CHALMERS
UNIVERSITY OF TECHNOLOGY

Master's Thesis in

MODELLING of VEHICLE to GRID INTERACTION

A study of the potential benefits of adding Electric Vehicle fleet to the Fossil free Energy District (FED) system

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ABSTRACT

The purpose of this thesis is to study the possibility of adding an Electric vehicle (EV) fleet to the existing Fossil free Energy District (FED) system and reap the benefits of using Vehicle to Grid (V2G) services. The thesis presents a theoretical perspective of the participation of EV fleet in V2G as well as ancillary services (frequency regulation in this thesis). The optimization tool General Algebraic Modelling System (GAMS) was used to perform a load dispatch based on the dispatch model determining the charging and discharging patterns of the electric vehicles. The objective of the optimization was to minimize the net cost of the system while still satisfying the grid constraints. In addition to the optimization, sensitivity analysis on different parameters of the model was performed, namely charging facility, fleet size and, EV model.

The study found out that using EV fleet for V2G services without any ancillary services is not beneficial. In fact, it is worse than the fleet charging from the grid. However, with the addition of frequency regulation, the fleet achieves a lower net cost than the case where the fleet was charging from the grid.

Keywords: Vehicle to Grid; Fossil free Energy District system; Electric Vehicle fleet; frequency regulation: load dispatch

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Tushar Kataria, Göteborg, 2018

Contents

List of Figures

List of Tables

Nomenclature

Abbreviations

AAR Automatic Activated Reserve

ANN Artificial Neural Network

AR Auto-Regressive

ARMA Auto Regressive integrated Moving Average

BEV Battery Electric Vehicles

CDF Cumulative Density Function

DER Distributed Energy Resources

EU European Union

EV Electric Vehicles

EVSE Electric Vehicle Supply Equipment

FED Fossil-free Energy District

FO Fleet Operator

G2V Grid to Vehicle

GAMS General Algebraic Modelling System

GHG Green House Gases

HWT Holt-Winters Method

IC Intra-Day Cycle Exponential Smoothing

ICEV Internal Combustion Engine Vehicles

LP Linear Programming

MAE Mean Absolute Error

PDF Probability Density Function

PEV Plug-In Electric Vehicles

PHEV Plug-In Hybrid Electric Vehicles

PV Photo Voltaic

RES Renewable Energy Sources

RISE Research Institutes of Sweden

SAE Society of Automotive Engineers

SOC State Of Charge

SSE Squared in-Sample Error

SVD Singular Value Decomposition Exponential Smoothing

UC Unit Commitment

V2G Vehicle to Grid

V2G-NM Vehicle to Grid- Net Metered

V2H Vehicle to Home

V2L Vehicle to Load

V2P Vehicle to Premise

Symbols

α Hourly smoothing parameter

δ Daily smoothing parameter

ϵ Error parameter

η_{ch} Charging Efficiency

η_{dis} Discharging Efficiency

λ Shape factor for Inverse Gaussian Distribution

μ mean

ω Weekly smoothing parameter

ϕ Auto Regressive (AR) adjustment parameter for first-order residual auto-correlation

σ Standard Deviation

σ^2 Variance

C_f Number of full charging cycles possible during the lifetime of the battery

D_f Battery degradation cost per unit of energy throughput at full discharge cycles

E_{ch} Energy added during Charging Phase

E_{dis} Energy removed during Discharging Phase

E_{max} Maximum Electricity consumption in a hour during the time period of analysis

E_{rated} Rated Battery Capacity

$E_{reg,down}$ Regulation Down Energy content

$E_{reg,up}$ Regulation Up Energy content

E_{usable} Usable share of the battery

B Battery Investment cost

d Day state variable

E Energy Content of the Battery

e Error term

El Actual Demand (in kWh)

h Hour of Operation

i BEV battery number

k	k-step ahead forecast from forecast origin
l	Hourly state variable
m1	Number of time periods in a day
m2	Number of time periods in a week
ps	Length of the sample period
w	Weekly state variable
y	Demand Forecast (in kWh)

1 INTRODUCTION

This master thesis is going to deal with the potential of introducing Vehicle to Grid (V2G) interactive systems to provide support to the Electrical grid in the Fossil free Energy District (FED) system. The FED system is a joint venture between the *city of Gothenburg, Johanneberg Science Park, Göteborg Energi, Business region Göteborg, Ericsson, Research Institutes of Sweden (RISE), Akademiska Hus, Chalmersfastigheter and Chalmers University of Technology* with each partner contributing with their expertise and knowledge to make FED attractive for other European cities as well [1]. The support would be in the form of ancillary services which is further explained in detail in the following sections.

1.1 Background

In the present day world, fossil fuels dominate the energy sector. The power sector was responsible for 30% of the Green House Gases (GHG) emissions in EU-27 for the year 2011 compared to 20.3 % for the transportation Sector [2]. The impetus should be laid on reducing the emissions from these two sectors as they are the major contributors of emissions. The other emissions contributing sectors are beyond the scope of this thesis.

To reduce the GHG emissions from Power sector more Renewable Energy Sources (RES) like wind, solar, biomass etc. is being introduced into the generation system. The trend in the transportation sector is to introduce more Battery Electric Vehicle (BEV) and Plug-in Hybrid Electric Vehicle (PHEV) with their number surging each year around the globe. The Plug-in Electric Vehicle (PEV) require electricity from the electrical distribution system which links the power and transportation sectors together. A massive introduction of PEV can cause grid instabilities like congestion, overloads amongst other problems wreaking havoc in weak distribution systems or in areas with high penetration rates [3].

Most cars stay put in a position for majority of the day, sometimes up to 90-95 % of the daytime. This leaves ample charging time for the PEV and for the remainder of the time, the battery remains idle. This idle time can be utilised for exchange of power between the grid and the vehicle and still leaving the vehicle with ample charge to be driven when required and we get a chance for the Vehicle to Grid (V2G) electricity supply. V2G is bidirectional charging meaning that the vehicle can charge and discharge from the grid. V2G can be used for several purposes like peak load levelling i.e. the EV batteries can provide electricity back to the grid when the electricity demand reaches its peak value during the day. Thus, the EV owner can generate an income from their parked vehicle. Another purpose served by V2G is to provide backup power to buildings and homes in case of a power failure. V2G can also provide ancillary services like frequency regulation, spinning reserve and non-spinning reserve [4].

A brief introduction about the Swedish Electricity system is essential as to fully appreciate the work done in this thesis. The market consists of several independent actors, namely [5]:

- Electricity Generators.
- Network Owners or Distribution System Operators (DSO's).
- Transmission System Operator (TSO) i.e. *Svenska Kraftnät.*
- Consumers.
- Traders as electricity suppliers and balance providers.
- Marketplaces, primarily *Nord Pool* - the leading power market in Europe.

The Electricity generators generates power and feeds it into the network. The Network Owners are responsible for transmitting the electrical energy from the producer to the consumer. This takes place via the national, regional and local grid, all owned by different network companies. *Svenska Kraftnät* owns the national grid and has the role of TSO. This means ensuring that the plants of the Swedish electricity system are working together in an operationally-reliable way and that production and import corresponds to consumption and export. The regional networks transmit electricity from the grid to the local networks, and in some cases to large-scale consumers, for instance industries. The local networks distribute electricity to the consumers within a certain geographical area. The consumers, everyone from industries to households, take electricity from the electricity network and consume it. The consumer must have an agreement with an electricity trader to be able to buy electricity. The consumer also has an agreement with the network owner in order to be connected to his network. For connection and transmission, the consumer pays a network fee (network account).

The power trading company sells electricity to the final customers. The power trader can have the role of electricity supplier and balance provider. Both roles can exist within the same or different companies. The electricity supplier has a supply agreement with the consumer. The balance provider is financially responsible for the electricity that the trader sells always being in balance with the electricity purchased to cover consumption. Organised marketplaces, for example the power exchange *Nord Pool*, as well as brokers, provide standard agreements which make it easier for the players on the market to do business with each other. The bulk of the trade in electricity on the market takes place via bilateral agreements between electricity producers and electricity traders.

1.2 AIM

The aim of this thesis is to study the potential benefits of adding an EV fleet to the FED system. The study is carried out by presenting a load dispatch model for the EV fleet comprised entirely of cars with V2G capacity. The EV fleet is owned by the Fleet Operator (FO) and is also used as a car rental service. The Fleet Operator exchanges electricity to and from the FED system, and thus can be assumed as an extension of the FED system, as shown in figure 1.1.

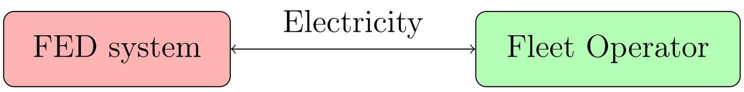


Figure 1.1: Exchange of Electricity

To carry out the load dispatch, firstly the electricity demand of the FED system has to be obtained using forecast methods from historical data. Then the driving data is used in the SOC model to determine the charging/discharging pattern, which is optimized using the optimization tool General Algebraic Modelling Systems(GAMS) with the objective of minimizing the net cost of the system keeping grid constraints in mind. The net cost comprises of electricity cost of the FED system and, the revenue and costs associated with V2G and ancillary services.

1.3 Limitations

- A car rental service is considered in this thesis for simplicity and to avoid the aggregation process of private vehicles, albeit privately owned Electric Vehicles are going to form the bulk of the V2G market.
- Only the DC Fast charging methods are being considered in this thesis. AC charging methods are not being considered.
- The implication of introducing a large number of EV's on the cost/ revenue of V2G is not considered.
- The Swedish, Nordic or European Union (EU) Grid is not considered, only the effects on the local FED system is considered.
- The load forecasting includes an exponential smoothing method which is not 100 percent accurate and will always have error, therefore the load forecast should not be completely relied upon. Further load forecasting methods like Artificial Neural Network (ANN) and Auto-Regressive integrated Moving Average (ARMA) can be studied in future research work [6].
- The Driving pattern utilises probabilistic methods which are again, not perfect and will have errors, therefore, the SOC determined will not be completely accurate.
- No costs for V2G infrastructure and equipment have been included in this study.
- No taxes or subsidies have been considered while determining the revenue generated by the car rentals. The total rental revenue just provides an insight in the introduction of V2G car rental service into an system which only consumes electricity.

1.4 Other Aspects

Every research attempt should be aimed to improve the human life, therefore, certain United Nations (UN) sustainable development goals [7] are tried to be included and followed in this thesis. The sustainable development goals are shown in table 1.1.

Table 1.1: United Nations (UN) Sustainable Development Goals

Goal number	Goal	Description
3	Good Health and Well-Being	Ensure healthy lives and promote well-being for all at all ages
7	Affordable and Clean Energy	Ensure access to affordable, reliable, sustainable and modern energy for all
9	Industry, Innovation and Infrastructure	Build resilient infrastructure, promote sustainable industrialization and foster innovation
11	Sustainable Cities and Communities	Make cities inclusive, safe, resilient and sustainable
12	Responsible Consumption and Production	Ensure sustainable consumption and production patterns
13	Climate Action	Take urgent action to combat climate change and its impacts
15	Life on Land	Sustainably manage forests, combat desertification, halt and reverse land degradation, halt biodiversity loss

Societal Aspects

UN sustainability goal number 3 deals with maintaining good health and well being of all humans. This thesis deals with promoting the growth of PEV's in the transportation sector which will directly reduce the local air pollution in the area and indirectly reduce the GHG emissions by trying to increase the penetration of RES in the power sector which will reduce respiratory diseases causing several human deaths each year. V2G will also give a chance to PEV car owner or the FO to earn an extra income by providing electricity to the grid. V2G may lead to both reduced cost for integrating RES and reduced cost for EV owner. Goal number 9 deals with developing Industry and Infrastructure which leads to empowerment of the society. The innovation in V2G system infrastructure will lead to more money in hand of consumers as customers will also become producers.

Ethical Aspects

UN sustainability goal 12 deal with ethics and morals required to operate the PEV fleet. The PEV fleet is meant as a support to the electrical grid and not to replace the power sector as the primary purpose of a PEV should be to be used as a means of transport with power production being the secondary purpose. We should not buy a PEV only to trade in the electricity market.

Ecological Aspects

UN sustainability goals 7, 11, 13 and 15 deal with ecological aspects, this thesis makes PEV's even more lucrative for consumers and thus, increases the number of PEV's in the transportation Sector. More PEV's replacing Internal Combustion Engine Vehicles(ICEV) means lesser GHG emissions which would help in reducing the prevalent global warming. Deforestation occurs due to petroleum extractions in Amazon forest [8] and other high biodiversity regions leading to loss of flora and fauna. PEV would reduce the extent of deforestation as they replace ICEV's leading to less petroleum extraction.

1.5 Thesis Outline

This thesis is divided into six chapters including the current *Introduction* chapter. The other chapters are divided in the following way:

1. Chapter 2 presenting state of the art infrastructure. Chapter 3 named *Methodology* deals with presenting the method followed to carry out the thesis along with the developed net cost minimization model.
2. Chapter 4 named *Case Study Statement* presents the case being studied in this thesis along with its intricacies.
3. Chapter 5 named *Results* presents the results from the simulation in different scenarios.
4. Chapter 6 named *Discussion* presents a detailed explanation of the results and their relevance. The assumptions and limitations observed in the thesis are analysed and, alternative paths to achieve better results are presented.
5. Chapter 7 named *Conclusion* concludes the thesis work with some final comments.

2

State of the Art infrastructure

In this chapter, the state of the art technology in charging station and PEV is reviewed.

2.1 Charging station Infrastructure

The different EV charging levels are shown in table 2.1. The table explains about the available and under development charging stations for the EV's. In this thesis, only DC fast charging is going to be considered.

It is clear from table 2.1, that the DC chargers are less time consuming than there A.C. counterparts for charging a PEV. In the upcoming future, we will have DC fast-charging for private or public usage [11] with public DC superchargers becoming more common with each passing day. The question arises which charging level to choose between DC level 1 and level 2, the choice has to be made based on the investment and operational costs and, also the power capacity.

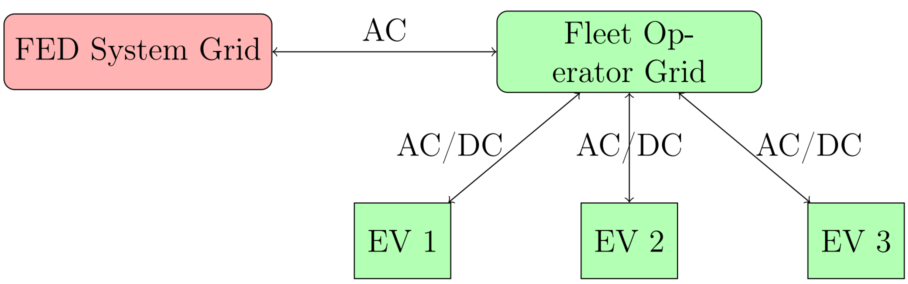


Figure 2.1: Charging Infrastructure

Table 2.1: AC/DC Charging Level Characteristics as per SAE J1772 standard [9, 10]

Power Level	Voltage Level (V)	Current Capacity (A)	Power Capacity (kW)	Remarks
AC Level 1	120 V A.C.	12/16	1.4/1.9	Single phase supply- PHEV: 7h BEV: 17h
AC Level 2	240 V A.C.	up to 80	19.2	1 or 3 phase supply, 3 kW charger - PHEV:3h, BEV:7h
AC Level 3	-	-	> 20	Under Development
DC Level 1	200 - 500 V D.C.	< 80	up to 40	3 phase supply, 20 kW charger - PHEV:22 min, BEV:1.2 h
DC Level 2	200 - 500 V D.C.	< 200	up to 100	3 phase supply, 45 kW charger - PHEV:10 min, BEV:20 min
DC Level 3	200 - 600 V D.C.	< 400	up to 240	Under development

2.2 PEV selection and Fleet Size

The PEV progression through the years is shown in the table 2.2. The first column denotes the PEV generation, the second column tells about the power flow exchange capabilities between the vehicle and the grid. The third column 'Communication Characteristic' gives the communication pathway between the PEV and the grid. Communication in this sense, means the regulation of electricity flow between the PEV and the grid. The fourth column of the table gives us details about the power flow exchange between the PEV and the grid, and its purpose and usage.

