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Master Thesis

Economic feasibility analysis of Vehicle-to-Grid service from an EV owner's perspective in the German Electricity Market

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Abstract

The increasing number of Electrical Vehicles (EV) has led to a tremendous amount of inaccessible electric energy stored in the EV batteries. Vehicle-to-grid (V2G) services can utilize this energy to profit the EV owners' and stabilize the grid during faults and fluctuations. This thesis presents a novel way of estimating the profitability of V2G from the EV owner's perspective. The main contribution of this thesis is the formulation of a profit model that includes the EV battery degradation due to V2G. The work done so far considers fixed battery degradation cost, whereas in this work, an online battery degradation model is used. This model takes into account the parameters that represent real-life scenarios resulting in more accurate battery degradation estimation. The V2G profit model uses the electricity price signal from the German energy market for the year 2019 and estimates the annual profit.

The first part of the thesis calculates the profitability of V2G, where EV can participate freely in energy arbitrage. This analysis explores the range of profit when EV participates in V2G purely based on the EV owner's discretion. A sensitivity analysis is done with respect to battery capacity, battery efficiency, and driving distance. The second part of the thesis evaluates the profitability of EV participating in the German energy market's frequency regulation ancillary service.=. The analysis compares the profitability of EV participating in primary, secondary, and tertiary frequency regulation services.

The results of this thesis provide several findings, the potential profit from V2G services should encourage EV owners' to participate in the V2G services. Additionally, participating in V2G service can extend the life of the battery. However, this depends on the battery technology and battery usage during V2G services. Ancillary services provide higher potential profit compared to energy arbitrage because of the high remuneration scheme. The ancillary services with both capacity and energy payment result in higher profit compared to ancillary services with only capacity payment.

Abbreviations

aFRR	automatic activation Frequency Restoration Reserve.
DOD	Depth Of Charge.
DSO	Distribution System Operator.
EOL	End Of Life.
ERCOT RTM	Electric Reliability Council of Texas Real-Time Market.
EV	Electric Vehicle.
FCR	Frequency Containment Reserve.
ISO-NE	Independent System Operator New England.
LMO	Lithium Manganese Oxide.
LMP	Locational Marginal Price.
LPF	Lithium Iron Phosphate.
mFRR	manual activation Frequency Restoration Reserve.
NCA	Nickle Cobalt Aluminium.
NMC	Nickel Cobalt Manganese.
NYISO	New York Independent System Operator.
PJM	Pennsylvania-New Jersey-Maryland Interconnection.
RES	Renewable Energy Sources.
RTE	Round Trip Efficiency.
SEI	Solid Electrolyte Interphase.
SOC	State Of Charge.
TSO	Transmission System Operator.
V2G	Vehicle To Grid.
VPP	Virtual Power Plant.

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1. Introduction

The global energy sector is moving from fossil fuel based to carbon-neutral power generation. The obvious reason for this "Energy transition"[1] being the adverse effect of traditional power generation mechanisms on the environment. Germany is one of the most important players in the European energy market exporting a large amount of electricity to neighbouring countries. With the deadline set to phase out nuclear energy by 2022 [1], Germany will have to rely on Renewable Energy Sources (RES) to meet its energy requirements. In 2018, 37.8% of electricity consumed by Germany was produced from RES [2]. Since the power output from RES depends on the weather conditions and the geographical location, it is neither reliable nor predictable. In order to mitigate the fluctuations in RES power output, robust, decentralized, and intermittent power sources are required. Currently most of the energy markets use traditional ancillary services to overcome imbalance on the grid [3]. An alternative solution is to use the batteries to increase the reliability of the grid [4]. Particularly using an EV battery for the grid support referred to as Vehicle-to-grid (V2G). The V2G concept has been one of the hot topics since its introduction in 1997 [5]. The main advantages of V2G is that it can be used as a storage for RES energy and as dynamic energy storage unit. This will reduce the need for dedicated storage systems to store energy generated from RES. V2G can also provide grid ancillary services like black-start capability, frequency and voltage regulation. EVs can act as a distributed source of energy reducing the transportation and maintenance cost for the Distribution System Operators (DSO). Recently V2G has gained traction again due to the decreasing cost and increasing capacity of the EV batteries. The cost of EV batteries have dropped from $1000/kWh in 2010 to $273/kWh in 2016 and the downward trend continues [6]. The capacity of the modern day EV battery is up to 100 kWh [7] and most of the EVs are not utilized for 95% of the time [8]. According to International Energy Agency, the estimated number of EVs will be 250 Million by 2030 [9]. With this vast amount of electric energy stored in EVs, it is certain that V2G will play a huge role in the future of energy markets.

1.1. Problem Statement

Though the concept of V2G was introduced in 1997, and despite its multi-functional applications, it has not been implemented worldwide. One reason is the high cost of new infrastructure required to support V2G and additional infrastructure to make it compatible with the existing grid architecture. The second reason is that the EV owners are not willing to participate in V2G as they are not fully aware of the advantages or remunerations from connecting their vehicles to the grid. Also, the owners are afraid of the battery degradation caused by V2G, in addition to battery degradation due to driving. The estimation of battery degradation is complex as it depends on many factors including temperature, previous battery degradation and amount of charge/discharge. The third reason is social anxiety and driving profile [10]. Social anxiety is the fear of discharging the EV battery due to V2G, below the battery charge required for emergency travel or unexpected travel. The availability of EV for V2G depends on the EV driving profile. If the EV uses its complete energy for driving then, there is nothing left for the V2G service.

The technical challenges hindering V2G have been extensively discussed in the literature put forth by the authors in [11], [12], and [13]. These include the infrastructure required for the grid, charging stations, EVs and the communication amongst them. As of this day, there are around 50 active V2G projects around the world [14]. On the other hand, the socio-economical feasibility study is equally important for V2G to be more than just a prototype. The literature study concerning the socio-economic feasibility can be classified into five categories.

1. Economical or the business models: Here, the roles of entities like DSO, aggregator, EV, and it's owner in V2G are defined and analyzed. The business model for V2G for different types of services like frequency regulations, spinning reserve, bulk storage are discussed in [15] [16][17][18][19][20]. In addition to that, the income from participating in V2G services is discussed in [21] and [16]. The type of services that can be offered through V2G and the corresponding remuneration schemes are proposed in this literature. The type of contracts between different entities [22] and cash flow between these entities[23] have also been discussed in such models.

