekday driving behaviour and is run for a 24 hour period commencing at 13:00 h until 12:59 h the following day, for both the summer and winter seasons.

The Swedish market is then analysed by adapting the model for a second case study and assuming the same portfolio of vehicles is located in Stockholm, Sweden in price area SE3. Swedish market prices replace Norwegian prices as input parameters and the model is once again run for one weekday in the summer and winter periods. Regarding the FCR-D market; only Sweden is analysed, since the FCR-D price in Norway is zero due to the immense supply of regulation [40].

4.2. Vehicle Data

Through their contracted customer base, Tibber has access to direct first hand data related to driving behaviour and vehicle parameters. Therefore it was possible to gather the necessary data required for input into the optimization model. Namely, these parameters include: $SOC_{arr}$, $SOC_{dep}$, $T_{arr}$, $T_{dep}$, $E_{max}$, $P_{max}$.

Firstly, hourly data points for each vehicle were collected over a span of more than 4 months, amounting to over 900 000 data points. This sample was reduced
by removing weekend and holiday dates. Next, the hours where the query 'is at home' varied from the previous hour were extracted, amounting to over 68 000 data points. These represented the hourly intervals in which the vehicles either departed from home or arrived to home. These data points were paired to create "trips"; made up of one arrival and the next departure. Finally, Matlab scripts were created to extract the single longest trip per vehicle during the 24 hour period starting from 13:00 h. Therefore, if a vehicle departed and arrived several times during the 24 hour period, it was assumed that it is only 'available' during the single longest time period that it is home. Explicitly, if a vehicle arrives at 17:00 and departs at 19:00, and once again arrives at 21:00 and departs at 7:00 the following day, then the model only considers the 10 hr period between 21:00 and 7:00 and ignores the initial two hours when the vehicle was first home. This is a conservative approach that generally underestimates the flexibility of the resource.

The Tibber data possessed hourly granularity since vehicle were communicated with in hourly intervals. In order to move to fifteen minute granularity, synthetic arrival times at 15 minutes, 30 minutes and 45 minutes prior to the hourly time of arrival were introduced. In other words; given a the $T_{arr}$ of 19:00, 3 synthetic data points were created at $T_{arr}$ of 18:15, 18:30 and 18:45. In this way, a more realistic representation of reality is modelled, as opposed to hourly granularity, where it is possible that a vehicle arriving at 18:05 in reality, is recorded as arriving at 19:00.

At this point the 6 parameters outlined above could be determined for each trip. A resulting pool of trips and their associated parameters was obtained for each of the 806 Tesla vehicles. Another Matlab script was utilized to take random samples from each pool in order to create driving behaviour scenarios as indicated in Figure 4.1.

It must be noted that the Tibber fleet of Tesla vehicles possesses considerably greater capacity than a fleet representing the true market mix of EV models. The distribution of battery capacities for the Tesla vehicles examined in the case studies are outlined in Table 4.1.

<table>
<thead>
<tr>
<th>Battery Capacity (kWh)</th>
<th>Number of Vehicles</th>
<th>% of Fleet</th>
</tr>
</thead>
<tbody>
<tr>
<td>60</td>
<td>7</td>
<td>1%</td>
</tr>
<tr>
<td>70</td>
<td>32</td>
<td>4%</td>
</tr>
<tr>
<td>75</td>
<td>339</td>
<td>42%</td>
</tr>
<tr>
<td>85</td>
<td>234</td>
<td>29%</td>
</tr>
<tr>
<td>90</td>
<td>109</td>
<td>14%</td>
</tr>
<tr>
<td>100</td>
<td>85</td>
<td>11%</td>
</tr>
</tbody>
</table>
4.3. Market and Price Data

The three price parameters used as input in the model are publicly available. The day-ahead ($\lambda^{DA,E}$) and real-time (RPM) price ($\lambda^{RT,E}$) are all available on the Nord Pool platform and can be downloaded in .csv format. Meanwhile, the FCR-N & FCR-D regulation prices ($\lambda^{DA,R}$) are available from the Statnett and Svenska krafhabit data portals for Norwegian and Swedish market data respectively. For each season, an average of daily historical prices was used for both the day-ahead and FCR prices where perfect price information was assumed. The motivation for this assumption is that the daily FCR price trajectories on weekdays shows very similar magnitudes throughout a given season.