First generation PEV's form the major portion of the electric vehicles available today with only charging capabilities from the grid and, these vehicles are expensive to manufacture. The user has the ability to alter and set the charging window, with no or minimal communication with the grid. These vehicles have AC level 1 charging for the PHEV's and AC level 2 for the BEV's with a peak power transfer rate of 19.2 kW using standard SAE J1772 AC coupler between the EV and the wall outlet. The second generation PEV's will have improved communications with the aggregator and, will

Table 2.2: Progression of PEV-Grid Interactions [12]

PEV Generation	Power Flow	Communication Characteristic	PEV-Grid Interaction Characteristics
First	Grid to Vehicle (G2V)	over cell phone (if any)	G2V with manual driver programmed "grid friendly" charge window
Second	G2V	Grid to PEV communications via aggregator. Real-time broadcast of CO_2 and price information to PEV	G2V with limited regulation up and down ancillary services G2V with advanced intelligent charging aligned with renewable generation
Third	G2V + Vehicle to Load (V2L)	Electric Vehicle Supply Equipment (EVSE)-PEV communication only	V2L for construction site generator
	G2V + Vehicle to Home (V2H)	EVSE-PEV communication only	V2H for home backup generator
	G2V + Vehicle to Premise (V2P)	EVSE-PEV communication only	V2P as building backup generator
	G2V + Vehicle to Grid - Net Metered (V2G-NM)	EVSE-PEV communication only	V2G-NM: Local generation with reverse power flow of excess energy and net-metering
Fourth	G2V + advanced V2G	Assured secure two-way Grid-PEV communication	V2G-advanced: Grid ancillary services provided by two-way power flow of PEV battery energy and/or local generation

be lower in cost than their predecessors. These vehicles will be more efficient and possess enhanced battery control and, we can see some of the modern day electric vehicles possessing these qualities. The aggregator can control the charging process based on real time tracking of energy prices using internet services. This intelligent way of charging will reduce the costs and, also provide limited frequency regulation grid ancillary services by mostly halting the charging process. Mostly AC level 2 chargers are used for these vehicles.

The bidirectional charging facility is introduced in the third generation PEV's along with the introduction of DC high capacity charging interface, between the PEV and the charger supporting a maximum power flow of up to 100 kW. This kind of charging is seen in Tesla BEV's with several superchargers being placed in the United States of America and other parts of the world [13]. The Vehicle to load (V2L) reverse power flow configuration will allow the PEV to act as an construction site generator to an isolated load. In the Vehicle to Home (V2H) configuration, the PEV helps as a backup to a family house. In the Vehicle to Premise (V2P) configuration, the PEV can support a larger isolated building or a command centre or a mobile hospital. There is no communication or coordination with the grid in these configurations, communication happens only between the PEV and the load. Basic Vehicle to Grid (V2G-NM) interaction can help make the PEV as a storage unit to capture low cost non-peak energy or local generation from photo-voltaic panels and supply it back to the grid at peak hours.

The fourth generation PEV will possess advanced communication and control capabilities helping the aggregator to increase their revenue through use of battery and gasoline generator. PEV's would have greater abilities to be used for grid ancillary services in addition to the acting as non-peak hours energy storage units. All the other facilities characteristic of the previous generation are also present. Unfortunately, the fourth generation PEV is not yet available.

Some of the available PEV are listed in table 2.3 with their battery capacity in kWh. Battery capacity is an important parameter in selecting the PEV for this thesis, considering that the FED system electricity demand varies in the range of 3500-7500 kWh/h. A PEV with a small battery capacity like Volvo XC90 or Toyota Prius would not be able to contribute much to the FED system whereas, a PEV like Nissan Leaf or Tesla Model S with high battery capacities would be able to supply in exceptional cases, the entire FED system electricity demand assuming a reasonable fleet size.

Table 2.3: Battery Capacity of Various PEV

Serial number	Car Model	EV type	Battery Capacity (kWh)
1	Nissan Leaf	BEV	40 [14]
2	Tesla Model 3	BEV	75 [13]
3	Tesla Model S P100D	BEV	100 [15]
4	Volvo XC 90	PHEV	9 [16]
5	Toyota Prius	PHEV	8.8 [17]
6	BYD e6	BEV	61.4 [18]
7	Chevrolet Volt 2018	PHEV	18.4 [19]

The fleet size will be decided by the Fleet Operator and mainly depends on the business opportunity around the *Chalmers* campus.
Business Opportunity : The most important factor while selecting fleet size, would be the number of customers willing to use the car rentals. If there are less customers willing to use the service, the fleet size should be smaller and *vice versa*. There are two factors to consider in business opportunity:-

1. **V2G services** - More revenue would be generated if the fleet size is greater, especially with large battery capacities.
2. **Rental Revenue** - Rentals generate more revenue than V2G service revenue, therefore, a greater percentage of the fleet should be used for renting out rather than for V2G services.

3

METHODOLOGY

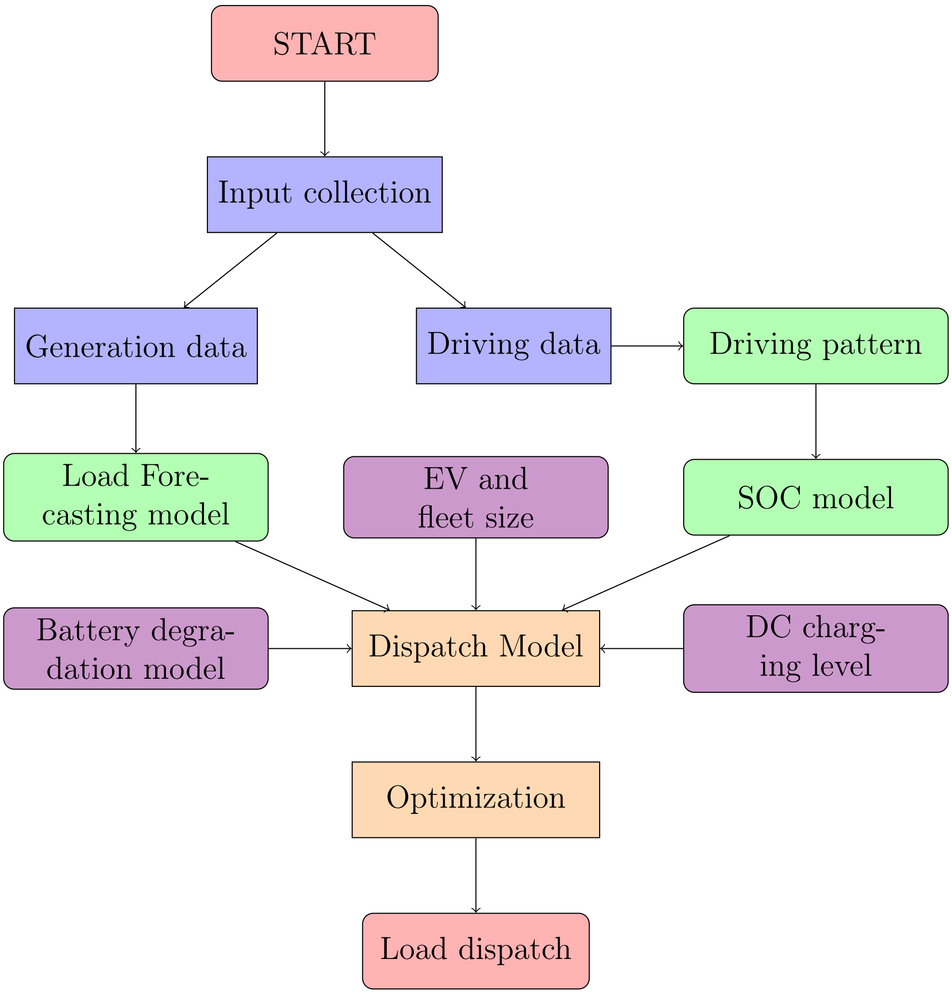


Figure 3.1: Flow Chart for Methodology

In this chapter, the method by which the thesis is carried out is described. Firstly, the methodology is presented in terms of a flow chart in figure 3.1, and is explained hereafter. The thesis starts with collection of data namely generation data and driving data. Generation data is used in the load forecasting model to determine the load forecast of the FED system which forms the input for the dispatch model and is explained in section 3.1. Driving data is used to develop the driving pattern for the car rental service and is explained in section 3.2. The driving pattern acts as an input for the SOC model, helping to determine SOC and, its use in dispatch model is explained in section 3.3. The other inputs to the dispatch model is the EV, fleet size and the DC charging level. The dispatch model and optimization is explained in section 3.5. Battery degradation is also included in the dispatch model and is explained in section 3.4. The optimization process gives the load dispatch i.e. the net cost optimal charging and discharging pattern of the electric vehicles.

3.1 Load Forecasting Model

A method is required to forecast the electricity demand of the FED system for a short time period. It is seen that univariate methods only require historical load data to forecast electricity demand for short time periods [6] and can be used in this thesis. Some of the reliable univariate forecasting methods commonly used are:

1. Holt-Winters exponential smoothing (HWT).
2. Intra-day Cycle exponential smoothing (IC).
3. Singular Value Decomposition based exponential smoothing (SVD).
4. Auto-Regressive integrated Moving Average (ARMA).
5. Artificial Neural Network (ANN).

SVD gives the best result amongst these methods [6] but is complex to apply and, this is where the HWT method is appealing due to its simplicity and ease of application, being even more simpler than the IC method. ARMA and ANN methods are not able to outperform HWT and IC methods, therefore, these methods are not going to be considered. Keeping these factors in mind, only HWT method will be used in this thesis.

The forecast accuracy of the HWT method is measured by using the term Mean Absolute Error (MAE). Other accuracy measures like Root Mean Square Error (RMSE) and mean absolute percentage error gave similar values as MAE [6]. Here, the time step period used is hourly as the FED electricity data is hourly. MAE is calculated by using the following expression:

$$MAE = \frac{1}{(ps - k + 1)} \sum_{h=Start\ of\ Prediction\ Period}^{h=End\ of\ Prediction\ Period-k} |El(h) - y(h)| \tag{3.1}$$

where ps is the length of the sample period, k is the k-step ahead forecast from forecast origin, h is the hour of operation, El is the electricity demand and y is the forecast.

Holt-Winters Method (HWT)

Holt-Winters method (or triple exponential smoothing) is a method to forecast data in a series provided they are seasonal i.e. they are repetitive over a period of time. This method incorporates hourly, daily and weekly repeating patterns to forecast data as seen in equation (3.4), (3.5) and (3.6). HWT method is presented in terms of equations (3.2)-(3.6) [20].

The forecasting method requires sample data which is obtained from FED demand data. The sample period is from 1st of January, 2016 00:00 hours to 31 st of December, 2016 23:00 hours with 1-hour time period. $m1$ and $m2$ are the number of time periods in the day and week, respectively and have the following values in the thesis $m1 = 24$ and $m2 = 24 * 7 = 168$. The prediction period is from the 1st of January, 2017 00:00 hours to the 28th of February, 2017 23:00 hours.

$$y_h = l_{h-1} + d_{h-m1} + w_{h-m2} + \phi e_{h-1} + \epsilon_h \tag{3.2}$$

$$e_h = y_h - (l_{h-1} + d_{h-m1} + w_{h-m2}) \tag{3.3}$$

$$l_h = l_{h-1} + \alpha e_h \tag{3.4}$$

$$d_h = d_{h-m1} + \delta e_h \tag{3.5}$$

$$w_h = w_{h-m2} + \omega e_h \tag{3.6}$$

where h is the hour of operation, y is the demand forecast, l is the hourly state variable, d is the day state variable, w is the weekly state variable, ϕ is the Auto Regressive (AR) adjustment parameter for first-order residual auto-correlation, ϵ is the error parameter, e is the error term, α is the hourly smoothing parameter, δ is the daily smoothing parameter and ω is the weekly smoothing parameter.

The error term (ϵ_h) is modelled as a normal distribution with zero mean and constant variance σ^2, the variance being calculated from the FED electricity demand data. Equations (3.2) and (3.3) can be rewritten as:-

$$y_h = l_{h-1} + d_{h-m1} + w_{h-m2} + e_h \tag{3.7}$$
$$e_h = \phi e_{h-1} + \epsilon_h \tag{3.8}$$

The first four weeks of data was used to initialize the state variables, l_h, d_h and w_h. Forecast was set equal to the electricity demand for the first four weeks and e_h was calculated using equation (3.3). The smoothing parameters and Auto-Regressive (AR) adjustment parameter α, δ, ω and ϕ lie in the range of 0 to 1 and are constrained in this range. To determine the values of these parameters, we need to minimize the mean of Squared in-Sample Errors ($\overline{SSE_h}$) for the sample period which is represented by the expression:

$$SSE_h = (y_h - El_h)^2 \tag{3.9}$$
$$\overline{SSE_h} = \frac{1}{8784 - 4 * 7 * 24} \sum_{h=4*7*24+1}^{8784} (y_h - El_h)^2 \tag{3.10}$$

The procedure involves creating vectors of parameters from a uniform distribution limited between 0 and 1. The number of vectors depends upon the available computational facility, in this thesis, 70 thousand vectors were created with 64 GB RAM but, a lower number of vectors will also give a sufficient result if we reiterate the process. SSE was calculated for each vector for the entire sample period and the ten vectors having the lowest SSE values were selected. The ten vectors acted as the initial values in quasi-Newton algorithm to further reduce the SSE values. Thus, a vector producing the lowest SSE value was obtained. This vector was found to match the FED electricity demand but further multiplying factor correction was required which was implemented by iterative methods, varying the factor between 1 and 2 in a MATLAB program and, calculating the SSE for each value. The lowest SSE yielding factor was selected. The vector and factor was used to calculate the forecast in the forecast period. After that, the MAE was calculated using the equation (3.1) in the forecast period, with MAE fixing the future forecast period:-

$$MAE = \frac{1}{(1416 - k + 1)} \sum_{h=8785}^{h=10200-k} |El(h) - y(h)| \tag{3.11}$$

To determine the cumulative error for the entire time period, a new variable by the name of *Average difference* is introduced for the forecast period:

$$Average\, difference(in\, percent) = \sum_{h=10201}^{10224} 100 * \frac{|El(h) - y(h)|}{24 * El(h)} \qquad (3.12)$$

3.2 Driving Pattern

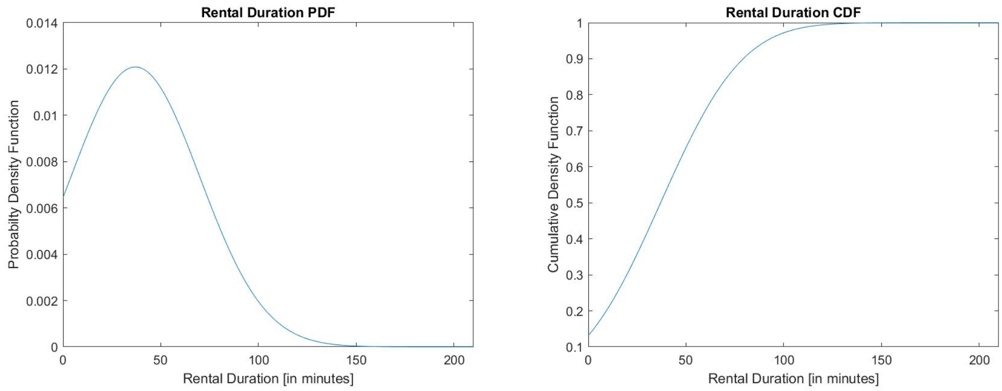
The EV fleet is assumed to be stationed in the *Chalmers* parking area, therefore, the customers would have to perform a round trip to return the car back to the facility. The car rentals would be for travel inside the city of *Gothenburg* and a driving environment having the following characteristics are assumed to exist:

1. Gradual acceleration from standstill [21].
2. No harsh braking [22].
3. Maximum speed of 50-60 kmph and a lower average speed.