2. Socio-behavioral analysis [10] [24]: Here, range anxiety and social barriers discouraging V2G services are discussed. The behavior and the driving profiles of the EV owners with different occupations and EVs are analyzed. These analyses will help in predicting the amount of penetration of EVs into the V2G market and propose ways to encourage more EV owners to participate in the V2G energy market.

3. Impact of political and geographical factors [20] [25] [22] [26] [27]: The policies formulated by the government and energy market framework are specific to regions and have a great impact on the implementation of V2G services. The policies and the market framework are strongly dependent on the geographic position, as there are various factors like climate, electricity production, and consumption, which are geographical. The policy friendliness and the geographical advantages and disadvantages are studied here.

4. Smart V2G charging and discharging [28] [29] [30] [31] [32]: The algorithms which maximize V2G profit are discussed here. The algorithms put forth smart schedules for V2G charging and discharging. These schedules are designed and developed to increase the V2G profit for all the entities involved. The scheduling algorithms are aimed to meet the requirements of the ancillary service and grid demand.

5. Battery degradation [33] [34] [35] [36] [37] [38] [39]: The V2G services affect the battery life as it involves additional charging and discharging. The battery degradation cost

and the reduction in battery life due to V2G are discussed here.

For efficient economic feasibility analysis, it is necessary to analyse V2G as a combination of all the above factors. Especially the combination of battery degradation and economic analysis. This combination is crucial as it affects the EV owner's desire to participate in the V2G market the most. The authors in [33] and [40] used a fixed battery degradation cost rate (cost/kWh) to estimate the total battery degradation cost due to V2G. Authors in [35], [34] and [39] use the number of charge and discharge cycles to estimate the battery degradation cost. The number of cycles is calculated for a fixed depth of discharge. These methods are not very precise as battery degradation depends on factors like temperature, SOC, DOD, and time of discharge. Also, the EV battery has varying DOD for every charge and discharge cycle. These methods do not give incremental battery degradation cost, which can be used to develop efficient charging and discharging schemes, that can maximize EV owner's profit and decrease battery degradation cost. The economic feasibility model should be able to predict the profit considering real-life driving patterns and electricity price signal. In order to encourage EV owners to enter the V2G market, it is necessary to create awareness of the revenue generated from V2G participation at an individual level. Economic feasibility analysis, where an aggregator decides when and how the V2G arbitrage takes place shows that an aggregator may earn profit, and EV may incur loss [41]. The EV battery may be exploited at the cost of increasing the profit for the controlling entity (like aggregator). Instead, a feasibility analysis where EV owner is completely responsible for when the V2G services take place is necessary. Ideally, a study purely driven by profit for EV owners would encourage penetration of EVs into the V2G market. The energy market policies and regulations influence the profitability of V2G. Germany being at the center of the European energy market, an economic feasibility analysis of V2G from EV owner's perspective considering the German energy policies is necessary.

Therefore, the problem at hand is to evaluate the economic feasibility of the V2G concept from EV owner's perspective considering the EV battery degradation and EV driving patterns in the German energy market.

1.2. Contributions

This thesis aims to develop a model that computes the profit earned by an EV providing V2G service in the German energy market. The following contributions accomplish this goal:

1. Analyse the different battery degradation models and select a suitable model for V2G battery degradation modelling.

2. Put forth different V2G profiles and estimate the respective battery degradation cost.

3. Create a V2G profit model that takes price signals from the German electricity market as input and evaluates profit for various V2G profiles considering battery degradation.

4. Analyse sensitivity of different factors that affect EV owner's profit.
5. Calculate the profit due to V2G as an ancillary service in the German energy market.

1.3. Assumptions

Following are the high-level assumptions which are valid throughout the thesis:

1. The technical feasibility of the V2G concept is not discussed in this work and the infrastructure required for V2G is considered available.
2. A power supply buffer is assumed to be connected to the grid for voltage and frequency regulation. If the current EV penetration is not able to handle the grid load, the power supply buffer will handle it.
3. The analysis is done purely from EV owner's perspective. The profit analysis does not consider the aggregator or any other entity in the V2G market.
4. Only the German energy market is considered for evaluation. All the prices are for the German energy market.
5. A Lithium-Ion battery of Lithium Metal oxide constitute is assumed for analysis throughout the thesis.

1.4. Document Structure

Chapter 2 describes the background knowledge required to understand the terms and the concept discussed in this work. Chapter 3 deals with the state-of-the-art technologies and the existing work related to this thesis. It also mentions the results obtained in the previous work by other researchers. Chapter 4 explains the V2G profit calculation model proposed in this work and analyzes the result obtained. Chapter 5 explains the profit calculation model for V2G ancillary services and also discusses the results obtained. Chapter 6 compares the results and observations from chapters 4 and 5 with the existing literature. Lastly, chapter 7 provides the conclusion and lists future work and improvements to this work.

2. Background

2.1. V2G Concept

The Vehicle-to-Grid concept envisions the connection of EVs with an on-board battery to the distribution grid, allowing the discharge of the battery to supply the grid and its utilities [5]. The grid will use the battery to compensate for the fluctuations in the grid. When there is a shortage of power in the grid, the EV will discharge it's energy to the grid and when there is a surplus of generation, the EV battery will charge. In the case of unidirectional V2G, EV can only charge from the grid if there is a surplus of generation and cannot discharge to the grid. The unidirectional V2G does not require many changes to the existing grid architecture [42], except for the charging algorithm, and the communication of information. In bidirectional V2G, energy can be transferred from and to the EV battery. Bidirectional V2G requires a change in the on-board EV charging subsystem, the off-board charger, grid power distribution system, communication and charging control mechanism [42]. An EV offering V2G service is paid as per the electricity market regulations for the energy transferred during V2G service. Since the capacity of a single EV is too little compared to the requirements of the electricity market, a fleet of electric vehicles connected to the grid is grouped, and it serve as a "Virtual Power Plant" (VPP)[43]. Grouping the EVs increases the capacity of the aggregator and handles the dynamic connect/disconnect of the EVs in the group. An "aggregator" acts as a middleman between the VPP and the electricity market [44]. The aggregator draws the contract with the electricity market. The EVs (owners) get paid based on their availability and the amount of energy transferred as per the contract. The architecture of the V2G service involving an aggregator is shown in figure 2.1. The aggregator at any point of time should know the capacity of all the EVs connected and also track their connect and disconnect timings. This will help the aggregator to draw an efficient contract with the electricity market. The energy utilization of the aggregator can be further optimized by implementing smart scheduling similar to the implementation in [45].