Figure 4.2 portrays the day-ahead, FCR-N and average real-time prices in bold, while the 15 real-time price scenarios are indicated by the thin lines. The characteristic shape of the FCR-N price (in red) should be noted; increasing dramatically between the hours of 12am and 5am. Similarly, Figure 4.3 indicates the market price parameters for SE3 in Sweden. While the dramatically higher FCR-N prices should be noted for Sweden, the characteristic increase in primary regulation price once again occurs in the early hours of the morning, this time between 11pm and 4am.

$\lambda^{RT,E}$ prices from one historical day were used to represent one real-time price scenario. Therefore, historical prices were extracted for weekdays during summer and winter periods. If there are roughly 20 weekdays per month, this corresponds to 20 real time price scenarios per month. Assuming each seasonal period comprises 3 months, 60 real-time price scenarios are then determined. A fast-forward selection algorithm [41] was then used as a scenario reduction technique to select the $N^w_X = 15$ most representative scenarios per season.

For the FCR-D formulation, the dispatch to contract ratio ($R_{dc}^{dc}$) was calculated from system frequency data sampled from the Svenska krafhabit website [42]. $R_{dc}^{dc}$ is
equal to 0 at a system frequency of 49.9 and 1 at 49.5; meaning that the volume of contracted FCR-D reserves are increasingly activated as the frequency drops beyond 49.9 and are fully activated at 49.5. The highest $R_{dc}^t$ within each hour of the day was selected. 105 days of frequency data was sampled in Spring 2018 with Figure 4.4 showing the 1st, 10th, 50th (median), 90th and 99th percentiles of the days. The 99th percentile was selected for use; representing the day with the highest 1% of activation or the ’worst case’ scenario for an aggregator where the greatest volume of its bid is required to be activated.
4.3. MARKET AND PRICE DATA

Figure 4.3: SE3 summer; Day-ahead, FCR-N, average real-time price and real-time price scenarios

Figure 4.4: 1st, 10th, 50th, 90th and 99th percentile days of recorded system frequency below 49.9
Chapter 5

Results

5.1. Price Area NO5 Case Study

Table 5.1 outlines the breakdown of results for the initial case study of the aggregation of Tibber’s 806 Tesla vehicles for a 24 hour period in summer and winter, with market prices based on price area NO5, Norway. As per the mathematical formulation, the aggregator’s expected profit is the sum of the day-ahead and expected real-time energy cost and the return from provision of primary regulation. It is observed that the expected real-time energy cost is negative in summer and is therefore representing a return from arbitrage between the day-ahead and real-time markets. Thus, the overall expected energy cost for charging of the EVs in summer time is \(1969.37 - 106.76 = 1862.61 \text{ NOK}\). The expected return from providing primary regulation of 1042.45 NOK is almost 55% of the charging cost. The dramatic reduction in regulation return for the winter period is attributed to the fact of winter FCR-N prices being a fifth of summer prices.

Table 5.1: Breakdown of Results for Model N Case Study of N05

<table>
<thead>
<tr>
<th></th>
<th>summer</th>
<th>winter</th>
</tr>
</thead>
<tbody>
<tr>
<td>Aggregator Expected Profit</td>
<td>-873.30 NOK</td>
<td>-2154.49 NOK</td>
</tr>
<tr>
<td>DA Energy Cost</td>
<td>1969.37 NOK</td>
<td>2179.14 NOK</td>
</tr>
<tr>
<td>Exp. RT Energy Cost (Revenue)</td>
<td>-106.76 NOK</td>
<td>52.93 NOK</td>
</tr>
<tr>
<td>Regulation Return</td>
<td>1042.45 NOK</td>
<td>191.25 NOK</td>
</tr>
<tr>
<td>CVaR</td>
<td>-923.81</td>
<td>-2235.61 NOK</td>
</tr>
</tbody>
</table>

The aggregated load curve of the EV fleet is visualised in Figure 5.1 with the thin lines portraying the various scenarios of driving behaviour. The right hand y-axis displays the mean number of vehicles "home" at each 15 minute interval, showing the largest drop as drivers leave for work between 7am and 8am. It can be observed that charging is shifted to the hours of higher FCR-N prices, depicted in Figure 4.2 as between 12am-5am, in order to maximise return. Meanwhile, the optimized day-ahead energy (E-DA) & FCR-N regulation bids (R-DA) are shown in
Figure 5.2, together with the total average real-time consumption (E-RTav) and the corresponding scenarios of real-time consumption (thin green lines). Hours where energy arbitrage is carried out can be observed where the day-ahead energy bid varies from the real-time energy consumption. This is clearly illustrated at 11am for instance, where the model has optimized to buy a volume of energy (day-ahead) in excess of the real-time consumption, in order to sell in the real-time at a higher price.