These factors are important for determining the driving range of the car, also harsh driving reduces the driving range and is not energy efficient. Driving range is an important parameter which will be later used in the SOC model to find the hourly SOC for a EV being driven around *Gothenburg*. The driving pattern data was taken from the research paper by Sprei et al. [23], the paper deals with free-floating car sharing services and has vast data from 32 different cities in both Europe and North America. I have used the rental duration data, Geo distance data and the number of rentals per car per day data for *Stockholm* from the research paper. The reason for selecting *Stockholm* is obvious to the extent that it is a Swedish city and no comprehensive data was available for *Gothenburg*. The data in the research paper was adapted for round trips in the car rental model.

The geo distance data in the research paper is equivalent to displacement between source and the destination of the person driving the car and is not equal to real world distance, but due to the lack of research on difference between distance and displacement in real world driving, the geo distance is assumed equal to the distance travelled by the car. The geo distance mentioned in the above research paper deals with mostly one way trips but this thesis has round trips, so to compensate this issue all the geo distance values have been doubled.

It was observed during the literature review, that the geo distance varied according to an **Inverse Gaussian** (μ, λ) distribution [24, 25] while the rental duration varied according to **Normal** (μ, σ) distribution. The rental duration was modelled according to a normal distribution with mean (μ) and standard deviation (σ) values from the *Stockholm* Data [23]. The allocation of rental duration for each car was done at random according to an **Uniform** distribution considering the shortest rental duration of 15 minutes (to be qualified as a trip) and the maximum rental duration according to the given *Stockholm* data. The rental duration Probability Density function (PDF) and Cumulative Density functions (CDF) from *Stockholm* data are shown in figures 3.2a and 3.2b.



(a) Rental Duration Probability Density Function

(b) Rental Duration Cumulative Density Function

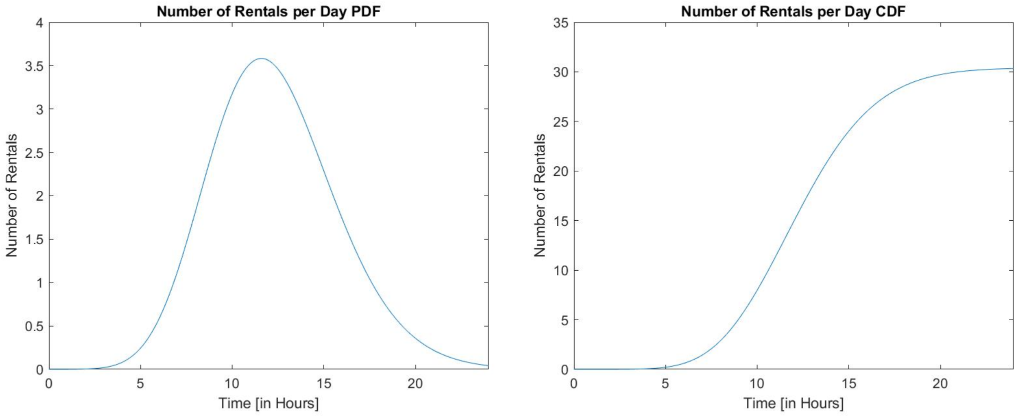
Figure 3.2: Rental Duration

The number of rentals PDF and CDF are shown in figures 3.3a and 3.3b. These figures represent the number of cars rented out during a time period. The distance travelled by each car varies as a linear function of the rental duration. The rental times were determined with the help of a cumulative density function of the **Inverse Gaussian** distribution for the number of rentals per day.

3.3 State of Charge (SOC) Model

State of Charge (SOC) is a measure of the charge retained by the battery at any instant of time. SOC is determined as the ratio of energy stored in the battery to the rated battery capacity:-

$$SOC(i,h) = \frac{E(i,h)}{E_{rated}(i)} \tag{3.13}$$



(a) Number of Rentals Probability Density Function (b) Number of Rentals Cumulative Density Function

Figure 3.3: Number of Rentals

Here, i denotes the EV number and h denotes the hour of operation and $E_{rated}(i)$ is the rated battery capacity of the EV i. SOC estimation during any hour of operation depends upon the availability status of the vehicle. The influence of availability on SOC is explained in figure 3.4. There are five modes in which an EV can be operated during a given time period, h [26]:

1. **EV charging**: EV is plugged to the grid and is being charged, subject to losses with efficiency, η_{ch}.
2. **EV-V2G**: EV is injecting power into the grid from the battery, subject to losses with efficiency, η_{dis}.
3. **EV in reserve capacity**: EV is plugged in, but is neither charging nor is it injecting power into the grid. Keeping the SOC in mind, the aggregator can call-in the service of the EV for charging or discharging.
4. **Driving Mode**: The EV is being driven around, and the energy in the battery is being consumed.
5. **EV unused**: EV is plugged in, but the aggregator is not going to use the service of the vehicle battery.

SOC is limited between 0 and 1, but, according to the Owner's manual of Tesla Model S, the battery can get permanently damaged if the State of Charge reaches 0, so, to avoid permanent damage the SOC would be limited so as to not go below than 0.05 [27]. The value of minimum SOC (SOC_{min}) was set at 20 percent of the battery capacity [28] to make sure that the battery never discharges below the manufacturer's recommended SOC value of 0.05 during the driving phase.

$$0.2 \leqslant SOC(i,h) \leqslant 1 \tag{3.14}$$

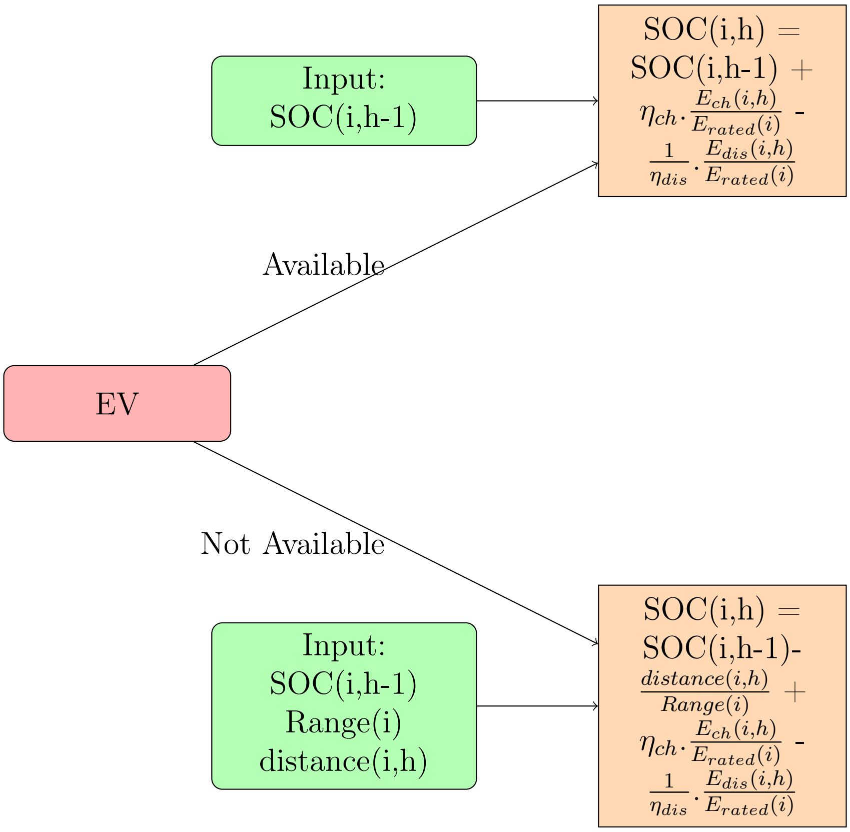


Figure 3.4: SOC Determination based on Availability

The **Available** status in figure 3.4 means that the EV is operating in any of the modes 1,2,3 or 5 whereas, **Not Available** status means that the EV is operating in mode 4 i.e. being rented and driven. The SOC equation can be generalised as:

$$SOC(i,h) = SOC(i,h-1) - \frac{distance(i,h)}{Range(i)} + \eta_{ch} \cdot \frac{E_{ch}(i,h)}{E_{rated}(i)} - \frac{1}{\eta_{dis}} \cdot \frac{E_{dis}(i,h)}{E_{rated}(i)} \tag{3.15}$$

Where distance(i,h) is the distance travelled by the EV 'i' in the hour 'h', η_{ch} is the charging efficiency, $E_{ch}(i,h)$ is the charging done by the EV 'i' in the hour 'h', η_{dis} is the discharging efficiency and $E_{dis}(i,h)$ is the discharging done by the EV 'i' in the hour 'h'.

The SOC equation would change if we involve frequency regulation in the system and will be expressed as:

$$SOC(i,h) = SOC(i,h-1) - \frac{distance(i,h)}{Range(i)} + \eta_{ch} \frac{(E_{ch}(i,h) + E_{reg,down}(i,h))}{E_{rated}(i)} - \frac{1}{\eta_{dis}} \frac{(E_{dis}(i,h) + E_{reg,up}(i,h))}{E_{rated}(i)} \quad (3.16)$$

$E_{reg,up}$ is the energy supplied by the EV 'i' during the hour 'h' to the grid to increase the frequency up to its nominal value. Similarly, $E_{reg,down}$ is the energy consumed by the EV 'i' during the hour 'h' from the grid to bring the frequency down to its nominal value.

3.4 Battery Degradation

EV electro-chemical batteries have limited life time due to the fading of active materials due to charging and discharging cycles [29]. This cycle ageing is caused by the growth of cracks in the active materials, a process similar to fatigue in materials subjected to cyclic mechanical loading [30]. This battery degradation can be quantified in terms of money using the expression [31] under the assumption that only full discharge cycles are being used:

$$D_f(i) = \frac{B(i)}{C_f(i) * E_{usable}(i)} \quad (3.17)$$

where D_f is the battery degradation cost per unit of energy throughput at full discharge cycles, B is the battery investment cost, C_f is the number of full charging cycles possible during the lifetime of the battery and E_{usable} is the usable share of the battery. In this case, as the battery can be discharged from E_{rated} to a SOC of 0.2, E_{usable} is (1-0.2) = 0.8. The number of full cycles possible during the lifetime is calculated using the expression:

$$C_f(i) = \frac{Battery\ Lifetime\ Mileage(i)}{Range(i)} \quad (3.18)$$

To calculate the battery degradation cost (in SEK), an assumption can be made regarding the battery cycle ageing for simplicity, that ageing occurs only during the discharge stage of the cycle such that a discharging cycle causes the same ageing as a full cycle, while a charging cycle does not affect the battery life.

$$Battery\ Degradation\ Cost = \sum_{i=1}^{100} \sum_{h=1}^{24} E_{dis}(i,h) * D_f(i) \tag{3.19}$$

The battery degradation cost changes for the scenario in which frequency regulation is involved:

$$Battery\ Degradation\ Cost = \sum_{i=1}^{100} \sum_{h=1}^{24} [E_{dis}(i,h) + E_{reg,up}(i,h)] * D_f(i) \tag{3.20}$$

3.5 Dispatch Model

The dispatch model is going to be developed for a single day and it entails the charging/discharging done for each EV. The frequency regulation up and down performed by each EV is a part of the dispatch model too.

3.5.1 Optimization approach

Unit Commitment (UC) determines the optimal dispatch charging/discharging schedule for the available EV's with V2G services [32]. Various Optimization techniques can be used to solve the UC problems involving the V2G technology like:
1. Linear Programming(LP)
2. Mixed Integer Non-Linear Programming (MINLP)
3. Particle Swarm Optimization (PSO)
4. Genetic Algorithm (GA)
5. Quadratic Programming (QCP)

Traditionally, Linear Programming (LP) and Quadratic Programming (QCP) are used for UC optimization [33]. LP optimization technique is going to be used for optimizing in this thesis due to having only linear relations between the variables.

3.5.2 Optimization Objective Function

The objective function of the optimization is to minimize the net cost of the system, which can be represented by the various costs and revenues depending on the scenario (described later in case study statement chapter). The general net cost expression can be summed as:

$$\begin{aligned} Net\,Cost = {} & Electricity\,cost + Peak\,power\,cost + EV\,charging\,cost \\ & - EV\,discharging\,revenue - Rental\,Revenue \\ & - Regulation\,Up\,Revenue + Regulation\,Down\,Cost \\ & + Battery\,Degradation\,Cost \end{aligned} \tag{3.21}$$

The costs and revenues which form the net cost and involved in the dispatch model are stated below:

1. Electricity cost - The FED system consumes electricity from the national grid and is calculated according to the equation (3.22). The market hourly electricity price was obtained from the **Nord Pool** website [34].

$$Electricity\,cost = \sum_{h=1}^{24} forecast(h) * El.\,price\,per\,hour(h) \tag{3.22}$$

2. Peak Power Cost - The peak power cost is calculated using the equation (3.23). E_{max} is the maximum electricity consumed in a hour during the entire 24 hour period, whereas power tariff is obtained from the website of **Göteborg Energi** [35]. The peak power cost is a monthly cost, so to factor the daily influence, the cost has been divided by 30.

$$\text{Power Tariff} = 36.2 \text{ SEK/kW}$$

$$Peak\,power\,cost = \frac{1}{30} * E_{max} * power\,tariff \tag{3.23}$$

3. EV charging cost - The EV charging cost can be expressed in the equation (3.24). E_{ch} is the amount of charging required (in kWh) by an EV i during the hour h.

$$EV\,charging\,cost = \sum_{h=1}^{24} \sum_{i=1}^{100} E_{ch}(i,h) * El.\,price\,per\,hour(h) \tag{3.24}$$

4. EV discharging revenue - The EV discharging revenue can be expressed in the equation (3.25). E_{dis} is the amount of discharging performed (in kWh) by an EV i during the hour h.

$$EV\,discharging\,revenue = \sum_{h=1}^{24} \sum_{i=1}^{100} E_{dis}(i,h) * El.\,price\,per\,hour(h) \tag{3.25}$$

5. Rental Revenue - The EV's are rented out generating revenue in the process, and is expressed in the equation (3.26). Many taxi services and car rental service providers charge the customer based on the time period and distance of the trip and this pricing scheme is followed in the thesis. The time factor rate (in SEK per minute) and Distance factor rate (in SEK per km) are taken from the **UBER X** service website [36]. These rates were halved accounting for the factor that no labour costs are involved in rentals. The Rental Revenue obtained here is indicative at best, and is not completely accurate.

$$Rental\ Revenue = \sum_{i=1}^{100} \big(Time\ factor\ rate * Rental\ Duration(i) \quad + \\ Distance\ factor\ rate * Distance\ travelled(i)\big) \quad (3.26)$$

6. Regulation Up Revenue - Frequency regulation up generates revenue and is expressed in equation (3.27). The regulation up price is obtained from the **Nord pool** website [37].

$$Regulation\ Up\ Revenue = \sum_{h=1}^{24}\sum_{i=1}^{100} Regulation\ Up\ Price(h)* \\ E_{reg,up}(i,h) \quad (3.27)$$

7. Regulation Down Cost - Frequency regulation down involves a cost which is less than the electricity brought on the spot market and is expressed in equation (3.28). The electricity for regulation down is brought on the regulation market obtained from the **Nord pool** website [37].

$$Regulation\ Down\ Cost = \sum_{h=1}^{24}\sum_{i=1}^{100} Regulation\ Down\ Price(h)* \\ E_{reg,down}(i,h) \quad (3.28)$$

8. Battery Degradation Cost - Battery degradation cost is calculated using equations (3.19) or (3.20) depending on whether frequency regulation is involved or not.