The following are the basic terminologies involved in V2G:

1. Distribution System Operator (DSO): Entity responsible for distributing power (low and medium voltage) to the household or buildings from the TSO.

2. Transmission System Operator (TSO): Entity responsible for transporting high voltage power from power generators to DSOs.

3. Grid: Network through which electric power flows. The network connects electricity producers and consumers.

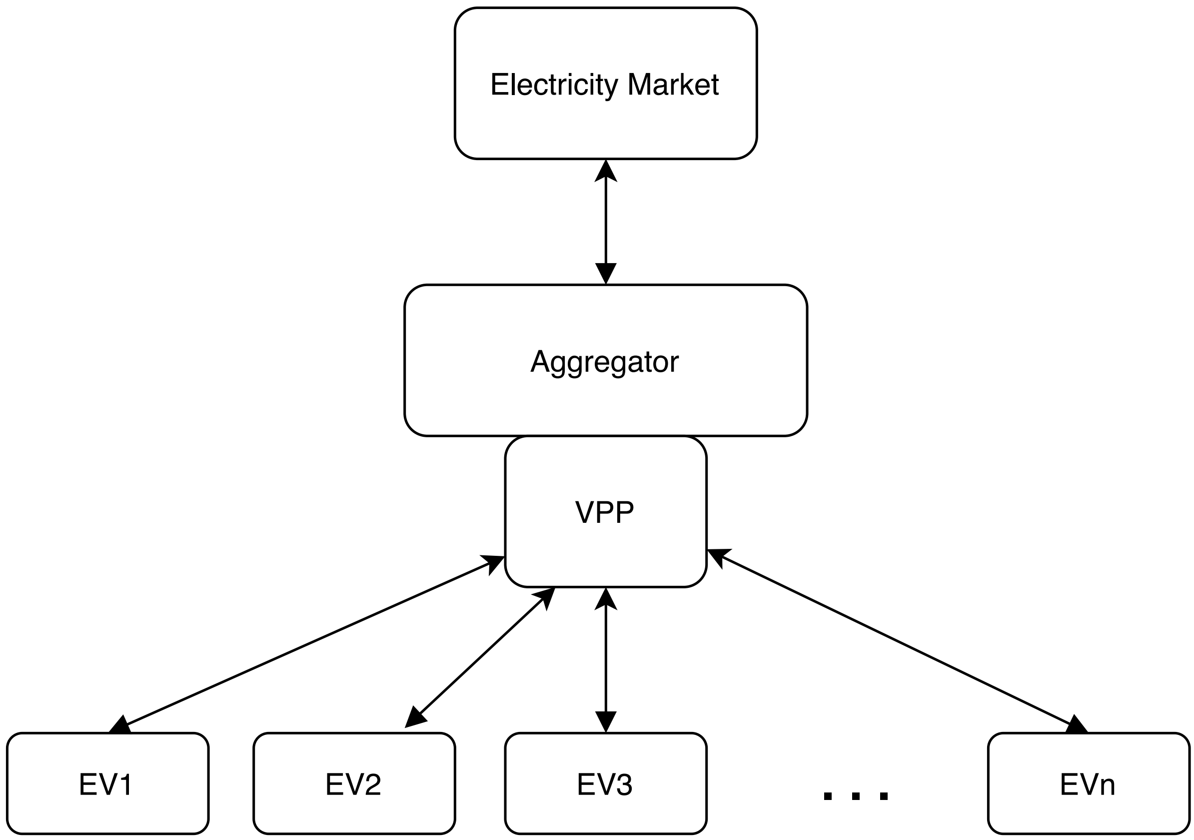


Figure (2.1) Architecture of V2G service with multiple EVS. [44]

4. Unidirectional charging: The flow of electricity is only in one direction. The electric energy flows from the charger to the battery.
5. Bidirectional charging: The flow of electricity is bidirectional. The EV can charge from the grid and also discharge to the grid.
6. Distributed energy generation: The power is generated at the point of consumption.
7. Dynamic pricing: The price of electricity is not fixed and keeps changing according to the demand.

2.2. Ancillary Services

An electric grid balances the supply and demand of the grid. The electric grid is said to be balanced if the frequency of the grid is constant. In Germany, this frequency is 50Hz [15]. Whenever the frequency deviates, frequency regulation is required to stabilize it. Along with the frequency, the voltage of the electric supply must be maintained constant for the loads to work as expected. These two mechanisms are called "frequency regulation" and "voltage regulation" respectively. In some cases, when voltage and frequency deviate from their limits and the regulation operation cannot control it, the grid has to be shutdown. In case of power failure, the whole grid must be restarted and this process is called "system restoration". For frequency regulation and voltage control the grid relies on power generators and remunerates them for their services. These services are called ancillary services and the entities who provide the service are called ancillary service providers. These service providers are activated only when the frequency or the voltage of the grid deviates from the standard value. Figure 2.2 shows the different ancillary services accepted by modern-day electric grids. There are further classification in voltage control and system restoration ancillary service, but those are not discussed here as it is not in the scope of this thesis.

