Exploring the Business Case of a Risk-Averse Electric Vehicle Aggregator in the Nordic Market

Jacob Dalton, Lars Herre and Lennart Söder
Department of Electric Power and Energy Systems
School of Electrical Engineering and Computer Science
KTH Royal Institute of Technology, 10044 Stockholm, Sweden
Email:{jdalton, lherre, lsod}@kth.se.

***Abstract*—The Nordic power system is facing the challenge of the ongoing decrease of synchronous generation along with increased penetration of inverter based renewable generation leading to reduced system inertia. Meanwhile, the electrification of the transport sector will result in a significant amount of additional electrical loads. However, 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 storage with availability, energy and capacity constraints.**

In this paper, we use first hand data of a real EV fleet of Tesla vehicles and their historical driving patterns to develop a two-stage stochastic optimization problem. This model maximizes the profit of a risk-averse EV aggregator that aims to place optimal bids on the day ahead in both energy and Frequency Containment Reserve (FCR) markets. Only uni-directional charging is examined, while we take into account uncertainty from prices and vehicle utilization. Case studies are carried out modelling individual vehicle driving behavior in different Nordic price areas in both winter and summer.

We identify a strong alignment of EV availability and periods of high FCR prices. Results show that consumption is shifted largely towards early hours of the morning. 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 met in Sweden.

***Index Terms*—ancillary services, aggregation, balancing markets, demand side management, electricity prices, electric vehicles.**

I. Introduction

The Nordic power system is undergoing a major shift from centralized synchronous generation towards distributed, inverter based renewable generation. Furthermore, an increasing number of HVDC interconnections add to reduced system inertia. It is estimated that more than a 20% reduction in annual mean inertia will occur between 2020 and 2040 [1]. Additionally, economy wide electrification, particularly in the transport, steel and cement manufacturing industries will see the introduction of new electrical loads with potentially greater demand peaks [1]. In the transport sector, electric vehicle (EV) loads are introduced with rapid growth in both private transportation and logistics. Due to these challenges, the traditional focus on the supply side is becoming increasingly insufficient for ensuring system stability. Concurrently, the concept of demand side management is becoming widely recognized as an essential element with growing attention. In more advanced markets such as France for instance, large industrial players have been taking part in the balancing mechanism since 2003 [2], while the potential flexibility in the German industrial sector is estimated to be as large as 4.5 GW in the medium-term [3]. However, the sectors of commerce and industry only present one half of the total economy wide electricity demand [4] 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 mobilized and the value extracted through aggregation.

To this end, passenger EVs immediately stand out as a critical load in the context of residential demand side management. EVs and their chargers pose as the quintessential 'low hanging fruit', 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. A single full electric vehicle's energy demand is comparable to that of a single family dwelling [5]. 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^{o}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 [6]. For the Nordics, this penetration is far more dramatic, with a 15-fold increase of EV units from 2017 to 2030. This prediction corresponds to 4 million electrified passenger vehicles in the Nordics by 2030. Consequently, 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 [7].

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. Most studies publish results of lower charging costs and increased aggregator profits through arbitraging energy prices by using EV flexibility. Literature can mainly be divided into bi-directional charging, also referred to as vehicle-to-grid (V2G), and uni-directional charging; where a only a time-shift in charging occurs.

In [8] 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. The authors use synthetic EV parameters and driver behaviour to model time of arrival, departure and SOC at arrival uncertainty. The results showed a heavy influence of the size of the penalty for un-instructed energy deviation on the aggregators bidding strategy and resulting profit.

Three different optimization problems of independent aggregators making day-ahead decisions in the wholesale and secondary reserve markets are presented in [9]. Synthetic EV data was created in order to determine so called "flexible periods" while the impact of forecast errors and uncertainty was considered through the comparison of results of perfect forecasts with a naive forecasting method. The authors build upon this previous study in [10] 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.

The optimal scheduling behaviour of a risk-averse aggregator is modelled in [11]. 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. A different method is exploited in [12], 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.

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 [9], [10], [13]–[18], or utilize a small first hand data sample and extrapolate to a larger synthetic sample [12], [19]. 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 paper revolves around determining an explicit value of the inherent flexibility of EV charging.

In this paper, we explore the business case of an EV aggregator that has real-time information and control over its heterogeneous fleet of EVs. We make use of a two-stage stochastic optimization problem that a risk-averse aggregator would solve on the day-ahead in order to maximize its profits in the energy and balancing markets. We take into account uncertainty from EV availability and real-time energy prices. We study the profitability of active participation in the FCR-N and FCR-D markets with typical prices in summer and winter in Norway and Sweden.