These costs and revenues are essential in determining the **net cost** of the system, which is the variable that will be the minimized to achieve the optimal solution. The net cost varies according to the existing scenario and the different scenarios are explained in the next chapter.

3.5.3 Optimization Constraints

The constraints faced in optimization are mentioned over here:

1. Grid Congestion or Transmission Line Limits: The load on the line connecting the FED system and the Fleet must never be greater than the Grid Congestion limit. The congestion limit was set at 1 MW accounting for the power transfer between the FED system and the fleet in the possible future. Assuming an average value for the power, the constraint can be expressed in terms of energy transfer as:

$$\sum_{i=1}^{100}(E_{ch}(i,h) + E_{dis}(i,h) + E_{reg,up}(i,h) + E_{reg,down}(i,h)) \leqslant Grid\,Congestion\,limit \quad (3.29)$$

2. SOC Limitation: The SOC of each EV battery can vary between 0.2 and 1 as described in section 2.5 with equation (3.14) expressed as:

$$0.2 \leqslant SOC(i,h) \leqslant 1$$

3. Maximum Energy Flow Restriction: The energy transfer (including charging and discharging) between the FED system and an individual EV in the fleet cannot be greater than the usable share of the battery. Since, the SOC can vary between 0.2 and 1, the usable share of the battery is 80 percent.

$$E_{ch}(i,h) + E_{dis}(i,h) + E_{reg,up}(i,h) + E_{reg,down}(i,h) \leqslant 0.8 * E_{rated}(i) \quad (3.30)$$

4. Energy transfer limit: The values of E_{ch} and E_{dis} are limited between zero and E_{rated}.

$$0 \leqslant E_{ch}(i,h) \leqslant E_{rated}(i) \quad (3.31)$$
$$0 \leqslant E_{dis}(i,h) \leqslant E_{rated}(i) \quad (3.32)$$

5. No Electricity transfer while Driving: It is more of an obvious condition that no electricity transfer occurs when the EV is being driven.

$$E_{ch}(i,h) = 0 \quad \forall\, distance(i,h) \neq 0$$
$$E_{dis}(i,h) = 0 \quad \forall\, distance(i,h) \neq 0$$

$$E_{reg,up}(i,h) = 0 \quad \forall\, distance(i,h) \neq 0 \quad (3.33)$$
$$E_{reg,down}(i,h) = 0 \quad \forall\, distance(i,h) \neq 0 \quad (3.34)$$

6. Equal SOC for the beginning and end of the Day: The SOC of each EV should be the same at the beginning and end of the day.

$$SOC(i, h = 0) = SOC(i, h = 24) \tag{3.35}$$

7. Regulation Up and Down limits: In addition to these constraints, we have the regulation up/down limit constraints (set at 10 percent of the battery capacity).

$$0 \leqslant E_{reg,up}(i, h) \leqslant 0.1 * E_{rated}(i) \tag{3.36}$$

$$0 \leqslant E_{reg,down}(i, h) \leqslant 0.1 * E_{rated}(i) \tag{3.37}$$

4

CASE STUDY STATEMENT

In order to fully understand the benefits and drawbacks of the V2G concept, four scenarios would have to be considered.

- **Scenario 1** : In this scenario, only the FED electrical system is considered without an EV fleet, consuming electricity from the national grid.

- **Scenario 2** : The fleet operator enters in this scenario with the fleet having only Grid to Vehicle (G2V) ability. The fleet operator along with the FED system can be considered as one entity exchanging electricity between each other while the FED system consumes electricity from the grid. This scenario has two parts:
  A: The fleet EV's are charged in an uncontrolled manner from the FED system i.e. the EV charges to its maximum battery capacity as soon as it is plugged in.
  B: The fleet EV's are charged in a controlled manner from the FED system i.e. charging when electricity prices are low and providing electricity back to the FED system when electricity prices are high, so as to reduce the overall electricity costs of the FED system.

- **Scenario 3** : In this scenario, the fleet has V2G capability along with G2V (bidirectional charging) with the aim of controlled charging.

- **Scenario 4** : This scenario differs from the previous scenario as here, the car fleet also provides frequency regulation up and down.

Before analyzing the separate scenarios, we are going to define the inputs for the case study.

4.1 Case Study Inputs

4.1.1 PEV

For the purpose of this thesis, a PEV should be able to exchange electricity to and from the grid with the capacity of providing ancillary services. These services are provided by the fourth generation PEV and the third generation Vehicle to Grid - Net Metered (V2G-NM) facility. As stated in section 2.2, a fourth generation PEV has yet to be developed, therefore, we assume that the PEV used in this thesis is **third generation (V2G-NM)**.

The **Tesla Model 3** [13] with an anticipated battery capacity of 75 KWh and range of 220-310 miles (or 350-500 km approx.) can be used for modelling in this thesis accounting for the high battery capacity. A question might arise here, that why Tesla model S was not considered even though it has a higher battery capacity? The best explanation can be that model S is more expensive than model 3, almost twice the cost. The Tesla website claims that 170 miles worth of charging can be done in 30 minutes at any supercharger location or the battery can be charged to its full capacity of 75 kWh in a hour. This level of charging is within DC level 2 charging limits (up to 100 kW power capacity). Tesla Model 3 claims to have an estimated driving range of 220-310 miles based on usage, but, considering the driving conditions mentioned in section 3.2 a safe value of **250 miles (or 402 km)** for the driving range can be assumed. This driving range value is then used in the SOC model to determine hourly SOC of the EV's in the fleet.

4.1.2 Charging Station

The decision of selecting the DC charging level and the PEV are intertwined. Due to the selection of Tesla model 3 as the modelling EV in this thesis and, the condition of charging it within a hour, only **DC charging level 2** will be able to satisfy the charging requirements and thus, will be used for further analysis in this thesis.

4.1.3 Fleet Size

The fleet size is assumed to be **100** in this thesis due to lack of extensive business opportunity research around *Gothenburg*. The fleet size appears to be arbitrarily chosen, but 100 Tesla model 3 EV's have a combined capacity of 7500 kWh which is also the maximum electricity demand of the FED system for a hour.

4.2 Scenario 1: FED system

This scenario is the present day reality, without a Fleet Operator. Electricity cost and the Peak power cost are the costs incurred in this scenario and are calculated using equations (3.22) and (3.23). The net cost can be expressed using equation (3.21) as:

$$Net\ Cost = Electricity\ cost + Peak\ power\ cost$$

4.3 Scenario 2: FED system with Fleet Operator (only G2V facility)

The Fleet Operator now enters the FED system, only charging the EV's i.e. consuming electricity from the FED system.

4.3.1 Scenario 2a: FED system with Fleet Operator having no V2G facility - Uncontrolled charging

In addition to the Electricity cost and the Peak power cost (calculated using equations (3.22) and (3.23)), EV charging cost will also be added to the system (calculated using equation (3.24)). The charging happens in an uncontrolled manner (uncontrolled charging) i.e. the EV charges as soon it is plugged in to its rated capacity. The initial SOC for all cars is fixed at 1 [38].

$$SOC_{initial}(i) = 1 \quad \forall\, i \in 1:100 \tag{4.1}$$

The cars in the fleet are rented out generating rental revenue according to the equation (3.26) and the net cost is expressed using equation (3.21):

$$Net\ Cost = Electricity\ cost + Peak\ power\ cost + \\ EV\ charging\ cost - Rental\ Revenue$$

4.3.2 Scenario 2b: FED system with Fleet Operator having no V2G facility - Controlled charging

The charging happens in an controlled manner (controlled charging) in this scenario, i.e. the EV charges when the electricity prices are low. The initial SOC is same as in Scenario 2a (mentioned in equation (4.1)). Also, the net cost is same as in scenario 2a.

4.4 Scenario 3: FED system with Fleet Operator having V2G facility

This scenario deals with the Fleet Operator now having V2G facilities. Instead of the uncontrolled charging being performed in the scenario 2, here, the EV's would be charged in an optimal manner so as to to reduce the overall cost of the system. In addition to that, EV batteries would discharge and supply electricity to the FED system at times, when the demand is high or when the Electricity costs are high. To achieve controlled charging, an optimization will have to be performed which is described here after.

4.4.1 Optimization Objectives

In addition to the Electricity cost, Peak power cost, EV charging cost and rental revenue represented in equations (3.22), (3.23), (3.24) and (3.26), we have the discharging revenue calculated using equation (3.25). The SOC will be determined using equation (3.15). The charging efficiency (η_{ch}) and discharging efficiency (η_{dis}) are set at 0.95 in this thesis. The net cost will be optimized in **GAMS** and is expressed using equation (3.21):

$$\begin{aligned} Net\,Cost = {} & Electricity\ cost + Peak\ power\ cost + EV charging\ cost \\ & - EV discharging\ revenue - Rental\ Revenue + Battery \\ & \qquad Degradation\ Cost \end{aligned}$$

The optimization objective is to minimize the net cost keeping the constraints in check.

4.4.2 Optimization Constraints

The optimization constraints 1-6 mentioned in subsection 3.5.3 apply over here with the $E_{reg,up}$ and $E_{reg,down}$ set to zero.

4.5 Scenario 4: FED system with Fleet Operator providing Regulation Up and Down Service

The difference between this scenario and scenario 3 is that the car fleet provides **Frequency Regulation** ancillary service. The optimization approach would remain the same with the addition of regulation up revenue and regulation down cost to the net cost of the system.

Real time frequency control is needed in all power systems to maintain a steady grid. In an electric power distribution system, when the generation is more than the consumption, would result in the frequency going up. In this situation, regulation down is required which the EV can provide by charging its battery. Similarly, when the generation is less than the consumption leads to frequency going down. Here, regulation up is required which the EV can provide by discharging its battery or halting the ongoing charging process [31].The aim of these measures is to stabilize the frequency to its nominal value of 50.00 Hz.

In this thesis, the aim is to have an optimum EV charging/discharging dispatch pattern for the specific date of March 1, 2017, so, rather than looking at real time frequency data which is unavailable, we can utilize the Automatic Activated Reserve (AAR) values available on **Nord Pool** website [39] to decide the hour in which regulation up or down is required. AAR is the primary frequency control method to respond to a frequency deviation, done automatically within a few seconds after a disturbance occurs between the load and the generation. Also, capacity bidding is not involved.

4.5.1 Optimization Objective

The addition to Scenario 3 is the regulation up revenue and regulation down cost and they are calculated using equations (3.27) and (3.28). The SOC will be evaluated using equation (3.16). The net cost is calculated using (3.21). The optimization objective is to minimize the net cost keeping the constraints in check.

4.5.2 Optimization Constraints

The optimization constraints 1-7 mentioned in subsection 3.5.3 apply over here.

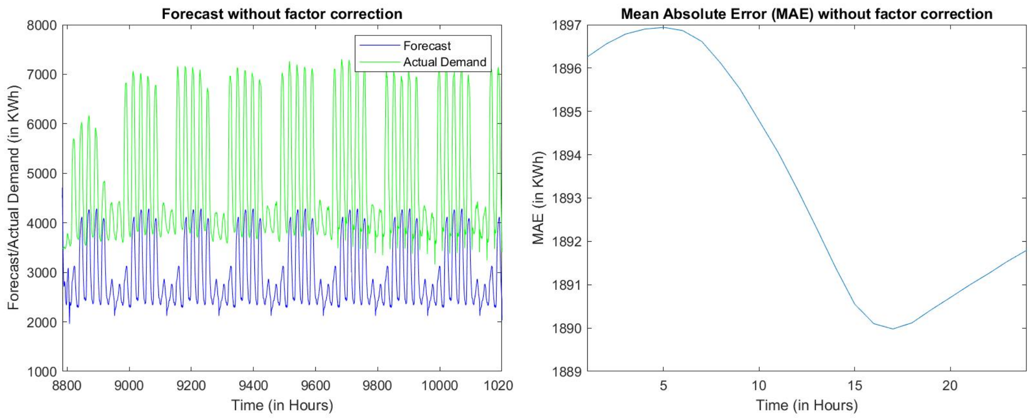
5
RESULTS

5.1 Load Forecasting by HWT method

The following value of the parameters were found to produce the least SSE (squared-in sample error):

$$\begin{aligned} \alpha &= 0.9508 \\ \delta &= 0.0069 \\ \omega &= 0.0723 \\ \phi &= 0.5461. \end{aligned}$$

After implementing these factors, the following forecast and Mean Absolute error (MAE) were achieved as shown in figure 5.1.



(a) Load Forecast without Multiplying Factor correction

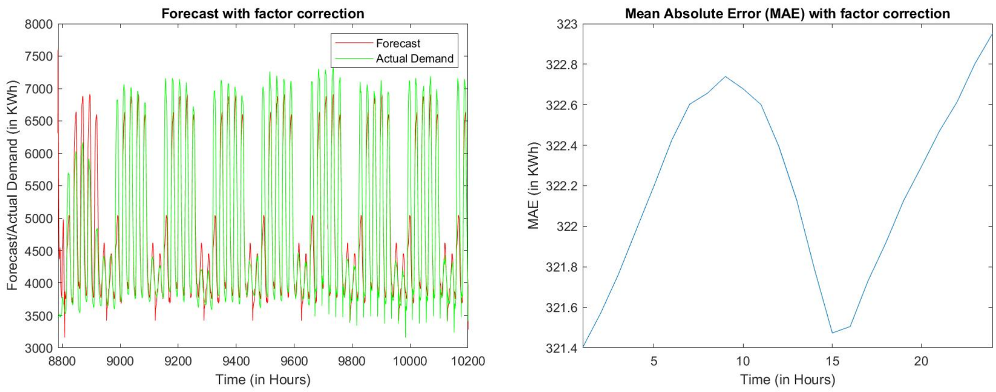
(b) MAE without Multiplying Factor correction

Figure 5.1: Results without multiplying factor correction

The forecast is shown to match the actual demand pattern but does not match it in magnitude. To rectify this magnitude variation, a multiplying factor is introduced having the following value:

$$multiplying\ factor = 1.6125$$

After implementing the multiplying factor, the following results were achieved as shown in figure 5.2. The forecast and actual demand for the desired EV charging/discharging dispatch day of March 1, 2017 is shown in figure 5.3.



(a) Load Forecast with Multiplying Factor correction (b) MAE with Multiplying Factor correction

Figure 5.2: Results with multiplying factor correction

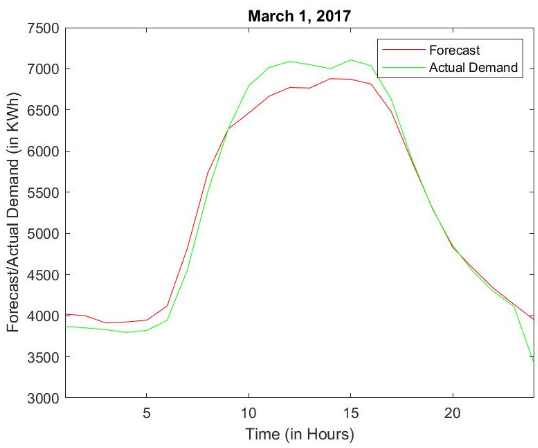
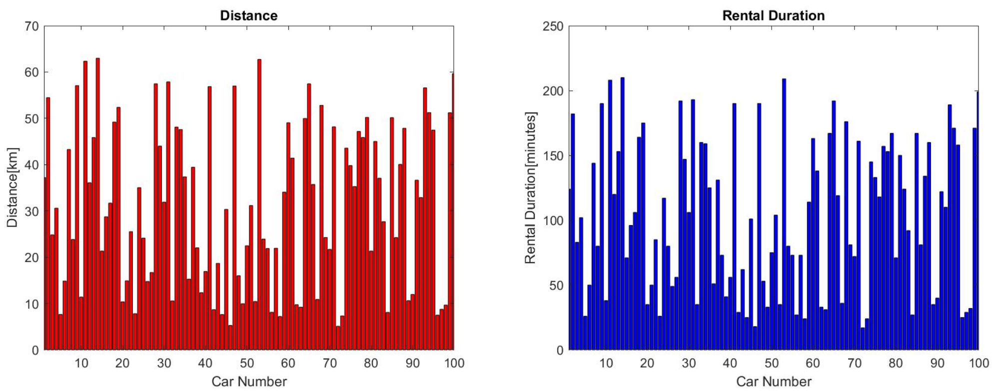


Figure 5.3: Forecast vs. Actual Demand on March 1, 2017

$$Average\ difference = 3.2859 \text{ percent.}$$

5.2 Car driving Pattern

Figure 3.2 shows the normal distribution curves of Rental Duration and figure 5.4 shows the variation of distance and the rental duration for each EV. Figure 3.3 shows the distribution curves for the number of rentals in a day. It can be understood from figure 3.3b that 30 cars out of the total of 100 are rented out in a day, therefore, only the values for the first 30 vehicles have been considered in the analysis for the day. The rental times are shown in Appendix A.2. Each EV travels a certain distance as shown in figure 5.4a, but the hourly distance values are required to determine the SOC according to the equation (3.15) and these values can be seen in Appendix A.1.