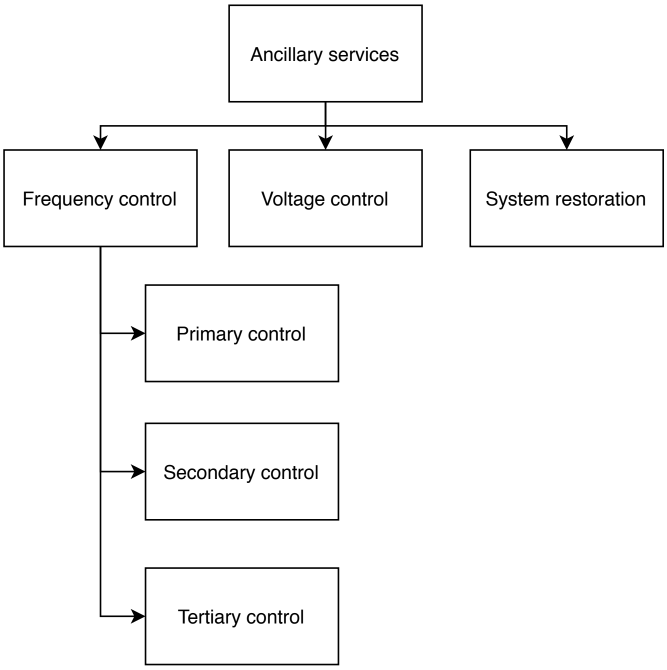


Figure (2.2) Classification of ancillary services in electricity market [18]

2.2.1. German Energy Market For Frequency Regulation

The German energy market allows three different frequency regulation services namely, primary, secondary and tertiary frequency control services as shown in figure 2.2. These three different frequency regulation services mainly differ based on the time within which these react to the frequency deviation. The primary, secondary and tertiary frequency regulation services in the German energy market are referred to as Frequency Containment Reserve (FCR), Automatic activation Frequency Restoration Reserve (aFRR) and Manual activation Frequency Restoration Reserve (mFRR), respectively. The name of these services come from the aim of the service and type of activation. The goal of FCR is to contain the grid frequency in the acceptable range as per the grid requirements. The Secondary control is referred to as aFRR, as it is activated automatically whenever the frequency of the grid is to be restored. The tertiary control reserve is referred to as mFRR, as it is activated manually. Any ancillary provider who can meet the requirements of the energy market must pre-qualify as per the prequalification process on the pq-portal [46]. Only the pre-qualified ancillary providers are eligible to offer ancillary services. In order to provide service, the ancillary service providers participate in an online auction on the www.regelleistung.net bidding platform [47]. Each service provider can place their bids for each of the services separately. The service providers get paid in two parts: one is capacity payment and the other is energy payment [17]. Capacity payment is the remuneration to the service provider for being available to provide the service. The capacity payment is paid even though the ancillary service is unused. Energy payment is paid for the exact amount of energy transferred to the grid. The capacity and energy payment differ for the type of frequency regulation. Germany follows the "pay as bid" rule for both capacity and energy payment [48]. This means all the participants whose bids are accepted are paid based on the individual bid and not the marginal price or common price. An ancillary service bid consists of three essential components such as power offer, power bid and energy bid [49]. Power offer is the capacity which the service provider promises to provide to the grid in terms of MW. Power bid is the capacity payment that the service provider would like to receive if the service provider wins the bid. The power bid is expressed in terms of €/MW. Energy bid is the energy payment the service provider would like to receive for the amount of energy transferred. The energy bid is expressed in terms of €/MWh. Table 2.1 shows the difference between the three frequency regulation services. The bid selection procedure is based on the power bid. The power bids from all the participants are arranged in increasing order of the capacity payment. The service providers are selected in the order from the lowest bid until the demand is met. All the selected service providers may not be activated. The service providers are activated only when there is a deviation in the frequency of the grid. The service provider is called or activated based on the energy bid. The service provider with the lowest energy bid is selected first. There is a possibility that a service provider is selected in the auction but never used. In such a case, they only receive the capacity payment. The German TSO forecasts the FCR, aFRR and mFRR demands and the bids are accepted based on the forecasted demands. In real-time operation, whenever grid frequency deviates from 50 Hz, the primary control reserves are activated first. The power injected or absorbed by the primary control is proportional to the deviation of the frequency. The primary control reserve provides positive frequency control (up-regulation) when the frequency of the grid is lower than 50 Hz and provides negative frequency control (down-regulation) when the frequency is above 50 Hz. If the primary control reserves do not restore the frequency, the secondary control reserves are automatically activated. If the frequency is still not restored, tertiary control reserves are requested to activate. Based on the request, the tertiary control reserves try to bring the frequency back to 50 Hz. All the control reserves have to adhere to the timings mentioned in table 2.1 by the German frequency regulation market.

2.3. Battery Terminology And Battery Degradation Basics

Electric batteries are used to store electric energy. Different types of batteries are available based on their chemical composition. Most popular batteries used in Electric vehicles are

Parameter	**Primary control reserve**	**Secondary control reserve**	**Tertiary control reserve**
Auction time	Daily	Daily	Daily
Offer period	One day	6 periods of 4 hours each (0-4am, ..., 8-12pm)	6 periods of 4 hours each (0-4am, ..., 8-12pm)
Min. offer capacity	1 MW	+/- 5 MW	+/- 5MW
Pooling of capacity	Possible	Possible	Possible
Separate Bidding for both Positive and Negative reserve	No	Yes	Yes
Payment type	Capacity payment only	Capacity and energy payment	Capacity and energy payment
Bid selection	Power bid	Power bid	Power bid
Calling of Reserve or activation	Proportional to frequency	Lowest energy bid	Lowest energy bid
Remuneration type	Pay-as-bid	Pay-as-bid	Pay-as-bid
Maximum ramp time	15 seconds	5 minutes	15 minutes
Active time	15 minutes	60 minutes	60 minutes

Table (2.1) Comparison between FCR, aFRR and mFRR services in the German energy market [50] [51] [47] lithium-ion based. In order to understand the battery specifications, it is important to know the following basic battery terminologies:

1. Battery capacity: The maximum amount of energy that can be stored in the battery. It is expressed in terms of kWh.
2. State of Charge (SOC): This indicates the amount of energy remaining in the battery. It is the ratio of available battery energy to the battery capacity. It is expressed in percentage.
3. Depth Of Discharge (DOD): Percentage of energy taken out of the battery or put inside the battery. The first case is charging and the latter is discharging. The DOD is calculated as per the equation (2.1). 30% DOD during a discharge operation implies 30% of the charge was removed from the battery. Sometimes, this is also referred to as Δ SOC.

$$\mathrm{DOD} = |\mathrm{SOC}(\mathrm{t_{end}}) - \mathrm{SOC}(\mathrm{t_{start}})| \tag{2.1}$$

   Where:
   $SOC(t_{start})$: SOC in % at the starting of the charge or discharge event.
   $SOC(t_{end})$: SOC in % at the end of the charge or discharge event.