The rest of this paper is structured as follows. In Section II the problem setup is outlined including the relevant markets, the various arrangements of the model used, together with the assumptions. Section III outlines the available data used in the study. Section IV portrays the mathematical formulation of the models, while Sections V and VI outline the case study results and a discussion respectively. Finally, Section VII provides a conclusion of the work.

II. Problem Setup

A. Aim

We want to explore the business case of an EV aggregator that has real-time control over its fleet and exploits this flexibility to participate in the energy and balancing markets. The aggregator's goal is to make optimal risk-averse day-ahead decisions under uncertainty. While we ensure risk-adversity and feasibility in the subsequent operation, the real-time control actions that would follow the day-ahead decisions are explicitly outside of the scope of this study. The aim is rather to give an estimation of potential profits for an aggregator, that will then have to weigh those against the cost of control systems and actions.

B. Markets Considered

This study is focused on the Nordic electricity markets, but can be used for most market setups that have a liberalized bidding system for energy and frequency regulation services. Here, we assume that the aggregator can enter and place bids in the following markets:

- E^{DA}: The day-ahead market for energy closes at 12:00 CET D-1 and is traded at the wholesale market Nordpool as a hourly product.
- E^{RT}: The real-time electricity price is found ex-post as the price of imbalance settlement.
- R: The market for frequency containment reserve in normal operation (FCR-N) and disturbed operation (FCR-D) is procured until 16:00 CET D-1 and 15:00 CET D-2 and operated by the TSO. (FCR-D was examined only for Sweden since the price for this product in Norway is negligible.)

We include an imbalance penalty to account for uninstructed real-time deviations from the DA energy bids.

C. Uncertainty

Two main sources of uncertainty are considered when modelling the optimal scheduling of an aggregator: *price* uncertainty and *availability* due to driving behaviour.

- *Price*: Perfect price information is assumed for day-ahead ($\lambda_t^{E^{DA}}$) and FCR prices (λ_t^R) which is in line with the literature [8], [15], [20]. If the study is conducted for summer and winter prices separately, a clear diurnal pattern of FCR-N prices can be identified. Price uncertainty is reflected via daily real-time ($\lambda_{t,w}^{E^{RT}}$) price trajectory scenarios ($\omega \in \Omega$) based on historical market data.
- *Availability*: Driving behavior can vary between vehicle type and owner. Driving behaviour scenarios were sampled randomly from the pool of historical EV trips. The database was obtained from historical trips of Tesla vehicles.

D. Risk Adversity - Conditional Value at Risk (CVaR)

The mathematical formulation described in Section IV accounts for risk adversity through the risk term CVaR. The risk term CVaR can be described as "the expected value of the profit of the $(1 - \alpha)$-quantile of the profit distribution" [21]. In other words, given a confidence interval α of e.g. 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. Hereby, the sum of the expected profit ($\mathbb{E}[\mathbf{\Pi}]$) and the bottom $(1-\alpha)$ percent of profits is maximized. In this work, a confidence interval of α = 90% is utilized.

E. Assumptions

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 operational business and contractual details of the EV aggregator with its end consumers however, is outside of the scope of this work. 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 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 analyzed irrespective of the business model of the aggregator and without the impacts that a specific customer contract type might have on the charging patterns. Furthermore, we make the following assumptions:

- The aggregator has perfect price information for day-ahead energy (λ_t^{EDA}) and frequency containment reserve markets (λ_t^R).
- The aggregator is a price taker and thus has no effect on market prices.
- The aggregator is capable of dynamic load control in real time operation. In other words, it has the capability to remotely switch on/off individual EV charging.
- Each vehicle is assumed to only have one charging cycle per day available for control by the aggregator. This charging cycle is selected as the single longest trip in each day. This assumption approximates the flexibility in a conservative way.
- The minimum bid size is always fulfilled. This assumption can be met in the Nordic context since Balance Responsible Parties are permitted to consolidate bids from various resources to meet minimum bid sizes [22].
- The real-time activation of primary FCR-N regulation has a zero mean character. This assumption is based on the fact that FCR-N is a symmetric product, aiming to maintain the frequency at 50Hz and thereby having approximately equal up & down regulation.