![Aggregated Load of Fleet of 806 Vehicles](image)

**Figure 5.1: NO5 summer - Aggregated Load of Fleet of 806 Vehicles**

**Optimal $\beta$ for NO5**

The methodology previously outlined for determining the optimal $\beta$ was carried out for the case study of NO5 in summer. The expected profit distribution is portrayed for $\beta = 0.3$ on the left and $0.45$ on the right of Figure 5.3. CVaR is depicted to increase with the change in $\beta$ while the expected profit is marginally decreased. Similarly, Figure 5.4 clearly indicates the optimal $\beta=0.45$. Both figures portray the trade-off between the hedging of risk and the concession of lower expected profits as previously described.
CHAPTER 5. RESULTS

Figure 5.2: NO5 summer - day-ahead energy & regulation bids, and real-time consumption scenarios

Figure 5.3: Expected profit distribution and CVaR for increasing β

5.2. Price Area SE3 Case Study

SE3 - Model N Case Study

The breakdown of results for the second case study of SE3 in Sweden are outlined in Table 5.2. Once more, the expected real-time "energy cost" is negative, indicating a return through the sale of energy in the real-time by the aggregator. Therefore,
5.2. PRICE AREA SE3 CASE STUDY

the expected cost of charging energy for the vehicles in the summer in SE3 is $2223.24 - 142.37 = 2080.87$ SEK. With a return from FCR-N provision of 3837.20, the entire cost of charging is surpassed and hence the recorded expected profit of 1679.35 SEK for the Tibber fleet. The reason this value is significantly greater when compared to the results from NO5, is almost entirely attributed to dramatically higher FCR-N prices offered in Sweden as shown in Figures 4.2 and 4.3.

Table 5.2: Breakdown of Results for SE3 Model N Case Study

<table>
<thead>
<tr>
<th></th>
<th>summer</th>
<th>winter</th>
</tr>
</thead>
<tbody>
<tr>
<td>Aggregator Expected Profit</td>
<td>1679.35 SEK</td>
<td>-104.08 SEK</td>
</tr>
<tr>
<td>DA Energy Cost</td>
<td>2223.24 SEK</td>
<td>2391.41 SEK</td>
</tr>
<tr>
<td>Exp. RT Energy Cost (Revenue)</td>
<td>-142.37 SEK</td>
<td>-40.38 SEK</td>
</tr>
<tr>
<td>Regulation Return</td>
<td>3837.20 SEK</td>
<td>2326.01 SEK</td>
</tr>
<tr>
<td>CVaR</td>
<td>1645.21</td>
<td>-164.06 SEK</td>
</tr>
</tbody>
</table>

SE3 - Model D Case Study

The model was altered to match the FCR-D market in Sweden and similarly run for summer and winter seasons with Table 5.3 displaying the results. Lower regulation return values occur due to the lower price of FCR-D regulation when compared to FCR-N. Despite the use of the 99th percentile day with the highest 1% of recorded $P_{dc}$, by observing Figure 5.5, one can see that the significance of instructed deviation (where the TSO has instructed activation) is minimal when compared to the uninstructed deviation stemming from energy arbitrage between day-ahead and real-time...
time markets. Figure 4.4 illustrates the fact that even in the 99th percentile case, the frequency only falls as low as 49.80 resulting in the highest $R^{dc}$ value of merely 0.05.