4. Round Trip Efficiency (RTE): Denotes the share of energy that can be successfully stored into or retrieved back from the battery. RTE is the product of charge efficiency and discharge efficiency. Charge efficiency is the ratio of the charge stored in the battery to the amount of energy consumed to charge the battery. Discharge efficiency is the ratio of the amount of energy that can actually be used to the energy stored in the battery. The efficiency is expressed in terms of percentage and indicates the amount of energy lost due to the internal impedance of the battery.
5. C-rate: Denotes the rate at which the charge and discharge takes place. A C-rate of 2C means that the fully charged battery is discharged in 0.5 hours. C-rate of 1C means that the fully charged battery is discharged in 1 hour.
6. SOC profile: Graph with battery SOC on y-axis and time on the x-axis. Denotes the usage of the battery and also charge and discharge events.

As the battery gets used, it undergoes degradation and loses its capacity. The losses can be reversible or irreversible. The reversible loss is referred to as self-discharge [52]. Those losses are recovered when the battery is fully charged again. On the other hand, degradation is an irreversible loss. The battery degradation is quantified in terms of capacity fade and power fade. Capacity fade is the decrease in the battery's capacity. Power fade is the increase in the internal impedance of the battery, resulting in a decrease in battery efficiency [53]. The capacity and power fade occur due to the chemical composition of the battery and internal reactions. The battery degradation occurs due to two aging mechanisms, calendar aging (when a battery is idle) and cycle aging (when a battery is in use). The degradation of lithium-ion battery is caused due to the formation of Solid Electrolyte Interphase (SEI), lithium plating, mechanical stress, transition metal dissolution, electrolyte decomposition and corrosion of current collectors [54]. These degradation mechanisms are sensitive to battery temperature, SOC, DOD, and C-rate [55]. The influence of these factors on the degradation mechanisms are complex to model. Hence, it is very difficult to estimate the amount of battery degradation. The battery degradation is not linear and follows nonlinear behaviour. As the number of charge and discharge cycles increases, the rate of battery degradation changes. Hence, the battery degradation estimation should include the battery's past usage in order to reflect the nonlinear behaviour. Different EV manufacturers use batteries with different chemical compositions. The battery degradation in each of these batteries is different from each other. It is not possible to have a general battery degradation model that can represent all the battery types. Few popular battery chemistries are explained below along with their unique characteristics [55].

1. NCA (Nickle Cobalt Aluminum): Best calendar life retainment and high specific capacity. Low sensitivity to high temperature and high SOC. Exhibits very less capacity fade. The temperature effect is dominant over the SOC effect. Highly prone to thermal runaway and is costly compared to other technologies.

2. LPF (Lithium Iron Phosphate): High sensitivity to temperature and lower sensitivity to SOC. The temperature effect dominates the SOC effect. This battery is least prone to thermal runaway and it exhibits less specific capacity.

3. NMC (Nickel Cobalt Manganese): High temperature sensitivity and variable SOC sensitivity. For some range of temperature and SOC, both the effects overlap and it is hard to determine which one causes the degradation. This battery chemistry provides the second best thermal runaway protection.

4. LMO (Lithium Manganese Oxide): High sensitivity to both temperature and SOC. Exhibits relatively less specific capacity compared to NMC and NCA. Exhibits the second best thermal runaway characteristics.

3. Related Work

3.1. Battery Degradation Modelling

The battery degradation model is used to predict the remaining life of the battery. The battery degradation depends on the temperature, SOC, DOD, C-rate, number of charge/discharge cycles, the capacity of the battery and the previous battery degradation [56]. Temperature, SOC, DOD and C-rate are called stress factors [55] as they directly affect the amount of degradation. Other factors like the number of charge/discharge cycles, time and previous degradation are dependent on battery usage. The modelling aims to find the mathematical relation between the amount of battery degradation and these parameters. Based on the modelling approach, the models are classified as [57]: electrochemical models, which are based on the theory of chemical reactions; empirical models, based on experimental data; and semi-empirical, a combination of both. Due to the complexity of electrochemical models, only the empirical and semi-empirical models are considered in the literature study. The empirical and semi-empirical models usually opt for accelerated life tests to analyse and model the battery degradation. Though this technique speeds up the modelling process, accelerated tests cannot represent a real-life environment. Hence, the models will either over or under predict the battery life [56]. The models use curve fitting techniques to fit the experimental data into empirical relations. The accuracy of these models depends on the amount of data collected and the range of parameters covered by test cases. An ideal battery degradation model should predict battery degradation both due to the calendar and cycle aging additive and independently. The model's input parameters should be the number of charge/discharge cycle, SOC, temperature, C-rate, DOD, time, and the battery capacity, without any range limitation. The model should be able to predict the remaining life of the battery, even for online diagnostics. The available battery degradation models have time resolution limitations, data limitations, the definition of the cycle, frequency limitation, and chemistry specificity [55]. Since the battery degradation is chemistry-specific, it is not possible to easily extend it to another battery type. Even the results of the models for the same battery type differ due to the varying test setup and assumptions made during the experiments. Considering these factors, the available battery degradation models are compared in table 3.1.

It is difficult to choose the best battery degradation model as each one has its advantages and disadvantages. The first thing to look for is the battery type and then the coverage of the model. For example, the Dubbary model considers low temperatures upto -27 degree Celsius, whereas, Uddin model considers temperatures upto 10 degree Celsius for the same battery type of NMC. Hence for low temperature application Dubbary model would be the obvious choice. The choice for this thesis would be a model based on the battery type commonly used in the EVs. A model that can easily be used independently to calculate the calendar aging and cycle aging in steps for different EV states in a day. Only the selection of a battery degradation model that suits EV vehicle application falls into the scope of this thesis. Hence, the battery models are not compared based on their mathematical equations and relations.