III. Available Data

A. Vehicle Data

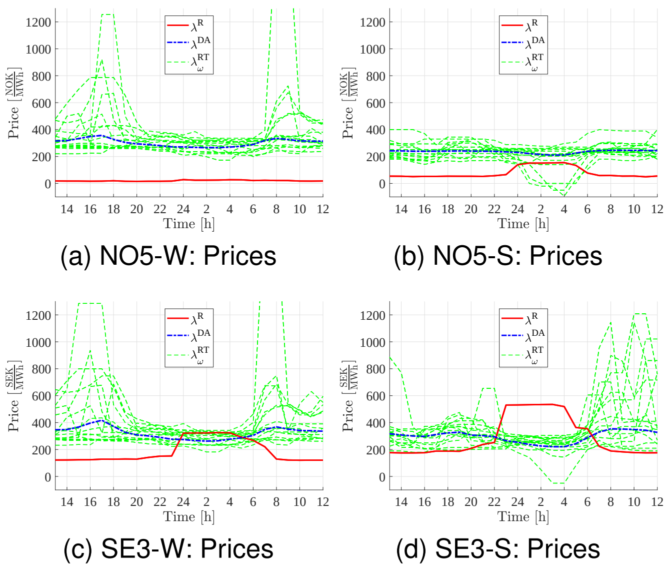
Through the company *Tibber* and their customer base, we have access to direct first hand data related to driving behaviour and vehicle parameters. Therefore it was possible to gather the necessary data required for input into the optimization model. These parameters are listed in Table I.

B. Market Price Data

The three price parameters used as input in the model are publicly available. The day-ahead (λ^{EDA}) and real-time price (λ^{ERT} in the *Regulating Power Market)* are publicly available on Nord Pool's website [23]. (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.) Meanwhile, the FCR-N & FCR-D regulation prices (λ^R) are available from the TSO's (*Statnett* and *Svenska kraftnät*) data portals for Norwegian and Swedish market data respectively. For each season (S: summer, W: winter), the hourly mean of historical prices was used for both the day-ahead energy and FCR-N prices where perfect price information was assumed. The motivation for this assumption is that the daily FCR-N price trajectories on weekdays shows very similar magnitudes throughout a given season.

TABLE I: Vehicle parameters in the historical database

SOC_ω^{arr}	Battery SOC at arrival	$\omega \in \Omega$
SOC_ω^{dep}	Battery SOC at departure	$\omega \in \Omega$
T_ω^{arr}	Time of arrival	$\omega \in \Omega$
T_ω^{dep}	Time of departure	$\omega \in \Omega$
$\hat{E}^{bat}$	Maximal battery capacity	fixed, vehicle dependent
$\hat{P}^{ch}$	Maximal charging power	fixed, vehicle dependent



(a) NO5-W: Prices (b) NO5-S: Prices
(c) SE3-W: Prices (d) SE3-S: Prices

Fig. 1: Prices in NO5 and SE3: Day-ahead energy (λ^{DA}), FCR-N (λ^R) and 15 scenarios of RT energy prices (λ_ω^{RT}).

An illustration of characteristic market data in price area NO5 is given in Fig. 1a and Fig. 1b. It portrays the day-ahead and FCR-N prices in bold, while real-time price scenarios are indicated by thin lines. The 15 real-time price scenarios were found based on a forward selection technique [24]. The characteristic shape of the FCR-N price should be noted; increasing dramatically between the hours of 12 am and 5 am. Similarly, Fig. 1c and Fig. 1d show the market prices 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 11 am and 4 am. Finally, it is clear from the figures that winter FCR prices are significantly lower than summer prices in both Norway and Sweden.

IV. Profit Maximization Problem

The objective of the risk-averse aggregator is to maximize the expected profit considering the Conditional Value at Risk (CVaR)

$$\max. \quad [(1-\beta)\cdot \mathbb{E}[\mathbf{\Pi}^*] + \beta \cdot \text{CVaR}] \tag{1}$$

while the level of risk aversion is determined by the parameter β as described in Section II-D.

The expected profit ($\mathbb{E}[\mathbf{\Pi}^*]$) is composed of the day-ahead income from accepted frequency containment reserve bids $\left(\Pi^R > 0\right)$, the day-ahead cost of energy $\left(\Pi^{E^{DA}} > 0\right)$, the expected cost (< 0) or revenue (> 0) from the purchase or sale of energy in the real-time market $\left(\Pi^{E^{RT}}\right)$, and finally the penalty due to deviation, in the form of a consumption imbalance fee $\left(\Pi^P\right) < 0$.

$$\mathbb{E}[\mathbf{\Pi}^*] = \sum_{t\in T} \Pi_t^R + \Pi_t^{E^{DA}} + \mathbb{E}\left[\Pi_t^{E^{RT}} + \Pi_t^P\right] \tag{2}$$

Index t denotes 15 min market intervals. While all the above markets are operated on an hourly basis as of today, the European markets are moving towards shorter market intervals. Since we study the future business case of an aggregator, we use 15 min intervals.

The constraints include vehicle dependent bounds on charging power and battery capacity and scenario dependent bounds on availability in terms of arrival and departure time. The profit maximization of the aggregator can be formulated as a mixed integer linear program (MILP) with the assumptions in Section II-E.

A. Market Participation Cases

Based on the general formulation of (1) and (2), we can modify the problem to study different cases of the aggregator's involvement. To this end, the total profits of the aggregator are labeled with the according superscripts.