Table 5.3: Breakdown of Results for SE3 Model D Case Study

<table>
<thead>
<tr>
<th></th>
<th>summer</th>
<th>winter</th>
</tr>
</thead>
<tbody>
<tr>
<td>Aggregator Expected Profit</td>
<td>-666.47 SEK</td>
<td>-2085.33 SEK</td>
</tr>
<tr>
<td>DA Energy Cost</td>
<td>2209.97 SEK</td>
<td>2361.68 SEK</td>
</tr>
<tr>
<td>Exp. RT Energy Cost (Revenue)</td>
<td>-115.49 SEK</td>
<td>-36.38 SEK</td>
</tr>
<tr>
<td>Regulation Return</td>
<td>1501.74 SEK</td>
<td>339.5 SEK</td>
</tr>
<tr>
<td>CVaR</td>
<td>-700.87</td>
<td>-2131.18 SEK</td>
</tr>
</tbody>
</table>

Figure 5.5: Instructed and Un-instructed Deviation
5.3. Value of Flexibility

The value of flexibility is determined through the comparison of results between the case where the aggregator is able to utilize dynamic load control, and the reference case where no flexibility is used (un-controlled charging). Flexibility harnessed through dynamic load control, can gain value via a number of use cases; firstly through purely energy arbitrage $E(\Pi^A)$ or secondly by entering both the energy and FCR markets and resulting in $E(\Pi^{N/D})$ from the full mathematical formulation described in section 3.1. Table 5.4 displays the aggregators expected profits for various seasons in the reference (Model R), energy arbitrage only (Model A) and the combined energy arbitrage & FCR-N/D (Model N/D) cases. One can observe increasing expected profits as the use cases for flexibility increase.

Table 5.4: Increasing Profits From Use of Flexibility

<table>
<thead>
<tr>
<th></th>
<th>NO5 winter</th>
<th>NO5 summer</th>
<th>SE3 winter</th>
<th>SE3 summer</th>
</tr>
</thead>
<tbody>
<tr>
<td>$E(\Pi^R)$</td>
<td>-2537.13 NOK</td>
<td>-2021.51 NOK</td>
<td>-2562.05 SEK</td>
<td>-2441.15 SEK</td>
</tr>
<tr>
<td>$E(\Pi^A)$</td>
<td>-2312.25 NOK</td>
<td>-1820.86 NOK</td>
<td>-2356.82 SEK</td>
<td>-1974.47 SEK</td>
</tr>
<tr>
<td>$E(\Pi^N)$</td>
<td>-2154.49 NOK</td>
<td>-873.3 NOK</td>
<td>-104.08 SEK</td>
<td>1679.35 SEK</td>
</tr>
<tr>
<td>$E(\Pi^D)$</td>
<td>-2085.33 SEK</td>
<td>-205.33 SEK</td>
<td>-666.47 SEK</td>
<td>-666.47 SEK</td>
</tr>
</tbody>
</table>

As previously discussed, if uncontrolled-charging is taken as the reference case and subtracted from the profits of other scenarios, it is possible to obtain a discrete value of flexibility. Explicitly, the value of flexibility (Model A) = $E(\Pi^A) - E(\Pi^R)$, while the value of flexibility (Model N) = $E(\Pi^N) - E(\Pi^R)$. Accordingly, Table 5.5 indicates the value of flexibility from the Tibber fleet per day.

Table 5.5: Value of Flexibility of Tibber Portfolio Per Day

<table>
<thead>
<tr>
<th></th>
<th>NO5 winter</th>
<th>NO5 summer</th>
<th>SE3 winter</th>
<th>SE3 summer</th>
</tr>
</thead>
<tbody>
<tr>
<td>Value of Flex. Model A</td>
<td>224.89 NOK</td>
<td>200.65 NOK</td>
<td>205.23 SEK</td>
<td>466.68 SEK</td>
</tr>
<tr>
<td>Value of Flex. Model N</td>
<td>382.64 NOK</td>
<td>1148.21 NOK</td>
<td>2457.97 SEK</td>
<td>4120.50 SEK</td>
</tr>
<tr>
<td>Value of Flex. Model D</td>
<td>476.72 SEK</td>
<td>476.72 SEK</td>
<td>476.72 SEK</td>
<td>476.72 SEK</td>
</tr>
</tbody>
</table>
Table 5.6: Value of Flexibility Per Vehicle Per Month

<table>
<thead>
<tr>
<th></th>
<th>NO5 winter</th>
<th>NO5 summer</th>
<th>SE3 winter</th>
<th>SE3 summer</th>
</tr>
</thead>
<tbody>
<tr>
<td>Value of Flex.</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Model A</td>
<td>8.37 NOK</td>
<td>7.47 NOK</td>
<td>7.64 SEK</td>
<td>17.37 SEK</td>
</tr>
<tr>
<td>Value of Flex.</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Model N</td>
<td>14.24 NOK</td>
<td>42.74 NOK</td>
<td>91.49 SEK</td>
<td>153.37 SEK</td>
</tr>
<tr>
<td>Value of Flex.</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Model D</td>
<td></td>
<td></td>
<td>17.74 SEK</td>
<td>66.06 SEK</td>
</tr>
</tbody>
</table>