Source	**Calendar aging params**	**Cycle aging params**	**Capacity fade, Power fade**	**Battery type**	**Online estimation**	**Findings**
Wang Model [58]	Time, T (Temperature)	C-rate,T, Capacity, throughput	Yes, No	NMC-LMO	Yes	SOC is not considered for calendar aging. DOD is not considered for Cycle aging. Low temperature analysis is missing.
NREL Model [59]	SOC, Time, T	SOC, DOD, C-rate, T	Yes, Yes	NMC	Not clear	The complete model is licensed. Covers high and low temperature dependency. Accommodates varying C-rate.
Millner Model [60]	No	SOC, DOD, T	Yes, No	LFP	Yes	C-rate dependency omitted. The model is based on theoretical crack propagation theory.

Table 3.1 continued from previous page

Source	**Calendar aging params**	**Cycle aging params**	**Capacity fade, Power fade**	**Battery type**	**Online estimation**	**Findings**
Uddin model [61]	SOC, Time, T	SOC, DOD, C-rate, T	Yes, Yes	NCA	Not clear	Equations are not given, only the results of the experiments are discussed. Battery life can be extended by discharging to lower SOC at high temperatures than, maintaining high SOC at high temperature.
Dubbary model [62]	SOC, Time, T	SOC, DOD, C-rate, T	Yes, Yes	NCA	Not clear	Equations are too complex to model. The curve coefficients change depending on the parameters. Hence the model works for discrete values of the parameters.
Fernandez model [63]	DOD, T, Time	Not clear	Yes, No	Li-Polymer	Not clear	There is no differentiation between calendar and cycle loss.
Redondo model [64]	SOC, Time, T	No	No, Yes	NMC, LFP	No	The focus of the paper is to analyse the power fade or efficiency.
Schmalstieg model [65]	SOC, Time, T	SOC, DOD, Capacity through-put.	Yes, No	NMC	Yes	C-rate omitted.

Table 3.1 continued from previous page

Source	Calendar aging params	Cycle aging params	Capacity fade, Power fade	Battery type	Online estimation	Findings
Wright Model [66]	SOC, Time, T	T, SOC, DOD	No, Yes	Not clear	No	The focus of the paper is to model resistance which will in turn indicate the power fade.
Xu Model [67]	SOC, Time, T	SOC, DOD, T	Yes, No	LMO	Yes	The model isolates calendar and cycle aging. It can be used to predict degradation for a specific EV state. It can be used for online battery degradation estimation.
Ecker Model [68]	SOC, Time, T	No	Yes, No	NMC	No	Cycle aging is omitted completely.
Petit Model [69]	SOC, Time, T	C-rate, T	Yes, No	NCA, LFP	Yes	DOD is not consider for Cycle aging.

Table (3.1) Comparison between existing battery degradation models.

3.2. Economic Feasibility Analysis

The first economic feasibility study on V2G was done by [5]. The analysis compared V2G against load control, commercial demand charges, and utility avoided costs. The study found, V2G provides five times more power per equipment dollar than direct load control, V2G is 50% cheaper than commercial demand charges, V2G is cheaper than most available avoided costs (in 1997 in the USA). A lot of feasibility studies very specific to use cases are done after that. The profitability of V2G can be accounted for in different ways, of which one is the monetary profit earned by selling electricity to the grid [33] [40]. Second, is the saving in terms of charging cost when compared to no V2G [29]. Third, the saving in terms of improving battery life by participating in V2G [61] . Fourth, is by participating in V2G ancillary service, where the EV offers services based on the contract with the energy market. The first and fourth cases look similar; however, in the first case, the energy market regulations are not considered and the energy transfer is optimized via smart scheduling algorithms to maximize profit. In the fourth case, the energy transfer is regulated by the energy market and the payments are done based on the pre-agreed contracts. The fourth case also involves grid to vehicle energy transfer as a part of the service. Authors in [33] investigated the monetary profit as mentioned in the first case by simulating grid demand for 2011 and 2012. A Tesla model 70D 70kWh battery with RTE 80% was considered with V2G availability from 0800 hours to 1700 hours and a daily driving distance of 32 miles. The grid demand for 2011 resulted in a V2G transfer for 58 hours. For calculating the monetary profit, a fixed night charging cost of 5.95 cents/kWh and during the day, real-time dynamic pricing from ERCOT RTM was considered. The degradation cost was set to 10.42 cents/kWh. The simulation estimated a profit of $338.56 for 2011 and $39.24 for 2012. Though the simulation parameters are the same, the profit values are different as the grid demand was different for the years 2011 and 2012. The authors in [40] estimated the monetary profit by simulating dynamic pricing from PJM, NYISO, and ISO-NE (three different cities) for 2008. An EV with 16 kWh LPF battery with RTE 85% and V2G availability from 1700 to 0700 hours (at home) was considered. The degradation cost was set to 4.2 cents/kWh. The equations (3.1) and (3.2) are used to calculate the profit.

$$\text{Profit}[40] = ((\text{LMP}_{\text{SELL}} + \text{T\_D}) * \text{DCH}_{\text{eff}} - (\frac{\text{LMP}_{\text{BUY}} + \text{T\_D}}{\text{CH}_{\text{eff}}})) * \text{kWh}_{\text{Trans}} - \text{Cost}_{\text{Degradation}} \tag{3.1}$$

$$\text{Cost}_{\text{Degradation}}[40] = \frac{\text{ReplacementCost} * \text{DOD}}{(0.8 - 1)} * \text{V2G\_deg\_coefficient} \tag{3.2}$$

Where:
LMP_{SELL} and LMP_{BUY}: selling and buying price of the electricity.
T_D: Transportation and distribution cost.
CH_eff and DCH_eff: Battery charge and discharge efficiency.
kWh_{Trans}: Energy transferred.
DOD: Depth of discharge. Percentage of battery used.
$V2G\_deg\_coefficient$: The battery degradation coefficient when the EV participates in V2G service. This coefficient is negative to indicate a loss in battery life.