- $\mathcal{R}$: The reference case: The aggregator acts as a retailer and has no control, i.e. charges the vehicles when they arrive with full power until they are fully charged.
- $\mathcal{A}$: Energy Arbitrage: The aggregator only participates in the energy markets, i.e. $\Pi_t^R = 0 \quad \forall t$.
- $\mathcal{N}$: FCR-N & Energy Arbitrage: The aggregator participates in the energy markets and FCR-N market with capacity offer R_t, i.e. $\Pi_t^R = R_t \cdot \lambda_t^{FCR-N} \quad \forall t$.
- $\mathcal{D}$: FCR-D & Energy Arbitrage: The aggregator participates in the energy markets and FCR-D market with capacity offer R_t, i.e. $\Pi_t^R = R_t \cdot \lambda_t^{FCR-D} \quad \forall t$.

$\mathcal{R}$ represents the reference case of uncontrolled charging, also referred to as 'dumb charging'. Its formulation is similar to $\mathcal{A}$. However, the binary parameter for vehicle availability is pre-treated to force the charging to commence when the vehicle is first home until it is full.

The variation between $\mathcal{N}$ and $\mathcal{D}$ stems from the fact that FCR-N is assumed approximately symmetrical while FCR-D is only up regulating. Therefore, as occurs in [8], the activation of bids must be considered via a *dispatch-to-contract ratio* (R_t^{dc}). This parameter provides the proportion of submitted FCR-D bids that will be activated in real-time and is directly related to the frequency in the Nordic synchronous grid. The activation of a FCR-D bid however, would result in a deviation from the day-ahead energy bid and resulting imbalance penalty. Therefore, we split the imbalance into instructed and uninstructed deviation where only the latter is penalized.

V. Results

A. Norway: Case Study in Price Area NO5

Table II outlines the breakdown of results for the initial case study of the aggregation of Tesla vehicles for a 24 hour period in summer and winter, with market prices based on price area NO5.

TABLE II: Case Study in NO5: Market Participation $\mathcal{N}$

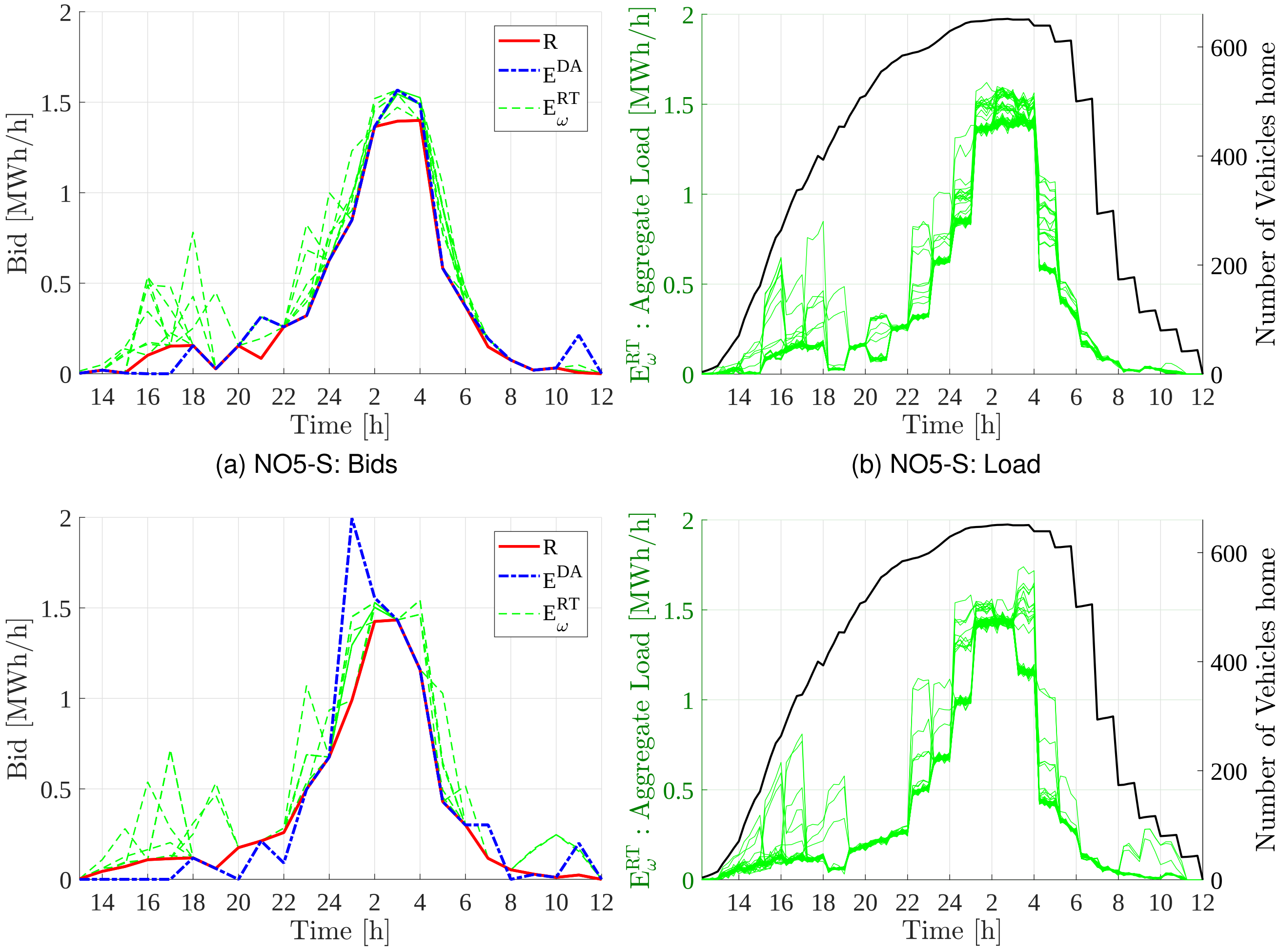
$\mathcal{N}$	**NO5-W** [NOK]	**NO5-S** [NOK]
Regulation Return	191.25	1,042.45
DA Energy Cost	-2,179.14	-1,969.37
RT Energy Cost (exp.)	-52.93	106.76
CVaR	-2,235.61	-9,23.81
Total Profit (exp.)	**-2,154.49**	**-873.30**