Figure 5.6: Value of Flexibility Per Vehicle Per Month for Various Use-Cases and Seasons (W/S) in NO5 & SE3

Table 5.6 and Figure 5.6 both display the value of flexibility per vehicle per month in summer (NO5-S, SE3-S) & winter (NO5-W, SE3-W) for the use cases represented by Model A, N and D. Understandably, this value increases with more use-cases of flexibility and is higher in the Swedish context compared to the Norwegian.
Chapter 6

Discussion

Assuming that return from regulation across the entire year is the average of the
return in the winter and summer periods, these results can be extrapolated to
determine that the revenue from providing primary FCR-N regulation amounts to
roughly 280 NOK per vehicle per year. This moderate value is largely attributed to
the relatively low FCR-N prices in Norway due to the presence of immense hydro-
electric resources that currently provide primary regulation at very low cost. When
carrying out the same assumptions for the Swedish results, a revenue from FCR-N
regulation of 1395 SEK per vehicle per year is obtained. Once again, this difference
stems almost entirely from the significantly higher FCR-N prices offered in Sweden
compared to Norway.

If the revenue from energy arbitrage is added to these values in order to deter-
mine the total value of flexibility per vehicle for an entire year, a value of 342 NOK
for Norway and 1470 SEK for Sweden is reached. Once more, it must be noted
that these values do not consider other revenue streams, such as end user retail
contracts, dependent on the business model of the aggregator and thus stem purely
from the inherent flexibility of the EVs.

Regardless, the significance of these values become more evident when compared
with the uncontrolled charging reference case represented by Model R. This case can
be viewed as the reference "cost of charging" an electric vehicle. Table 6.1 shows the
value of flexibility as a percentage of the cost of charging. It can be seen that even
in Norway, more than 50% of the cost of charging can be covered in summer by the
value of flexibility generated in Model N. While in Sweden, an EV can essentially
be charged 'for free' with 96% of the cost of charging being met by the value of
flexibility from Model N in winter and 169% in summer.

It should also be considered that depending on the need for additional hard-
ware/communication infrastructure, the marginal cost of scaling the dynamic load
control of EVs is potentially relatively low. Therefore, despite the per-vehicle val-
ues being moderate, particularly in Norway, an aggregator would be able to amass
considerable revenues at larger fleet sizes.

Meanwhile on a technical level, characteristics such as response time were not
Table 6.1: Value of Flexibility as Percentage of Cost of Charging per Day

<table>
<thead>
<tr>
<th></th>
<th>NO5 winter</th>
<th>NO5 summer</th>
<th>SE3 winter</th>
<th>SE3 summer</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Model R</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(Cost of Charging)</td>
<td>94.43 NOK</td>
<td>75.24 NOK</td>
<td>95.36 SEK</td>
<td>90.86 SEK</td>
</tr>
<tr>
<td><strong>Model A</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>% of Cost of Charging</td>
<td>8.37 NOK</td>
<td>7.47 NOK</td>
<td>7.64 SEK</td>
<td>17.37 SEK</td>
</tr>
<tr>
<td></td>
<td>9%</td>
<td>10%</td>
<td>8%</td>
<td>19%</td>
</tr>
<tr>
<td><strong>Model N</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>% of Cost of Charging</td>
<td>14.24 NOK</td>
<td>42.74 NOK</td>
<td>91.49 SEK</td>
<td>153.37 SEK</td>
</tr>
<tr>
<td></td>
<td>15%</td>
<td>57%</td>
<td>96%</td>
<td>169%</td>
</tr>
<tr>
<td><strong>Model D</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>% of Cost of Charging</td>
<td></td>
<td>17.74 SEK</td>
<td>66.06 SEK</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>19%</td>
<td>73%</td>
</tr>
</tbody>
</table>

considered in this work. Regardless, the use of EVs in providing frequency containment reserves has been proven in field tests ([43], [33]) to satisfy the technical requirements of Nordic TSO’s, with the observed response time of 5-6 seconds being well below the 63% in 60 seconds response mandated for FCR-N for instance.