A smart charging algorithm which discharges to the grid during the most expensive LMP (Locational Marginal Price) hour and recharges during the cheapest LMP hour was used. The algorithm assumed that the price signals are available before the simulation. A profit of $142–$249 was estimated without considering battery degradation and a profit of $12–$118 was estimated with battery degradation. The difference in profit values with and without battery degradation shows its effect on the V2G services. In [29] the authors estimated the profit due to V2G services in terms of the charging cost. The simulation assumed 5000 EVs at different starting SOCs and different limits for minimum and maximum SOC values to which the battery can be discharged or charged respectively. The EVs were assumed to be available on average around 9 hours, and each had a different driving duration. The electricity price signal from 12 Nov 2013 was assumed for all the days of simulation. A smart charging algorithm was developed that charges the EV when the buying price is below 60% of the maximum buying price for the day and discharges to the grid when the selling price is more than 80% of the maximum selling price for the day. The algorithm also takes care of the charging and discharging limits and availability of each EV. The saving in cost due to V2G is calculated as per the equation (3.3).

$$\text{Saving [29]} = \mathrm{P_{without}} - \mathrm{P_{with}} - \left(\frac{\mathrm{C} * \bar{\mathrm{P}}_{\mathrm{buy}}}{100} * \sum_{\mathrm{i}=1}^{\mathrm{N}}(\mathrm{SOC\_final_{EV_i,without}} - \mathrm{SOC\_final_{EV_i,with}})\right) \tag{3.3}$$

Where:
Saving: Amount of saving at the end of the simulation made by all of the EVs participating in V2G in comparison to no V2G .
$P_{without}$: Cost of charging EVs without V2G.
P_{with}: Cost of charging EVs in the with V2G after subtracting the amount of money they earn as a result of selling electricity back to the grid.
$\bar{P}_{buy}$: The average buying price of electricity during the simulation in £/kWh.
$SOC\_final_{EV_i,without}$: SOC of the ith EV at the end of the simulation in percentage without V2G.
$SOC\_final_{EV_i,with}$: SOC of the ith EV at the end of the simulation in percentage with V2G.
C: Nominal capacity of each EV in kWh.
N: Number of EVs considered for the simulation.
On simulation for five days, the EVs saved 13.6% on charging cost, which is £1799.77 for 5000 EVs. The authors in [61] estimated the saving from extending the battery life by providing V2G service. This is based on the theory that storing battery at higher SOC causes more degradation than discharging it to a lower SOC and storing it at lower SOC. The authors conducted experiments with 46 EVs with battery capacity 30kWh of type NCA. The vehicles were available for V2G from 0830 hours to 1700 hours. The smart charging algorithm was used to schedule the discharging so that the discharge event only occurs if it improves battery life. The results show that battery life is extended, and a saving of $555 per vehicle per year is achieved. This saving is only because of the extension of the battery life and not the revenue earned by selling (discharging) to the grid. All the economic feasibility analysis discussed till here are compared in table 3.2.

The choice of battery degradation model is very crucial as it depends even on the experimental procedure and test setup used to model. Authors in [62] (Dubbary model) and [61] (Uddin model) studied the impact of V2G on battery life. Uddin model used 3000mAh NCA battery and Dubbary model used a 3350 mAh NCA battery. Though the batteries are of the same type, the experiment's results were different because of the difference in the experimental procedure, test setup, and different V2G charging and discharging algorithms. Uddin model showed that the life of the battery could be extended with V2G service whereas, Dubbary model concluded that V2G service could reduce the battery life. The battery degradation is one of the most important factors in economic feasibility analysis and this can be seen in the results discussed earlier from [40]. The existing works discussed in this section, either neglect the battery degradation cost or consider a fixed cost. Since battery degradation depends on the usage and the state of the EV, an online model is necessary for an accurate estimation. The algorithms used to schedule V2G services except in the Uddin model are driven by the price signal and neglect battery degradation. Such an approach may exploit the battery at the cost of increasing the profit. An approach that gives equal emphasis on both the price signal and battery degradation is ideal.

The other important factor which influences V2G profit is the energy market. Because of different grid demand, each of the energy markets have different buying and selling prices. The different remuneration schemes in the energy markets result in different profit values. The authors in [21] did the V2G economic feasibility analysis for the German energy market, assuming 13% EV penetration (at the time approximately 5.5 million EVs). They estimated the break-even battery degradation cost of 0.059 EUR/kWh. Implying, if the battery degradation cost increases above 0.059 EUR/kWh, the V2G will no longer be profitable. With battery costs of 0.0475 EUR/kWh and 0.02375 EUR/kWh, fleet owners can earn upto 3.2 million and 10.6 million Euro monthly profit, respectively (with 13% EV penetration). The profit estimations of these analyses cannot be compared with others directly because the profit depends on several factors like energy policy, EV battery, driving profile, weather, battery capacity, battery chemistry and others. Though an agnostic economic V2G profit model is ideal, in reality it is complex and will result in either over or underestimation due to dependency on several variables. The more specific the assumptions are regarding these factors, the more realistic the profit values will be. Since the profit depends on the price signal in the corresponding energy market, it is necessary to consider the real-life price signals to get more accurate profit values.

3.3. Frequency Control Ancillary Service

The modern frequency control ancillary services are classified into primary, secondary and tertiary frequency regulation services, but it started as a single frequency regulation service. Authors in [17] studied the economic benefits of frequency regulation service along with the voltage regulation service. The authors considered a RAV4 EV with power capacity 15kW in their simulation. The simulation assumed capacity payment of 0.04 $/kW, energy payment of 0.10 $/kWh for a plugin duration of 6570 hours (18h per day) per year. Equation (3.4) was used to calculate the revenue.

$$\text{revenue [17]} = \mathrm{p_{cap}} * \mathrm{P} * \mathrm{t_{plug}} + \mathrm{p_{el}} * \mathrm{R_{d-c}} * P * t_{plug} \tag{3.4}$$

Where:
p_{cap}: Capacity payment in \$/kW
P: Capacity offered by the electric vehicle in kW
t_{plug}: Time duration for which the vehicle was available for the service in hours

p_{el}: Energy payment in \$/kWh
R_{d-c}: Dispatch ratio, the ratio of energy transferred to energy contracted by the EV, which is assumed to be 10%.
The cost is the sum of battery degradation cost, charging cost, annual capital cost and other infrastructural costs. A cost of \$2374 was estimated with battery degradation of 0.075 \$/kWh and round trip efficiency of 73%. The simulation estimated revenue of \$4928 and a cost of \$2374 with battery degradation of 0.075 \$/kWh and round trip efficiency of 0.73. The net profit earned by a single RAV4 EV was \$2554 per year. Though the equations from [17] can be used for both frequency regulation up and down separately, it cannot calculate both simultaneously. Authors in [70] came up with a single equation (3.5) to calculate both up and down regulations and develop an algorithm to maximize profit.