(a) Distance travelled by each EV (b) Rental duration of each EV

Figure 5.4: Distance travelled and Rental duration of each EV

5.3 Battery Degradation Cost per unit of Energy

Battery degradation cost is difficult to evaluate even with the simplistic equations (3.19) and (3.20), especially in a EV like Tesla Model 3 which has been recently launched. The difficulty is that the full battery life of the vehicle is still under doubt and only time would provide full disclosure. Tesla provides a battery warranty of 8 years (or 120,000 miles) [13] but certain forums [40] state that the battery might last for a lot longer at around 500,000 miles. These two values of battery lifetime mileage will be used for analysis and are termed as:

1. Case I - Battery lifetime mileage of 120,000 miles.

2. Case II - Battery lifetime mileage of 500,000 miles.

The battery lifetime mileage is necessary to determine the number of full cycles possible during the lifetime of the battery. The two cases give the following values for the full cycles possible in lifetime for the battery (C_f) using equation (3.18):

$$C_{f,I} = \frac{120,000}{250} = 480$$
$$C_{f,II} = \frac{500,000}{250} = 2000$$

The battery investment cost is taken to be 150 US dollars/kWh [41] (1 US dollar = 9 SEK approximately) which gives the following value of Battery degradation cost per unit of energy (D_f):

$$D_{f,I} = 3.516 \quad SEK/kWh$$
$$D_{f,II} = 0.844 \quad SEK/kWh$$

It is clear from the D_f values that case II will give lower battery degradation cost and for simplicity, we are going to use this value for further analysis in the thesis.

5.4 Scenario 1 Results

The electricity cost per hour values are shown in Appendix A.3. These values along with the forecast gives the Electricity cost according to the equation (3.22). The Power Tariff obtained from Göteborg Energi [35] and the max energy consumption gives the peak power cost. The results are presented in table 5.1.

Table 5.1: Scenario 1 results (All values in SEK unless otherwise stated)

Electricity cost	37893
E_{max}	6879.3 kWh
Peak power cost	8301
Net cost	**46194**

5.5 Scenario 2 Results

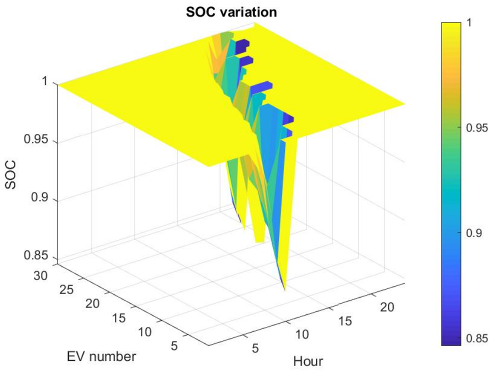
This section presents the difference in results between controlled charging and uncontrolled charging for the fleet having only unidirectional G2V facilities.

5.5.1 Scenario 2A: Uncontrolled Charging

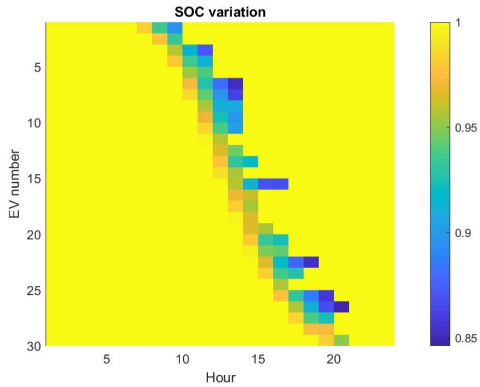
The Electricity cost of the FED system would remain the same in this scenario too i.e. **Electricity cost** = 37893 SEK. The cost of charging EV's to the rated capacity after being plugged in is shown here along with the new Peak Power Cost. The revenue generated from renting out the cars are also shown in table 5.2.

Table 5.2: Scenario 2A results (All values in SEK unless otherwise stated)

Electricity cost	37893
EV charging cost	59
E_{max}	6932.7 kWh
Peak power cost	8365.45
Rental Revenue	13924.45
Net cost	**32393**



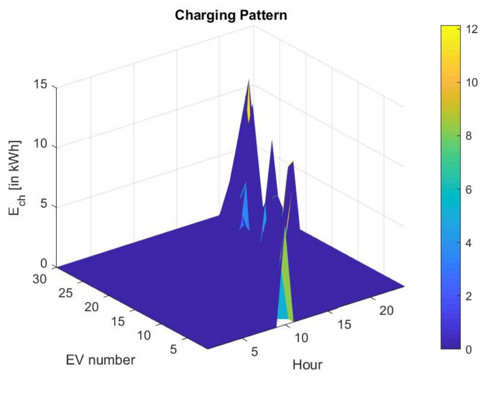
(a)



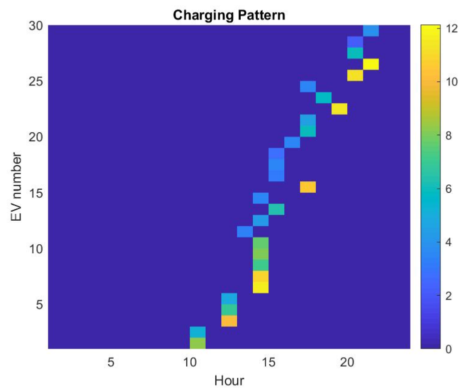
(b)

Figure 5.5: Scenario 2A - SOC variation

The peak power cost increases due to the EV charging done in the peak hour, yet we see a drastic reduction in net cost due to the rental revenue. The variation of SOC of each EV over the 24 hour period is shown in the figure 5.5a and 5.5b. The charging pattern of the EV's are shown in figure 5.6. The change in electricity demand with the addition of EV's is shown in figure 5.7a.

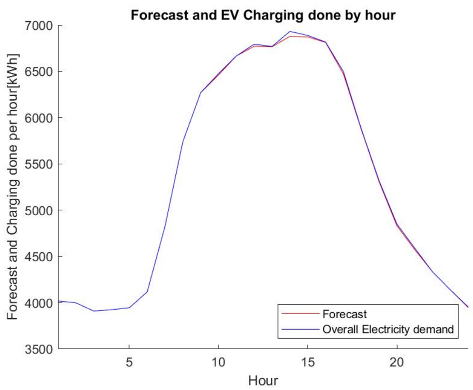


(a)

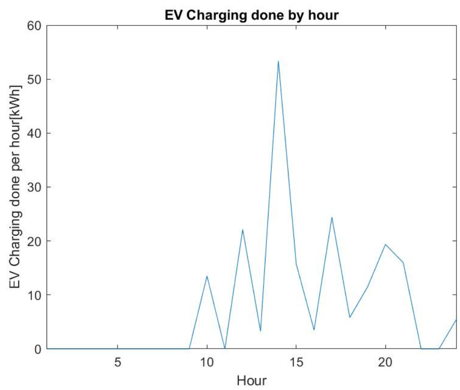


(b)

Figure 5.6: Scenario 2A - EV Charging pattern during the 24 hour period



(a) Forecast and EV Charging



(b) EV Charging done per hour

Figure 5.7: Scenario 2A - EV charging

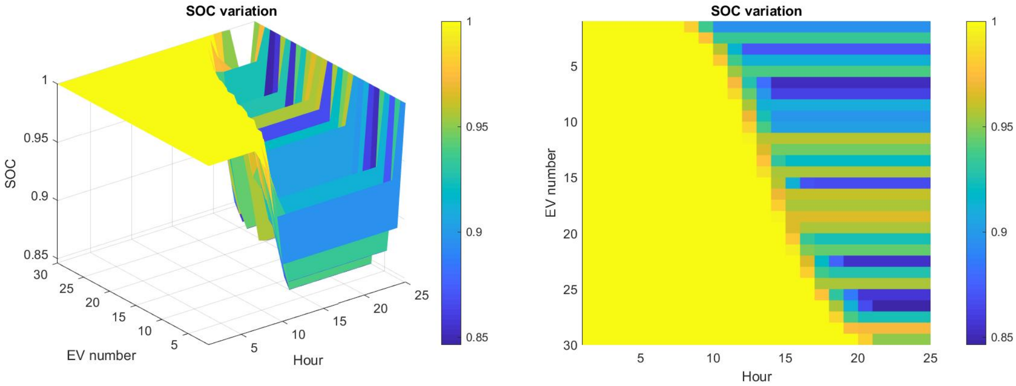
5.5.2 Scenario 2B: Controlled Charging

The difference in this scenario from scenario 2a is shown below in table 5.3. Controlled charging reduces the EV charging cost, as charging is done in the hours with lower electricity cost. Similarly, we see a reduction in peak demand and the peak power cost associated with it.

The variation of SOC of each EV over the 24 hour period is shown in the figure 5.8a and 5.8b. The charging pattern of the EV's are shown in figure 5.9 and change in electricity demand with the addition of EV's is shown in figure 5.10a. Figure 5.10b shows the hourly charging pattern of the fleet EV's.

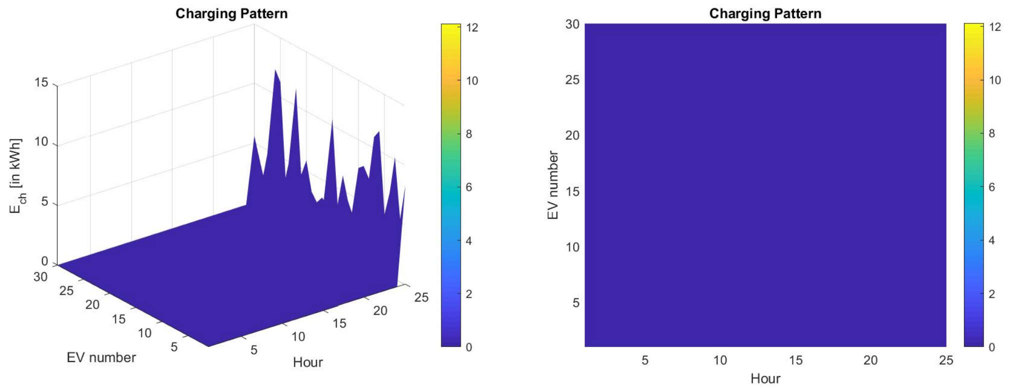
Table 5.3: Scenario 2B results (All values in SEK unless otherwise stated)

Electricity cost	37893
EV charging cost	55.14
E_{max}	6879.3 kWh
Peak power cost	8301.02
Rental Revenue	13924.45
Net cost	**32324.71**



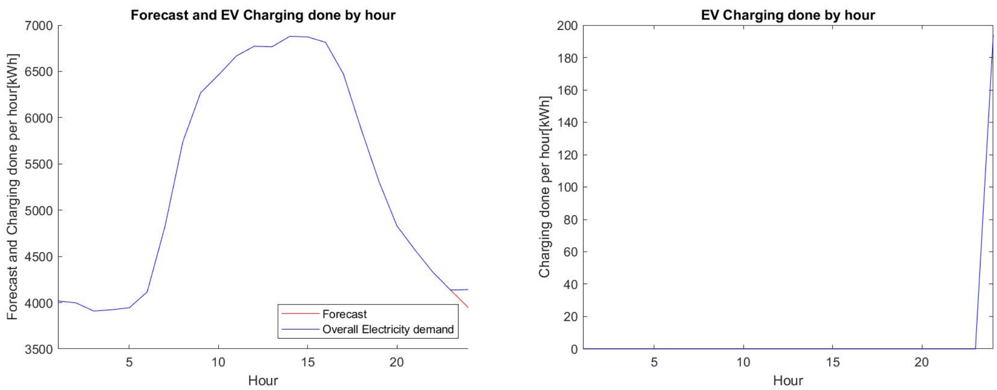
(a) (b)

Figure 5.8: Scenario 2B - SOC variation



(a) (b)

Figure 5.9: Scenario 2B - EV Charging pattern during the 24 hour period



(a) Forecast and EV Charging (b) EV Charging done per hour

Figure 5.10: Scenario 2B - EV charging

5.6 Scenario 3 Results

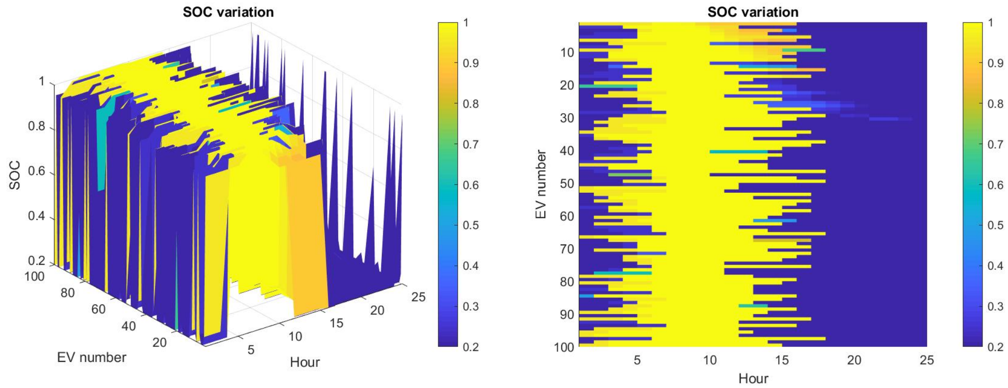
The Electricity cost of the FED system would remain the same in this scenario too i.e. **Electricity cost** = 37893 SEK. The cost of charging and discharging in a controlled charging manner is also shown over here in table 5.4.

Table 5.4: Scenario 3 results, battery degradation cost not included in the objective function (All values in SEK unless otherwise stated)

Electricity cost	37893
EV charging cost	1837.53
EV discharging revenue	1674.53
E_{max}	6049.2 kWh
Peak power cost	7299.38
Battery Degradation cost	9337.62
Rental Revenue	13924.45
Net cost	**40768.55**

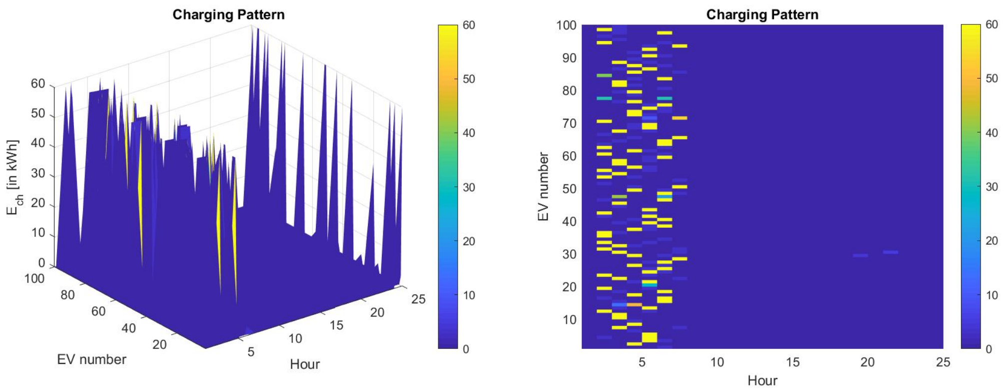
The battery degradation cost is calculated using the battery degradation cost per unit of energy ($D_{f,II}$) of 0.844 SEK/kWh. The values listed in table 5.4 were obtained considering the battery degradation cost as not a part of the objective function.