The aggregator's expected profit is the sum of the day-ahead and expected real-time energy cost and the return from provision of FCR-N. It is observed that the expected real-time energy cost is positive 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 EV charging in summer is 1,969.37 - 106.76 = 1862.61 NOK. The expected return from providing primary regulation (1,042.45 NOK) covers almost 55% of the charging cost. The lower regulation return in winter is attributed to lower FCR-N prices in the winter period, c.f. Figs. 1a and 1b.

The aggregated load curve of the EV fleet is visualized in Fig. 2b with the green lines portraying the aggregate load resulting from EV availability in various scenarios. The black line displays the mean number of vehicles that are 'home & connected' 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 between 12am-5am, c.f. Fig. 1b, in order to maximize return. Meanwhile, the optimized day-ahead energy (E^{DA}) & FCR-N regulation bids (R) are shown in Fig. 2a, together with the scenarios of real-time consumption. Energy arbitrage is carried out where the day-ahead energy bid varies from the real-time energy consumption. This is clearly illustrated at 11am for instance, where the optimal schedule is to buy a volume of DA energy in excess of the real-time consumption, in order to sell in the RT market at a higher price.

B. Sweden: Case Study in Price Area SE3

The breakdown of results for the case study in Sweden are outlined in Table III ($\mathcal{N}$) and Table IV ($\mathcal{D}$). Once more, the expected RT energy cost is positive, indicating a return through the sale of energy in real-time. Therefore, the expected cost of charging energy for the vehicles in summer SE3 is 2,223.24 - 142.37 = 2,080.87 SEK. With a return from FCR-N provision of 3,837.20 SEK, the entire cost of charging is surpassed and hence the recorded expected profit of 1,679.35 SEK for the *Tibber* fleet. The reason this value is significantly greater when compared to the results from NO5,



(a) NO5-S: Bids

(b) NO5-S: Load

(c) SE3-S: Bids

(d) SE3-S: Load

Fig. 2: Results for summer NO5-S and SE3-S case studies. The top figures show the optimal day-ahead bids as well as scenario dependent real-time energy consumption. The bottom figures show the number of available EVs as well as the scenario dependent utilized aggregated load from the pool of available EVs.

TABLE III: Case Study in SE3: Market Participation $\mathcal{N}$

$\mathcal{N}$	**SE3-W** [SEK]	**SE3-S** [SEK]
Regulation Return	2,326.01	3,837.20
DA Energy Cost	-2,391.41	-2,223.24
RT Energy Cost (exp.)	40.38	142.37
CVaR	-164.06	1,645.21
Total Profit (exp.)	**-104.08**	**1,679.35**

TABLE IV: Case Study in SE3: Market Participation $\mathcal{D}$

$\mathcal{D}$	**SE3-W** [SEK]	**SE3-S** [SEK]
Regulation Return	339.5	1,501.74
DA Energy Cost	-2,361.68	-2,209.97
RT Energy Cost (exp.)	36.38	115.49
CVaR	-2,131.18	-700.87
Total Profit (exp.)	**-2,085.33**	**-666.47**

is almost entirely attributed to dramatically higher FCR-N prices offered in Sweden as shown in Fig. 1.