Additionally, it must be noted that FCR-N and FCR-D markets were analysed separately within this work. However, it is understood that in reality, an aggregator would be capable of optimizing its portfolio and entering both markets in Sweden and therefore obtain higher revenues from simultaneously providing both FCR-N and FCR-D.

Finally, the unique characteristics of the fleet examined in this thesis must not be overlooked. The fleet was comprised entirely of Tesla vehicles with battery capacities of between 60 kWh and 100 kWh. Therefore, the fleet utilized in this study is not well representative of the market mix of EV models and their corresponding battery capacities. Firstly, no plug-in hybrid electric vehicles (PHEV) were considered, while secondly, it is well noted that the battery capacity of Tesla vehicles (Table 4.1) are considerably higher than other manufacturers; the closest in Tibber’s fleet being the Volkswagen e-Golf with 35.8 kWh. Consequently, the volume of available flexibility determined in this study, and hence the resulting revenues per vehicle, are greater than would be the case when considering Tibber’s current true fleet is composed of, additionally to Tesla vehicles, a number of Volkswagen, BMW and Volvo vehicles. However it must also be noted that the available flexibility is underestimated due to the assumption that only the single longest trip per vehicle is useful for the aggregator and all other trips are ignored.
Chapter 7

Conclusion

There exists little contention of the ever increasing importance of demand side management related to the balancing of the electricity grid. In the Nordic context; the phase out of synchronous generation and the growing introduction of intermittent renewable generation is observed. Adding to this the considerable inclusion of new electric loads, TSOs are facing a turbulent future and must examine all available resources for ensuring system stability. Promisingly, one such resource is that of electric vehicles, and this has been the focus of this work. A two-stage stochastic optimization model has been developed in an effort to quantify the value of flexibility present in controllable EV loads. The results offer an optimized high level day-ahead self-scheduling strategy for an electric vehicle aggregator operating in the Nordics.

Case studies were carried out using historical fleet data of 806 vehicles Norway, price area NO5, and Sweden, price area SE3. Results showed moderate revenue from participation in the FCR-N market in Norway but considerably higher regulation prices in Sweden result in greater revenues in the SE3 case study. In Norway, 342 NOK can be expected as revenue from energy arbitrage and FCR-N provision (Model N) per vehicle per year, while in Sweden the value is 1470 SEK. When compared to a reference "cost of charging case", up to 50% of the cost of charging can be covered in Norway, while the entire cost can be covered in Sweden.

In conclusion, it can be seen that the results drawn from this work go some way in confirming the existence of significant value in the inherent flexibility of electric vehicle charging in the Nordic context.
CHAPTER 7. CONCLUSION

7.1. Future Work

Further development of the model should allow for the simultaneous examination of FCR-N and FCR-D markets. This would provide a more realistic outlook of the potential value of EV flexibility since an aggregator would most likely optimize its portfolio to concurrently enter both markets to maximise profits.

One unique insight determined from this study is the considerable proportion of electric vehicles that are at home, but however are not connected to the charger. Analysis of Tibber data shows that up to 30% of electric vehicles that are home, are not connected to their chargers and are therefore un-controllable by the aggregator. It is understood that most previous studies in this area only examined driving behaviour and have not considered the possibility of drivers not connecting their vehicles to chargers despite being home. A comparison of results in this case versus a similar case where the ‘connection status’ is considered, may provide some insight into the value of engaging the end user, whereby they are educated to connect the vehicle whenever home in order to maximise their potential return.

Additionally, this model could be developed further to include specific end-consumer retail contracts within the objective function. Thereby, the aggregator’s full expected profit including revenue from electricity retail would be examined. As previously described, this was originally considered out of the scope of this work. However, through the inclusion of such terms, various contract types and structures could be studied and compared, potentially providing some insight into aggregator business models and the various options for the sharing of expected profit extracted from the use of flexibility.

Finally, further analysis could be carried out to examine the value of aggregation as done in [13]. Here, the problem was solved for a 1000 vehicle fleet, then repeated for varying ‘sub-fleet’ sizes. For example; two fleets of 500 vehicles, ten fleets of 100 and so on. The comparison of the aggregator’s expected profit with varying fleet size would give an indication of the value of aggregation. As was expected, it was found that with higher aggregation, the expected profit increases since the confidence of day-ahead load and vehicle availability forecasts increases with larger portfolios.
Bibliography