As the battery degradation is not a part of the objective function, high V2G participation is observed in terms of EV discharging revenue. Higher



(a) (b)

Figure 5.11: Scenario 3 - SOC variation

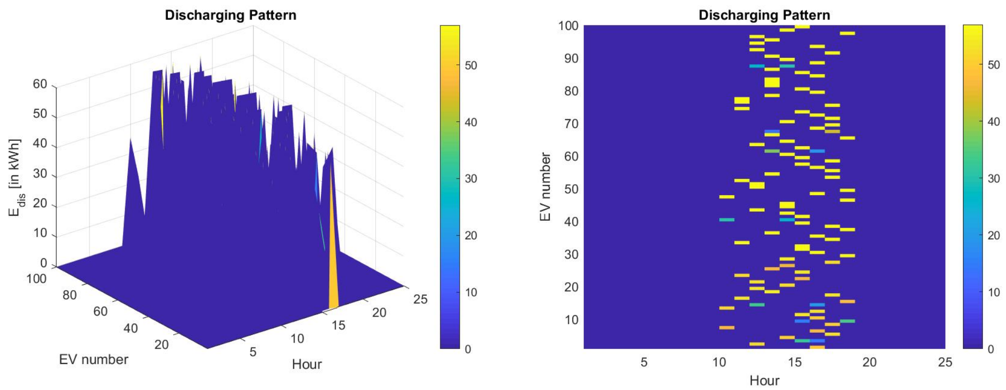


(a) (b)

Figure 5.12: Scenario 3 - EV Charging pattern during the 24 hour period

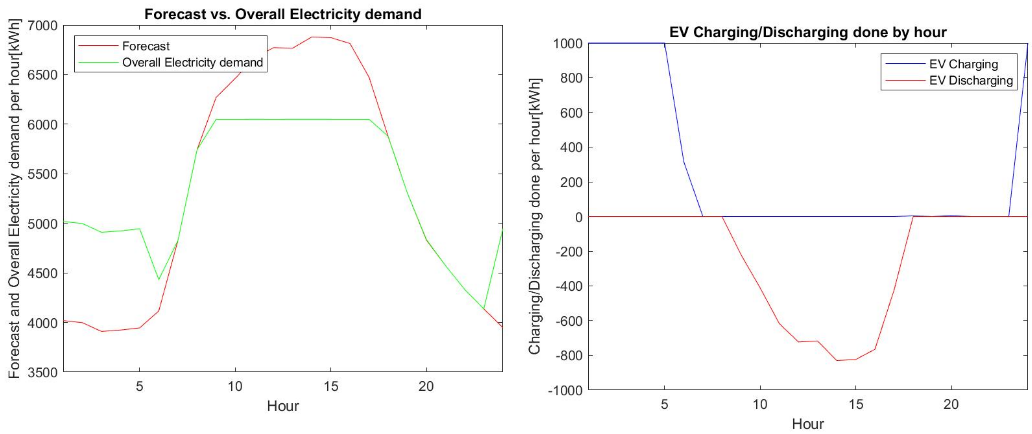
charging cost is observed to compensate for the increased discharging. The peak electricity requirement is reduced due to the EV's providing electricity back to the FED system during peak hours. It is clear from the results, that bidirectional charging facilities does not reduce net cost to such an extent to make V2G feasible.

The variation of SOC of each EV over the 24 hour period is shown in the figure 5.11a and 5.11b. The charging and discharging pattern of the EV's are shown in figures 5.12a, 5.12b, 5.13a and 5.13b. The change in electricity demand with the addition of EV's charging and discharging (or controlled charging) in comparison to the forecast is shown in figure 5.14.



(a) (b)

Figure 5.13: Scenario 3 - EV Discharging pattern during the 24 hour period



(a) Scenario 3 - Forecast vs. Overall Electricity Demand

(b) Scenario 3 - EV charging/discharging

Figure 5.14: Scenario 3 - EV Charging and Discharging

The optimization in **GAMS** software gave the following values when the battery degradation cost was considered as a part of the objective function. The results are shown in table 5.5.

These values clearly suggest that battery degradation cost per unit of energy ($D_{f,II}$) is so high, that the optimization restricts discharging of the batteries. Furthermore, this leads to only minuscule reduction in peak demand and a similar net cost as scenario 2 is witnessed. It would be safe to say that no real benefit of using V2G bidirectional charging is observed.

Table 5.5: Scenario 3 results, battery degradation cost as a variable in the optimization (All values in SEK unless otherwise stated)

Electricity cost	37893
EV charging cost	49.11
EV discharging revenue	1.88
E_{max}	6872.9 kWh
Peak power cost	8293.3
Battery Degradation cost	5.4
Rental Revenue	13924.45
Net cost	**32314.47**

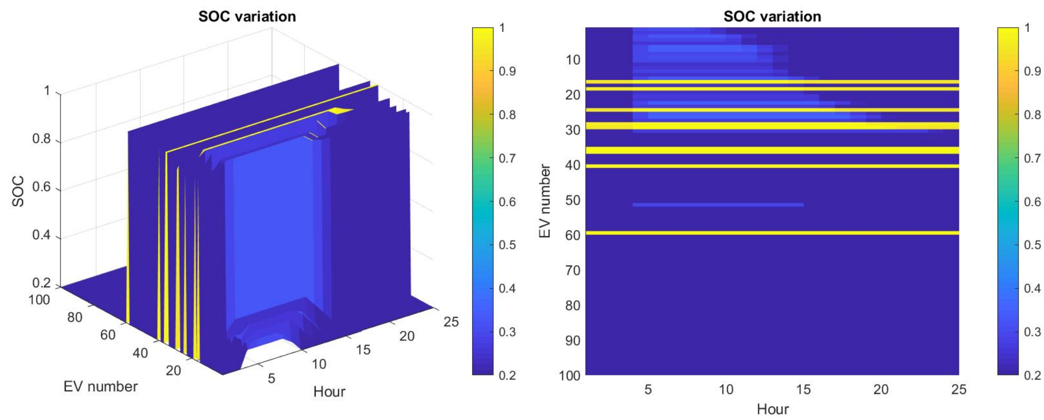
5.7 Scenario 4 Results

Frequency regulation is the differing feature between this scenario and scenario 3. Regulation up and down prices along with the automatic activated reserves are shown in Appendix A.4. The various cost and revenue values are shown in table 5.6 (battery degradation cost used as a part of the objective function).

Table 5.6: Scenario 4 results (All values in SEK unless otherwise stated)

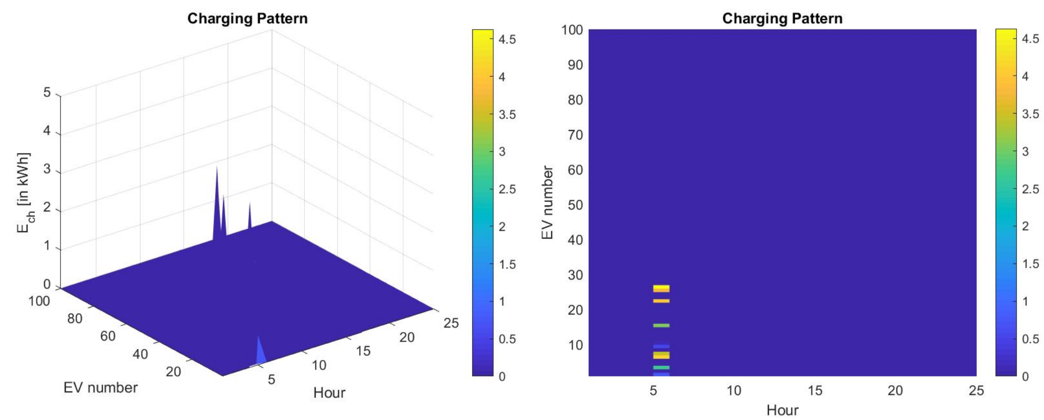
Electricity cost	37893
EV charging cost	6.64
EV discharging revenue	0
Regulation Up revenue	2.11
Regulation Down cost	41.29
E_{max}	6872.9 kWh
Peak power cost	8293.3
Battery Degradation cost	5.4
Rental Revenue	13924.45
Net cost	**32313.07**

Here, lower charging cost is observed relative to scenario 3 (when battery degradation cost is a part of the objective function), which is due to the facility of frequency regulation and it appears as additional regulation down cost. Regulation down helps us to charge the EV's from the grid when frequency has to be reduced down to the nominal value. Regulation up does the opposite, discharging the batteries to provide electricity back to the grid



(a) (b)

Figure 5.15: Scenario 4 - SOC variation

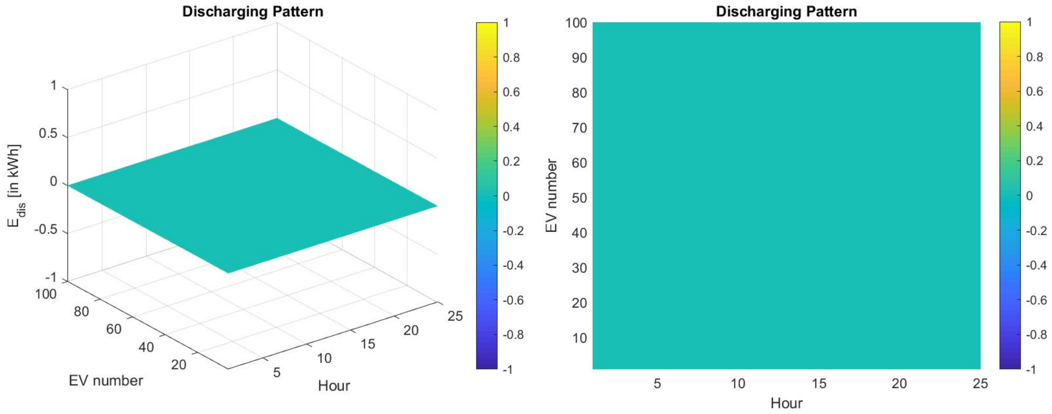


(a) (b)

Figure 5.16: Scenario 4 - Charging Pattern

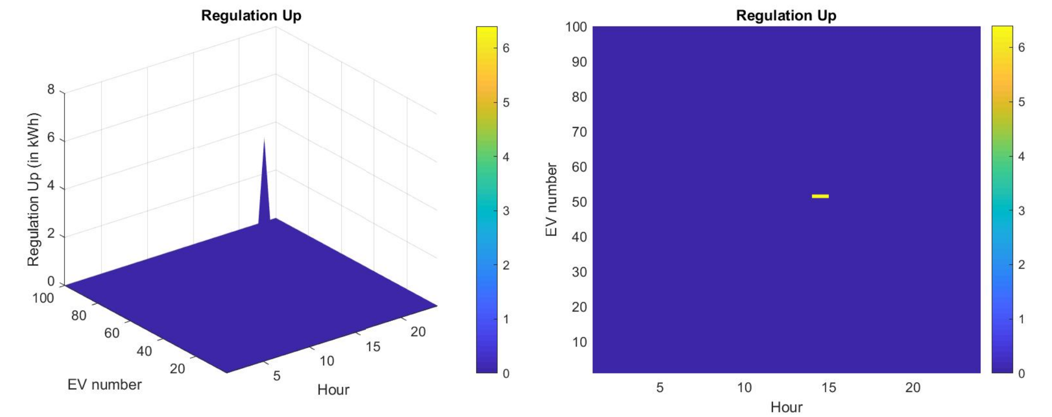
when the frequency has to be increased to its nominal value. The peak load demand and the net cost are similar to the previous scenario. Frequency regulation makes the bidirectional V2G feasible as net cost is comparable to scenario 2 (where battery degradation cost has not been considered) but no huge benefits are observed.

The SOC variation over the 24 hour period is shown in figure 5.15, charging and discharging patterns are shown in figures 5.16 and 5.17. Regulation up and down are shown in figures 5.18 and 5.19, the change in electricity demand is shown in figure 5.20a. Hourly charging/discharging patterns and



(a) (b)

Figure 5.17: Scenario 4 - Discharging Pattern



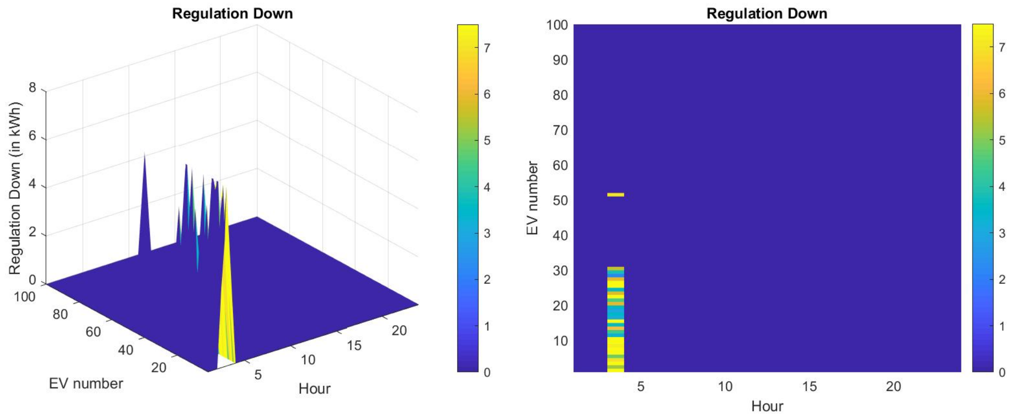
(a) (b)

Figure 5.18: Scenario 4 - Regulation Up

regulation up/down is shown in figure 5.20b.

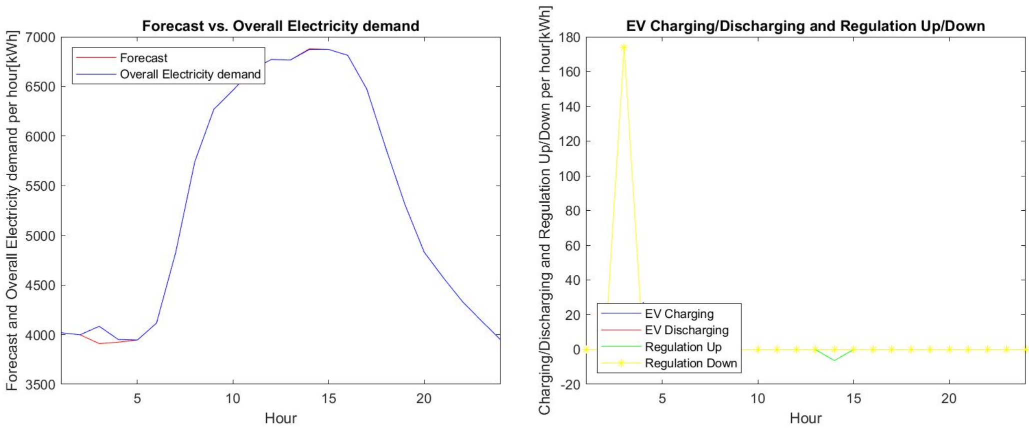
5.8 Scenario Comparison

The results from all the four scenarios have been compiled in table 5.7.