The model was altered to match the FCR-D market in Sweden and similarly run for summer and winter seasons with Table IV displaying the results. Lower regulation return values occur due to the lower price of FCR-D regulation when compared to FCR-N.

C. 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 ($\mathcal{R}$) of uncontrolled charging. Flexibility harnessed through dynamic load control, can gain value via a number of use cases; firstly through purely energy arbitrage ($\mathcal{A}$) or secondly by entering both the energy and FCR markets ($\mathcal{N}, \mathcal{D}$). Table V displays the aggregator's expected profits in summer and winter season in the reference case ($\mathcal{R}$), and all three different cases of market participation ($\mathcal{A}, \mathcal{N}, \mathcal{D}$).

TABLE V: Increasing Profits From Use of Flexibility

	NO5-W [NOK]	**NO5-S** [NOK]	**SE3-W** [SEK]	**SE3-S** [SEK]
$\mathbb{E}\left[\mathbf{\Pi}^{\mathcal{R}}\right]$	-2,537.13	-2,021.51	-2,562.05	-2,441.15
$\mathbb{E}\left[\mathbf{\Pi}^{\mathcal{A}}\right]$	-2,312.25	-1,820.86	-2,356.82	-1,974.47
$\mathbb{E}\left[\mathbf{\Pi}^{\mathcal{N}}\right]$	-2,154.49	-873.3	-104.08	1,679.35
$\mathbb{E}\left[\mathbf{\Pi}^{\mathcal{D}}\right]$			-2,085.33	-666.47

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 (VoF), e.g. in the arbitrage only case VoF($\mathcal{A}$) = $\mathbb{E}\left[\mathbf{\Pi}^{\mathcal{A}}\right]$ - $\mathbb{E}\left[\mathbf{\Pi}^{\mathcal{R}}\right]$. Accordingly, Table VI indicates the value of flexibility from the EV fleet per day, as well as the value of an average EV per month for different market participation cases.

TABLE VI: Value of Flexibility of the EV portfolio

		NO5-W	NO5-S	SE3-W	SE3-S
EV fleet per day $\left[\frac{NOK}{day}\right] / \left[\frac{SEK}{day}\right]$	VoF($\mathcal{A}$)	224.89	200.65	205.23	466.68
	VoF($\mathcal{N}$)	382.64	1,148.21	2,457.97	4,120.50
	VoF($\mathcal{D}$)	-	-	476.72	1,774.68
avg. EV per month $\left[\frac{NOK}{month}\right] / \left[\frac{SEK}{month}\right]$	VoF($\mathcal{A}$)	8.37	7.47	7.64	17.37
	VoF($\mathcal{N}$)	14.24	42.74	91.49	153.37
	VoF($\mathcal{D}$)	-	-	17.47	66.06

The value of flexibility per vehicle per month is visualized in Fig. 3 in summer (NO5-S, SE3-S) & winter (NO5-W, SE3-W) for the use cases $\mathcal{A}$, $\mathcal{N}$ and $\mathcal{D}$. Understandably, this value changes with the participation cases and is higher in the Swedish context compared to the Norwegian.

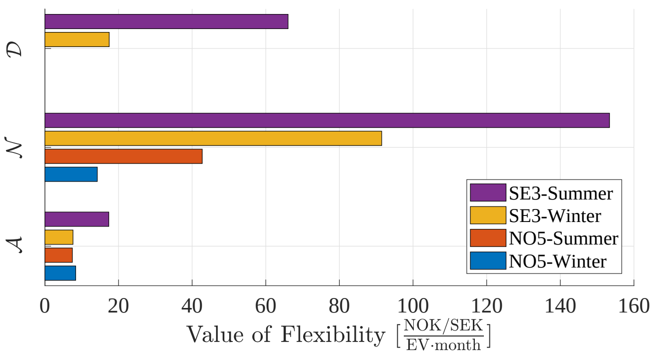


Fig. 3: Value of Flexibility per average EV per month for various market participation cases and seasons in NO5, SE3.

VI. 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 FCR-N 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 extensive use of hydro-electric resources that currently provide primary regulation at very low cost. When carrying out the same assumptions for the Sweden, a revenue from FCR-N regulation of 1,395 SEK per vehicle per year is obtained. This difference is mainly attributed to the significantly higher FCR-N prices in Sweden.

If the revenue from energy arbitrage is added to these values in order to determine the total value of flexibility per vehicle for an entire year, a value of 342 NOK for Norway and 1,470 SEK for Sweden is reached. Note 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.

TABLE VII: Value of Flexibility as Percentage of Cost of Charging per Day

	NO5-W	NO5-S	SE3-W	SE3-S
$\mathcal{R}$ (Charging Cost)	94.43 NOK	75.24 NOK	95.36 SEK	90.86 SEK
VoF($\mathcal{A}$)	8.37 NOK (9%)	7.47 NOK (10%)	7.64 SEK (8%)	17.37 SEK (19%)
VoF($\mathcal{N}$)	14.24 NOK (15%)	42.74 NOK (57%)	91.49 SEK (96%)	153.37 SEK (169%)
VoF($\mathcal{D}$)			17.74 SEK (19%)	66.06 SEK (73%)

The significance of these values become more evident when compared with reference cost of charging an electric vehicle ($\mathcal{R}$). Table VII shows the value of flexibility as a percentage of the cost of charging. It can be seen that even in Norway 57% of the cost of charging can be covered in summer by exploiting EV flexibility (in model $\mathcal{N}$). In Sweden, an EV can essentially be charged 'for free' with 96% of the cost of charging being met by exploiting EV flexibility in winter and 169% in summer (in model $\mathcal{N}$).

Similarly, a value proposition could be developed revolving around the cost of a home charging unit. A Tesla wall connector for instance, has a unit price of 5,200 SEK [25] (excluding installation labor). This cost could be recovered by the revenue generated in Sweden per vehicle within 3.5 years. One flexibility limitation is that 50% of the home chargers in the examined EV fleet have capacities of only 2 or 3 kW, which means that an empty 100 kWh Tesla vehicle would require more than 24 hours to be fully charged. Hence, it could be a significant value proposition to an end-user to offer an upgrade to a Tesla wall connector (with a capacity of up to 16.5 kW) and be able to recover this cost in 3.5 years.

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

Meanwhile, on a technical level, characteristics such as response time were not considered in this work. Regardless, the use of EVs in providing frequency containment reserves has been proven in field tests [26], [27] to satisfy the technical requirements of Nordic TSOs, with the observed response time of 5-6 seconds being well below the 63% in 60 seconds response mandated for FCR-N [28] for instance.

Additionally, it must be noted that FCR-N and FCR-D markets were analyzed separately within this work. However, in reality, an aggregator would be capable of entering both markets (in Sweden) and may obtain higher revenues from simultaneously providing both FCR-N and FCR-D.

Finally, the unique characteristics of the fleet examined in this paper must not be overlooked. The fleet was comprised entirely of Tesla vehicles with battery capacities of 60 - 100 kWh which is not well representative of the market mix of EV models and their corresponding battery capacities. First, no plug-in hybrid electric vehicles were considered, while second, the battery capacity of Tesla vehicles are considerably higher than other manufacturers; the closest in *Tibber's* current 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 in *Tibber's* real fleet that also comprises a number of Volkswagen, BMW and Volvo vehicles.

VII. Conclusion

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 approach for an EV aggregator operating in the Nordics.

Case studies were carried out using historical fleet data. Results showed moderate revenue from participation in the FCR-N market in Norway but greater revenues in Sweden due to considerably higher regulation prices. In Norway, 342 NOK can be expected as revenue from energy arbitrage and FCR-N provision per vehicle per year, while in Sweden the value is 1,470 SEK. Compared to a reference cost of 'dumb charging', up to 50% of the cost 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.

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References

[1] Svenska Kraftnät, "Systemutvecklingsplan 2018," Svenska Kraftnät, Sundbyberg, Tech. Rep. November 2017, 2018.

[2] SEDC, "Explicit Demand Response in Europe Mapping the Markets 2017," Smart Energy Demand Coalition, Tech. Rep., 2017.

[3] Agora Energiewende, "12 Insights on Germany's Energiewende," Agora Energiewende, Tech. Rep. February, 2013.

[4] Swedish Energy Agency, "Energy in Sweden - Facts and Figures 2018," Swedish Energy Agency, Stockholm, Tech. Rep., 2018. [Online]. Available: http://www.energimyndigheten.se/

[5] E. Xydas, C. Marmaras, L. M. Cipcigan, N. Jenkins, S. Carroll, and M. Barker, "A data-driven approach for characterising the charging demand of electric vehicles: A UK case study," *Applied Energy*, vol. 162, pp. 763–771, 2016. [Online]. Available: http://dx.doi.org/10.1016/j.apenergy.2015.10.151

[6] International Energy Agency, "Global EV Outlook 2017: Two million and counting," IEA Publications, Tech. Rep., 2017. [Online]. Available: https://www.iea.org/

[7] ——, "Nordic EV Outlook 2018," IEA Publications, Tech. Rep., 2018. [Online]. Available: https://www.iea.org/

[8] S. I. Vagropoulos and A. G. Bakirtzis, "Optimal bidding strategy for electric vehicle aggregators in electricity markets," *IEEE Transactions on Power Systems*, vol. 28, no. 4, pp. 4031–4041, 2013.