(a) (b)

Figure 5.19: Scenario 4 - Regulation Down



(a) Forecast vs. Overall Electricity Demand

(b) EV charging/discharging and Regulation Up/Down

Figure 5.20: Scenario 4 - EV Charging, Discharging and Frequency regulation

Scenario 1 i.e. the base case of the thesis, has the highest net cost and gave inspiration to introduce bidirectional V2G services. Scenario 2A introduces EV fleet into FED system (uncontrolled charging) and a drop in net cost is seen due to the revenue generated from renting out cars in the EV Fleet. Uncontrolled charging increases the peak demand leading to a higher peak power cost. To counter the rise in peak demand, we introduce controlled charging in scenario 2B which brings peak demand back to the base case level and reduces the net cost even further.

Table 5.7: Scenario comparison (3a- Battery degradation not a part of the objective function, 3b- Battery degradation is a part of the objective function)

Scenario	1	2A	2B	3a	3b	4
Electricity cost	37893	37893	37893	37893	37893	37893
EV charging cost	-	59	55.14	1837.53	49.11	6.64
EV discharging revenue	-	-	-	1674.53	1.88	0
E_{max} (in kWh)	6879.3	6932.7	6879.3	6049.2	6872.9	6872.9
Peak power cost	8301.02	8365.45	8301.02	7299.38	8293.3	8293.3
Regulation up revenue	-	-	-	-	-	2.11
Regulation down cost	-	-	-	-	-	41.29
Rental revenue	-	13924.45	13924.45	13924.45	13924.45	13924.45
Battery Degradation cost	-	-	-	9337.62	5.4	5.4
Net cost	**46194**	**32393**	**32324.71**	**40768.55**	**32314.47**	**32313.07**

Scenario 3 introduced bidirectional charging (G2V + V2G) in the system and presented an immensely difficult challenge during modelling. Battery degradation cost was the factor which presented the most difficulty to be integrated into the system. Whether the battery degradation should be treated as a part of the objective function was another challenge in itself. Considering the battery degradation cost as a part of the objective function limited the optimization, the model made discharging almost redundant so as to avoid battery degradation cost due to the high D_f value as can be seen in section 5.6. The results are seen in column '3b' of table 5.7. Considering battery degradation as not a part of the objective function (model is not going to optimize the degradation cost) gave the model freedom to utilize the V2G services from the car fleet as shown in table 5.7 column '3a'. EV fleet discharges in a controlled manner, bringing down the peak demand down and lowering the peak power cost but the price of using the battery degradation cost as not a part of the objective function is paid in a very high battery degradation cost and an increased net cost.

Scenario 4 introduces the ancillary service of frequency regulation to the bidirectional charging system. Additional revenue stream in terms of regulation up is introduced and yet we see a small decrease in net cost of the system. The peak demand of the system is only a bit less than the base case, and yet, not as low as scenario 3 (column 3a) which can be attributed to the opposing effect of battery degradation cost. Battery degradation cost increases as V2G services increase, so the model optimizes in such a way to give the minimum net cost which is evident by the much lower degradation cost.

5.9 Sensitivity Analysis

In this section, the effect of tweaking various factors on the system is analyzed.

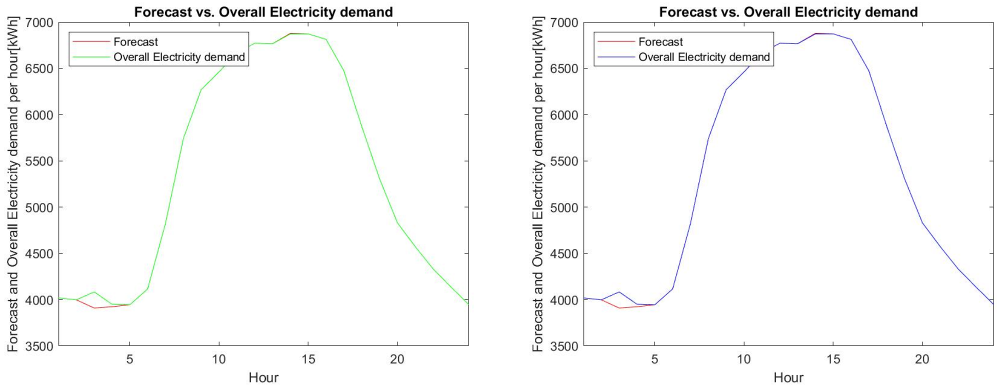
5.9.1 Change in charging facility

DC Level 2 charging limits have been used in this thesis, therefore, a sensitivity analysis based on charging limits can be performed. Instead of using the DC level 2 charger, we can use the DC level 1 charger (up to 40 kW power capacity) to compare the two levels of charging. Due to the SOC limit of equation (3.14), the EV battery could be charged to a maximum of 80 percent of its rated capacity i.e. 60 kWh in a hour with DC level 2 charger. With DC level 1 charger, the charging capacity is assumed to essentially halve to a maximum value of 30 kWh. The difference between the two in Scenario 4 is tabulated in table 5.8.

No discernible difference could be found while using level 1 and level 2 as seen in figures 5.21 and 5.22. Even the hourly charging/discharging and frequency regulation pattern is similar for both charging levels. It was found that DC level 1 charger used more EV's for charging and discharging than DC level 2 in such a way that the hourly charging/discharging and frequency regulation pattern remains the same.

Table 5.8: Difference between the DC charging levels (All values in SEK unless otherwise stated)

Charging level	DC Level 1	DC Level 2
Electricity Cost	37893	37893
EV charging cost	6.64	6.64
EV discharging revenue	0	0
E_{max}	6872.9 kWh	6872.9 kWh
Peak Power cost	8293.3	8293.3
Regulation Up revenue	2.11	2.11
Regulation Down cost	41.29	41.29
Battery Degradation cost	5.4	5.4
Rental Revenue	13924.45	13924.45
Net Cost	**32313.07**	**32313.07**



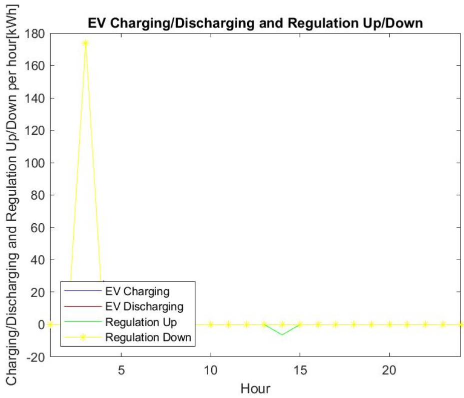
(a) DC level 1 (b) DC level 2

Figure 5.21: Charging facility - Overall electricity demand

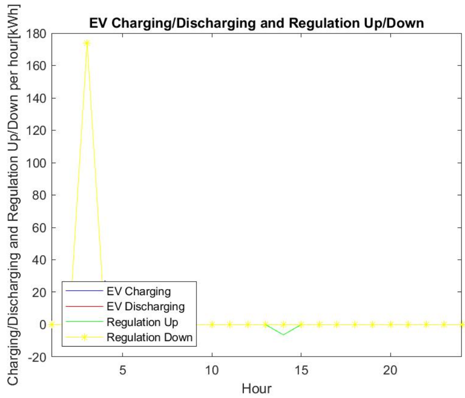
5.9.2 Changing the number of Electric Vehicles used

In the thesis, a fleet size of 100 cars has been used for analysis as a random choice due to the lack of business opportunity research. So, the effect of fleet size on the system has been subdued and not completely understood. To study the effect of fleet size, different fleet sizes are going to be used to perform a sensitivity analysis. We are going to see the results for:

1. 100 cars.
2. 50 cars.
3. 25 cars.



(a) DC level 1



(b) DC level 2

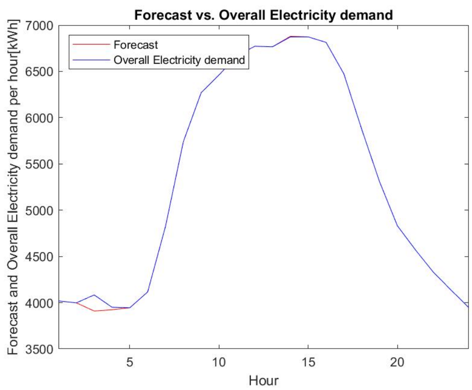
Figure 5.22: Charging facility - Charging/discharging pattern and Frequency Regulation

The sensitivity analysis is done using Scenario 4 conditions. The difference between the three fleet sizes is shown in table 5.9.

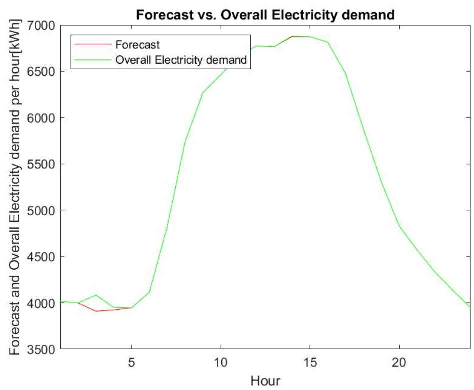
Table 5.9: Changing the fleet size (All values in SEK unless otherwise stated)

Fleet Size	100 cars	50 cars	25 cars
Electricity Cost	37893	37893	37893
EV charging cost	6.64	6.64	5.51
EV discharging revenue	0	0	0
E_{max}	6872.9 kWh	6872.9 kWh	6872.9 kWh
Peak Power cost	8293.3	8293.3	8293.3
Regulation Up revenue	2.11	2.11	2.11
Regulation Down cost	41.29	41.29	35.36
Battery Degradation cost	5.4	5.4	5.4
Rental Revenue	13924.45	13924.45	11791.02
Net Cost	**32313.07**	**32313.07**	**34439.44**
Capital cost	31,500,000	15,750,000	7,875,000

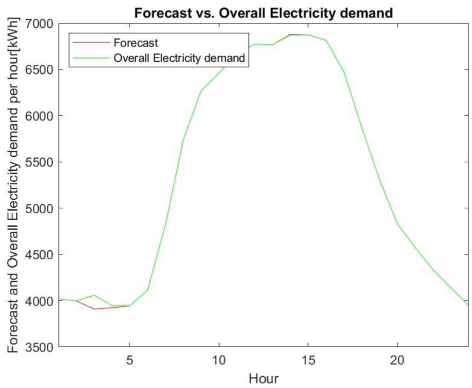
No difference in discharging revenue, regulation up revenue and peak power demand is observed among the three fleet sizes as can be seen in the table 5.9 and figures 5.23 and 5.24. Regulation down cost decreases when the fleet size is reduced to 25. The rental revenue remains unchanged between fleet size of 100 and 50 cars, which is due to the deterministic car driving pattern in which only 30 cars are rented in a day. This is also the reason



(a) 100 cars



(b) 50 cars



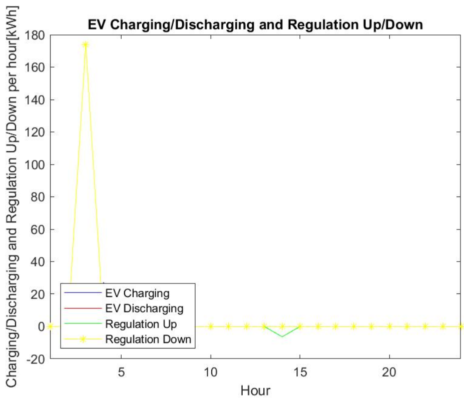
(c) 25 cars

Figure 5.23: Fleet size - Overall electricity demand

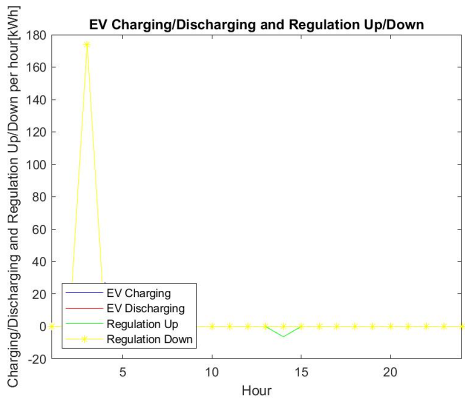
for reduction in rental revenue when 25 cars are used in the fleet. Battery degradation cost remains unchanged among the three fleet sizes due to similar discharging and regulation up pattern.

The capital cost mentioned above is the total investment made by the Fleet Operator in purchasing the cars for the fleet. A Tesla model 3 has an estimated cost of 35,000 US dollars [42] (assuming 1 US dollar = 9 SEK). This cost is indicative of the amount of investment made and not a determining factor in selecting the fleet size, as no life cycle assessment was done for the fleet.

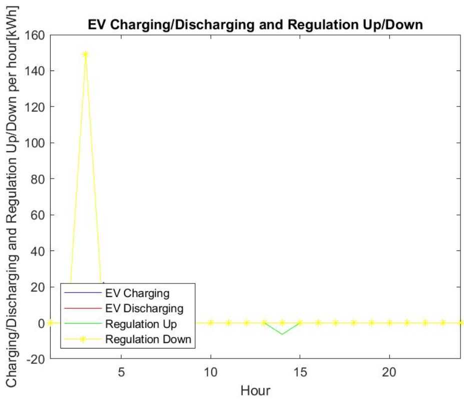
The net cost for the fleet size of 100 and 50 EV's does not justify the fleet size of 100 but a significant increase in net cost is observed when the fleet size is further reduced to 25. The correct fleet size would be somewhere be-



(a) 100 cars



(b) 50 cars



(c) 25 cars

Figure 5.24: Fleet size - Charging/discharging pattern and Frequency regulation

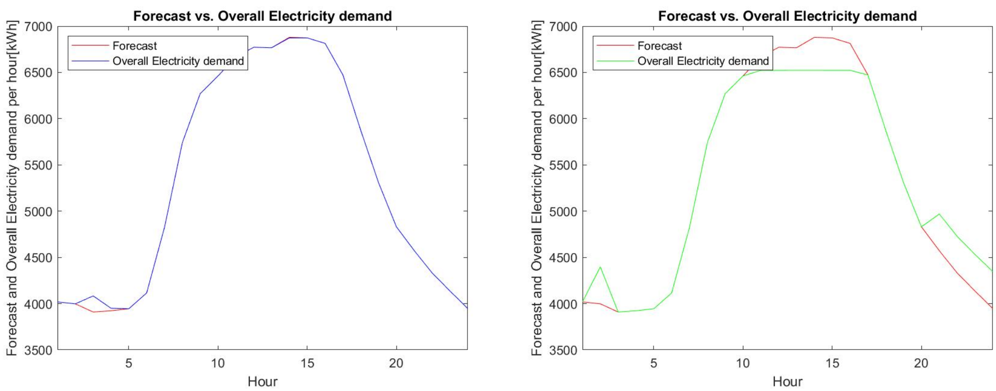
tween 50 and 25 EV's, which would be determined by appropriate business opportunity data and a life cycle assessment of the net cost to the system according to the fleet size. Of course, such an analysis is beyond the scope of this thesis.

5.9.3 Changing the EV model

This section deals with changing the EV to a Nissan leaf S in place of the Tesla model 3 used up till now and study the changes. Nissan leaf S has a driving range of 150 miles [43] as compared to 250 miles for the Tesla model 3. The Nissan leaf S has a lower battery capacity of 40 kWh [14] compared to 75 kWh battery capacity of Tesla model 3. Also, the Nissan leaf S comes at a cheaper price of 29,900 US dollars [14] compared to the 35,000 US dollars price tag of Tesla Model 3. The difference between the two electric vehicles are shown in table 5.10 and figures 5.25, 5.26.

Table 5.10: Different Electric Vehicles (All values in SEK unless otherwise stated)

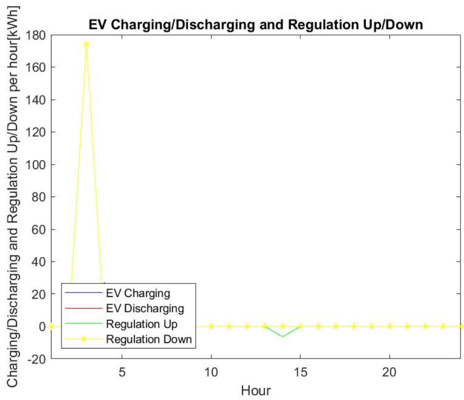
EV model	Tesla Model 3	Nissan Leaf S
Number of EV's	100	100
Range	250 miles	150 miles
Battery Capacity	75 kWh	40 kWh
Electricity Cost	37893	37893
EV charging cost	6.64	0
EV discharging revenue	0	296.24
E_{max}	6872.9 kWh	6522.15 kWh
Peak Power cost	8293.3	7870.06
Regulation Up revenue	2.11	214.95
Regulation Down cost	41.29	0
D_f	0.844 SEK/kWh	0.506 SEK/kWh
Battery Degradation cost	5.4	829.5
Rental Revenue	13924.45	13924.53
Net Cost	**32313.07**	**32156.913**
Capital Cost	31,500,000	26,910,000



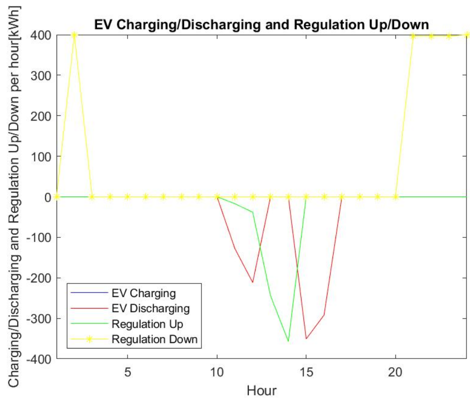
(a) Tesla model 3 (b) Nissan Leaf S

Figure 5.25: EV model - Overall Electricity Demand

The main difference between the two EV models besides the range and battery capacity, is the battery degradation cost per unit of energy (D_f).



(a) Tesla model 3



(b) Nissan Leaf S

Figure 5.26: EV model - Charging/discharging pattern and Frequency regulation

Nissan Leaf S has a lower battery degradation cost per unit of energy at 0.506 SEK/kWh compared to 0.844 SEK/kWh for Tesla model 3. This proves detrimental for Tesla model 3 as Nissan Leaf S excels in discharging revenue, regulation up revenue, regulation down cost and net cost despite having higher a battery degradation cost. Even the peak demand is less for Nissan Leaf S despite having a smaller battery capacity than Tesla model 3. This makes Nissan leaf S a superior choice for the EV.

5.9.4 Changing the Battery Degradation Cost per unit of Energy

A high value of battery degradation cost per unit of energy (D_f) hinders in V2G services as the optimization limits EV charging, discharging and regulation up on account of high degradation cost. In this section, the effect of changing the D_f values on the system is analyzed. Up till now, D_f value of 0.844 SEK/kWh has been used and proven to be high to an extent making V2G services unworthy, seen especially in scenario 3. Keeping this in mind, only values lower than 0.844 SEK/kWh are going to be used for sensitivity analysis as shown below, in scenario 4 conditions:

1. 0.844 SEK/kWh
2. 0.6 SEK/kWh
3. 0.4 SEK/kWh
4. 0.2 SEK/kWh

The results are shown in table 5.11.

Table 5.11: Varying D_f (All values in SEK unless otherwise stated)

D_f (in SEK/kWh)	0.844	0.6	0.4	0.2
Electricity Cost	37893	37893	37893	37893
EV charging cost	6.64	6.64	6.64	244.2
EV discharging revenue	0	17.41	42.46	379.77
E_{max} (in kWh)	6872.9	6813.9	6771.900	6461.7
Peak Power cost	8293.3	8222.11	8171.43	7797.11
Regulation Up revenue	2.11	21.52	35.34	248.02
Regulation Down cost	41.29	72.33	105.48	345.29
Battery Degradation cost	5.4	74.64	100.16	402.46
Rental Revenue	13924.45	13924.45	13924.45	13924.45
Net Cost	**32313.07**	**32305.34**	**32274.45**	**32129.82**

Decreasing D_f value to 0.6 SEK/kWh results in the fleet participating to a higher extent in V2G services, as can be seen by the increase in discharging revenue and regulation up revenue but the higher participation has a rebound effect on the battery degradation cost and regulation down cost. Still, a lower net cost is observed partly due to the reduction in peak demand.

Upon further reducing the D_f value to 0.4 SEK/kWh, even higher V2G participation is observed with lower net cost. The peak power demand decreases even more but the rebound effect in battery degradation is quite prominent in this case, thus limiting the decrease in net cost.

When D_f value is reduced to 0.2 SEK/kWh, a sudden increase is noticed in V2G services along with reduction in peak demand. Achieving a D_f value of 0.2 SEK/kWh is not possible with present day technology, as we see that Nissan Leaf 'S' could only achieve a value of 0.506 SEK/kWh. The battery degradation cost is lower than the previous case which is obvious due to the low D_f value.

6

DISCUSSION and Future Research Work

This chapter deals with interpreting the results obtained in the thesis and state their relevance for the possible introduction of EV fleet into the FED system. A thorough inspection of the assumptions is done so as to fully appreciate the effect they have on the results. Furthermore, discourse over the limitations is presented and alternative paths to achieve better results are suggested.

- **Load Forecasting**: Holt-Winters method was used to forecast the demand and presented accurate results with an average difference of **3.2859** percent (a value below 5 percent is acceptable). The average difference value and MAE increases as the time period increases, for a two day period the average difference is 3.2399 percent, three day period gives a value of 3.4376 percent, on the fourth day the value is 3.9313 percent, fifth day gives 3.7526 percent. On the sixth day, the value increases to beyond an unacceptable value of 5.6981 percent on account of the weekend day which is the major fault of HWT method, it lacks the sensitivity to account for a large drop or increase in the electricity demand and holidays.

  It is one of the major reason the optimization has been limited to a single day to avoid any major errors in forecast value. The average difference value could have been much higher if the optimization would have been performed for some other day or a time period greater than a single day was used. Future research can introduce ANNs as they have proven to be attractive for load modelling [6].

- **EV**: Choosing Tesla Model 3 as the EV for analysis was primarily based on the high battery capacity it offers. During the analysis, the high battery degradation cost per unit of energy (D_f) proved as an opposing force to the battery capacity, thereby, limiting the participation of the Tesla in V2G services. The sensitivity analysis performed between Tesla model 3 and Nissan Leaf S made it apparent that such a high battery capacity was not necessary in this case study. Nissan leaf S with a lower battery capacity performed better than Tesla model 3 in every V2G service because of a lower D_f value. In addition to that, the Nissan costs less than the Tesla making it an even more attractive option for V2G use. In the future research work, more EV's can be analysed to determine the best EV for V2G use.

- **Charging facility**: The DC level 2 charging station infrastructure was used for analysis assuming the requirement of the higher power capacity inherent to DC level 2. The sensitivity analysis performed between DC level 1 and 2 charging showed no differences between the net cost to the the system. The question arises on which of the two charging levels is more suitable for use in the case study, but the answer is out of the scope of this thesis, a research work based on life cycle assessment of both the charging levels would be able to answer the question better.

- **Fleet size**: The fleet size was assumed to be 100 cars strong for simplicity due to the lack of business opportunity data. Later on, the deterministic driving pattern showed that only 30 cars was rented out during the 24 hour period leaving the remaining 70 cars as reserve capacity during the period. The sensitivity analysis performed on changing the fleet size showed no difference in net cost when the fleet size was halved. A considerable increase in net cost occurs for a quarter fleet size. A future research work determining the business opportunity around the *Chalmers* campus would be essential to implement this model in practice, finding the number of customers willing to participate regularly would be quintessential for the project to be a success.

- **Driving Pattern**: A deterministic driving pattern data was developed for the thesis due to the lack of relevant car sharing driving pattern in the city of *Göteborg*. The problem with the deterministic driving pattern over here is that it is good for only one day, the pattern would repeat itself on the second day and so on. This was the top reason for a one day optimization performed in this thesis. Determining a driving pattern for a longer period of time is the most important work that needs to be performed for finding the lifetime benefits of implementing V2G.

- **Battery degradation affecting the scenarios**: Battery degradation cost is the major reason for the absence or a small presence of V2G in the electricity market. Many of the previously performed research suggest not implementing V2G services based on the high degradation costs, ultimately leading to replacement of batteries much before their actual life ends in usual conditions, when they are not used for V2G service. Scenario 3 shows a similar trend where high battery degradation cost makes the net cost to the system higher than scenario 2 where V2G services are not introduced. Only when frequency regulation is introduced along with V2G in scenario 4, is when the system is in a more profitable situation than scenario 2. A lot of research work is being done on the improvement of battery lifetime and making the batteries cheaper (involving battery chemistry) and as EV batteries become cheaper, V2G would become much more common in the electricity market.

7
CONCLUSION

This thesis was started with the aim of studying the benefits of V2G services for a EV fleet added to the FED system. With the increase of EV's in transportation sector, more opportunities are arising for V2G services. Thus, an EV fleet of 100 cars strength was introduced to the FED system for the purpose of studying V2G participation of the system.

The thesis started with forecasting the electricity demand of the FED system for a day based on historical data and using HWT exponential smoothing method. After that, a decision on the DC charging station infrastructure was made by analyzing the available technology and simultaneously, the EV representing the fleet was chosen based on the battery capacity giving maximum V2G participation ability. Thus, DC level 2 charging and Tesla model 3 were selected. The fleet strength was assumed to be 100 due to the lack of business opportunity data around the *Chalmers* campus. The driving pattern data was obtained using a deterministic model based on the data from the research paper by *Sprei et al.* A SOC model was developed to determine the energy stored in an EV battery and also, to establish a relation between the charging/discharging done and the distance driven by the EV. All these elements were combined to form a model in the optimization tool called *General Algebraic Modelling System* (**GAMS**). The objective function of the optimization was to minimize the net cost which comprised of electricity cost, peak power cost, charging cost, discharging revenue, rental revenue and frequency regulation revenue. The optimization also accounted for the battery degradation cost of the EV batteries and the constraints coming along with implementing V2G services and grid usage.

The following are the noteworthy points observed during the analysis:

- V2G services are only worthy to be implemented with ancillary services (frequency regulation in this thesis), V2G electricity exchange without ancillary services would be worse off than simple G2V electricity exchange.

- Battery degradation is the major drawback and V2G would prove to be infeasible until we reduce the battery degradation cost to a level much lower than today.
- Tesla model 3 is not the best option to use in this thesis due to the high battery cost. A cheaper Nissan Leaf 'S' with lower battery cost is much more suitable for V2G.
- Implementing DC level 2 charging may be not such a good idea in comparison to DC level 1, due to the high investment costs but presenting a clear choice between the two is not in the scope of the thesis. A life cycle assessment would be able to present a clear situation here.
- The fleet size of 100 proved to be too high for the results put forward by the deterministic model although, an analysis based on proper business opportunity research is required.

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Appendices

A
Tables

A.1 Hourly Distance values

The hourly distance values for each EV is shown over here on March 1, 2017. There are no rentals during hours 1-6.

Table A.1: Hours 7-12 on March 1, 2017

EV \ Hour	7	8	9	10	11	12
1	7.481	17.954	16.757	0	0	0
2	0	9.582	17.067	0	0	0
3	0	0	16.525	18.027	17.426	0
4	0	0	7.794	17.985	9.892	0
5	0	0	0.301	18.085	6.631	0
6	0	0	0	11.406	18.010	18.010
7	0	0	0	5.095	17.982	17.982
8	0	0	0	0	17.440	18.041
9	0	0	0	0	12.034	18.051
10	0	0	0	0	6.624	18.066
11	0	0	0	0	1.189	15.463
12	0	0	0	0	0	14.350
13	0	0	0	0	0	9.285
14	0	0	0	0	0	4.196

Table A.2: Hours 13-18

EV \ Hour	13	14	15	16	17	18
6	12.006	0	0	0	0	0
7	14.685	0	0	0	0	0
8	1.203	0	0	0	0	0
9	10.830	0	0	0	0	0
10	14.152	0	0	0	0	0
12	7.773	0	0	0	0	0
13	17.971	4.792	0	0	0	0
14	13.787	0	0	0	0	0
15	17.066	17.964	17.964	0.898	0	0
16	11.995	3.898	0	0	0	0
17	6.906	10.810	0	0	0	0
18	1.509	12.977	0	0	0	0
19	0	14.194	3.624	0	0	0
20	0	8.397	17.993	3.599	0	0
21	0	2.389	17.921	2.389	0	0
22	0	0	14.104	18.005	18.005	8.403
23	0	0	7.192	17.980	4.495	0
24	0	0	0	17.714	0	0
25	0	0	0	9.322	18.043	18.043
26	0	0	0	0	17.704	18.004
27	0	0	0	0	6.573	17.925
28	0	0	0	0	0	10.109

Table A.3: Hours 19-23

EV \ Hour	19	20	21	22	23
25	12.028	0	0	0	0
26	18.004	8.102	0	0	0
27	5.676	0	0	0	0
28	0.892	0	0	0	0
29	7.236	12.361	0	0	0
30	0	0	0.299	17.943	10.168

A.2 Rental Details

The Rental start and end times along with the rental duration are shown over here.

Table A.4: Rental Details

Car Number	Start of Rental (minutes)	Rental Duration (minutes)	End of Rental (minutes)
1	395	141	536
2	448	89	537
3	485	173	658
4	514	119	633
5	539	83	622
6	562	198	760
7	583	186	769
8	602	122	724
9	620	136	756
10	638	129	767
11	656	56	712
12	672	74	746
13	689	107	796
14	706	60	766
15	723	180	903
16	740	53	793
17	757	59	816
18	775	48	823
19	793	59	852
20	812	100	912
21	832	76	908
22	853	195	1048
23	876	99	975
24	901	51	952
25	929	191	1120
26	961	206	1167
27	998	101	1099
28	1046	37	1083
29	1116	65	1181
30	1259	95	1354

A.3 Hourly Electricity cost from Nord Pool

The hourly Electricity cost are obtained from Nord Pool [34] website.

Table A.5: Hourly Electricity cost on March 1, 2017

Hour	Electricity cost (in SEK per MWh)
1	264.10
2	260.28
3	252.43
4	244.20
5	274.15
6	286.88
7	295.59
8	306.59
9	313.86
10	313.10
11	310.04
12	308.12
13	298.74
14	294.15
15	295.01
16	301.42
17	306.50
18	310.80
19	328.70
20	310.04
21	307.45
22	303.15
23	298.17
24	284.20

A.4 Regulation Up and Down - Volumes and Prices

The Regulation Up/Down volumes and prices are obtained from the Nord Pool website on March 1, 2017 [37]. The regulation Up/Down volumes are the **Automatic Activated reserve values** [39] i.e. the primary frequency control values.

Table A.6: Regulation Up and Down - Volumes and Prices on March 1, 2017

Hour	Regulation Up Price (in SEK per MWh)	Regulation Up (in MWh)	Regulation Down Price (in SEK per MWh)	Regulation Down (in MWh)
1	265.35	5.7	264.10	0
2	261.62	0	260.28	-1.3
3	252.43	0	237.41	-2.4
4	244.20	3	237.41	0
5	274.15	0	248.22	-10.7
6	286.88	0	248.22	-1.4
7	295.59	2.4	258.94	0
8	306.59	0	269.75	-0.5
9	313.86	2.4	270.04	0
10	313.10	2.4	270.04	0
11	310.04	0.5	270.04	0
12	308.12	0.1	275.11	0
13	329.08	5.9	275.11	0
14	329.08	4.2	294.15	0
15	329.08	0	295.01	-1.3
16	329.08	0	310.42	-6.8
17	306.50	0	275.11	-6.5
18	310.80	1.5	275.11	0
19	328.70	3	275.11	0
20	332.04	1.4	310.04	0
21	339.89	0	307.45	-3.7
22	339.89	0	303.15	-4.5
23	339.89	0	298.17	-5.9
24	322.72	0	284.20	-12.2