[9] R. J. Bessa, M. A. Matos, F. J. Soares, and J. A. Lopes, "Optimized bidding of a EV aggregation agent in the electricity market," *IEEE Transactions on Smart Grid*, vol. 3, no. 1, pp. 443–452, 2012.

[10] R. J. Bessa and M. A. Matos, "Optimization models for an EV aggregator selling secondary reserve in the electricity market," *Electric Power Systems Research*, vol. 106, pp. 36–50, 2014. [Online]. Available: http://dx.doi.org/10.1016/j.epsr.2013.08.006

[11] I. Momber, A. Siddiqui, T. G. S. Roman, and L. Soder, "Risk averse scheduling by a PEV aggregator under uncertainty," *IEEE Transactions on Power Systems*, vol. 30, no. 2, pp. 882–891, 2015.

[12] E. Yao, V. W. Wong, and R. Schober, "Risk-Averse forward contract for electric vehicle frequency regulation service," *2015 IEEE International Conference on Smart Grid Communications*, pp. 750–755, 2016.

[13] M. Alipour, B. Mohammadi-Ivatloo, M. Moradi-Dalvand, and K. Zare, "Stochastic scheduling of aggregators of plug-in electric vehicles for participation in energy and ancillary service markets," *Energy*, vol. 118, pp. 1168–1179, 2017. [Online]. Available: http://dx.doi.org/10.1016/j.energy.2016.10.141

[14] T. W. Hoogvliet, G. B. Litjens, and W. G. van Sark, "Provision of regulating- and reserve power by electric vehicle owners in the Dutch market," *Applied Energy*, vol. 190, pp. 1008–1019, 2017. [Online]. Available: http://dx.doi.org/10.1016/j.apenergy.2017.01.006

[15] M. Shafie-Khah, M. P. Moghaddam, M. K. Sheikh-El-Eslami, and J. P. Catalão, "Optimised performance of a plug-in electric vehicle aggregator in energy and reserve markets," *Energy Conversion and Management*, vol. 97, pp. 393–408, 2015. [Online]. Available: http://dx.doi.org/10.1016/j.enconman.2015.03.074

[16] M. Shafie-khah, N. Mahmoudi, P. Siano, T. K. Saha, and J. P. Catalao, "A Comprehensive Model to Integrate Emerging Resources from Supply and Demand Sides," *IEEE Transactions on Smart Grid*, vol. 3053, no. c, pp. 1–13, 2017.

[17] E. Sortomme and M. A. El-Sharkawi, "Optimal charging strategies for unidirectional vehicle-to-grid," *IEEE Transactions on Smart Grid*, vol. 2, no. 1, pp. 119–126, 2011.

[18] ——, "Optimal scheduling of vehicle-to-grid energy and ancillary services," *IEEE Transactions on Smart Grid*, vol. 3, no. 1, pp. 351–359, 2012.

[19] B. Škugor and J. Deur, "Dynamic programming-based optimisation of charging an electric vehicle fleet system represented by an aggregate battery model," *Energy*, vol. 92, pp. 456–465, 2015.

[20] A. Van Der Veen and M. Kaisers, "Computing the value of flexibility in electricity retail, ahead and balancing markets," *IEEE PES Innovative Smart Grid Technologies Conference Europe*, 2017.

[21] L. Barroso and A. Conejo, *Decision making under uncertainty in electricity markets*. Springer US, 2006. [Online]. Available: http://ieeexplore.ieee.org/document/1709323/

[22] Svenska Kraftnät, "Slutrapport pilotprojekt Flexibla hushåll," Svenska Kraftnät, Sundbyberg, Tech. Rep. Svk 2016/1688, 2017.

[23] Nord Pool AS, "Nordpoolspot - Historical Market Data." [Online]. Available: http://www.nordpoolspot.com/historical-market-data/

[24] H. Heitsch and W. Römisch, "Scenario reduction algorithms in stochastic programming," *Computational Optimization and Applications*, vol. 24, no. 2, pp. 187–206, Feb 2003. [Online]. Available: https://doi.org/10.1023/A:1021805924152

[25] Tesla, "Installasjon av hjemmelading," 2018.

[26] S. Martinenas, M. Marinelli, P. B. Andersen, and C. Traholt, "Implementation and demonstration of grid frequency support by V2G enabled electric vehicle," in *2014 49th International Universities Power Engineering Conference (UPEC)*. IEEE, sep 2014, pp. 1–6. [Online]. Available: http://ieeexplore.ieee.org/document/6934760/

[27] M. Marinelli, S. Martinenas, K. Knezović, and P. B. Andersen, "Validating a centralized approach to primary frequency control with series-produced electric vehicles," *Advances in Life Course Research*, vol. 7, pp. 63–73, 2016.

[28] Expketra, "Summary and Description of the different rules of the Markets in Sweden." Expektra, Danderyd, Tech. Rep. 556818, 2017.