$$\text{profit [70]} = \sum_{j=1}^{24} P_l * R_{cj} * X_{2j} + E * P_i * \frac{(R_{uj} + R_{dj})}{2} * X_{2j} - P_v * R_{sj} * X_{1j} \tag{3.5}$$

Where:
j: index of time intervals. Hourly optimization, j = 1, 2, . . . , 24.
X_{1j}: 1, if BEV is charging at time interval j, 0 otherwise
P_v : Power of vehicle in kW
R_{cj} : Regulation capacity price at the time interval j in \$/ kW-h
P_l : Power of line in kW
R_{uj} : Regulation up price at the time interval j in \$/kWh
R_{dj}: Regulation down price at the time interval j in \$/kWh
R_{sj}: Electricity selling price at the time interval j in \$/kWh
E : Dispatch ratio

The first term in equation (3.5) is the capacity payment, the second term is the energy payment, and the third term is the charging cost. The second term has a division factor of two because the authors assumed the up and down regulation to be symmetrical. The simulation assumed a fixed driving pattern of 20 miles a day for a 24 kWh Nissan leaf. A power of 7.2 kW was assumed to be available for the ancillary service for 16 hours a day. The calculation also assumed a 10% dispatch ratio and estimated revenue of \$454.26 and a charging cost of \$266.58, resulting in a profit of \$187.68. The authors used the equation (3.5) as the objective function to maximize the profit. The estimated profit due to the frequency regulation service depends on the dispatch ratio, which is the ratio of actual energy provided by the EV as a part of V2G service to the contracted energy. The dispatch ratio indicates how often EV shall provide service to the grid. In reality, this cannot be quantified because the dispatch of regulation service depends on the frequency of the grid, which is not accurately predictable. The authors in [17] and [70] set the dispatch ratio as 10% for calculating the profit. The literature discussed above considers a general frequency regulation scheme, but the frequency regulation ancillary service is classified into primary, secondary, and tertiary services that follow different remuneration schemes. The authors in [26] estimated the profit of EV participating in the Italian energy market for primary and secondary frequency regulation schemes.

The revenue for primary frequency regulation was calculated as the product of capacity payment (€/MW), power offer (in MW), and availability. The availability for the service depends on the plugin duration and also the SOC limits for charging and discharging. The limits for SOC were set to as 25%< SOC <75%. The charging-discharging algorithm assumed the EV could only discharge (regulation up) to grid only when its SOC is greater than 75% and can discharge until 25%. Similarly, the EV can charge from the grid (regulation down) when the SOC is above 25% and can charge upto 75%. The limits are set to accommodate for immediate change from regulation up to regulation down or vice versa. The revenue for secondary frequency regulation was calculated as per the equations (3.6) and (3.7).

$$\mathrm{REM_{upres}}\ [26] = (\mathrm{AP_{upres}} - \mathrm{PUN}) * \mathrm{E_{upper}} \tag{3.6}$$

$$\mathrm{REM_{downres}}\ [26] = (\mathrm{AP_{downres}} - \mathrm{PUN}) * \mathrm{E_{down}} \tag{3.7}$$

Where:
AP_{upres}: Average price for the upward reserve in €/MWh for 2016.
PUN: Prezzo Unico Nazionale (PUN) equals to 50 €/MWh.
E_{upper}: Energy discharged to the grid in MWh.
$AP_{downres}$: Average price for the downward reserve in €/MWh for 2016.
E_{down}: Energy charged from the grid in MWh.

A fixed price was considered for both the primary and secondary frequency regulation schemes by the authors. The results of the simulation for primary and secondary regulations are compared in table 3.3. There is a huge difference in the remuneration scheme in the Italian energy market and the German energy market. In order to calculate the profitability in the German energy market it is important to consider the German ancillary service remuneration scheme. Authors in [71] calculated the revenue for secondary frequency regulation services in Germany. The simulation assumed a group of vehicles offering service via an aggregator. The revenue earned by each car in the group is given by equation (3.8). A profit of €8-108 was estimated.

$$\mathrm{R_i}\ [71] = \frac{\mathrm{t_{offer,i}}}{\mathrm{t_{total}}} * \mathrm{p_{res}} * \mathrm{P_{Total}} + \sum_{t=0}^{T}\left(\left(\frac{\Delta \mathrm{t_t}}{60\mathrm{min/h}}\right) * (\mathrm{p_{Act,t}} - \mathrm{p_{Ref,t}}) * \mathrm{P_{Act,i,t}}\right) \tag{3.8}$$

Where:
t_{offer}: Duration for which the vehicle offered the service.
t_{total}: Duration for which the aggregator offered the reserve.
p_{res}: Reservation price in €/kW.
P_{Total}: Contracted power in kW.
p_{Act}, p_{Ref}: Activation price and reference price in €/kWh.
$P_{Act,t}$: Power by which the car is activated by the aggregator, both in kW, t is the respective time step.
Δt: the duration of time step t in minutes.

Though the existing work gives a fair idea of calculating the profit generated by ancillary services, an ideal profit calculation would consider real-time pricing signal and battery degradation cost. Since the pricing scheme of the energy markets has been revised over the years, it is necessary to calculate the profit with the new regulations.

Source /Year /Country /model type	Driving pattern and V2G availability	EV specific characteristics	Battery degradation	Pricing scheme	Profit
[33] /2011 /USA /simulation	V2G availability: 8AM to 5 PM. Driving distance per day: 32 miles	Tesla Model 70D 70kWh battery. RTE: 80%	10.42 cents/kWh	Fixed night charging cost 5.95 cents/kWh. Dynamic pricing during day from ERCOT RTM.	$338.56/ EV/year
[40] /2008 /USA /simulation	V2G availability: 5PM to 7AM.	16kWh. LPF battery. RTE: 85%	4.2 cents/kWh	Considers dynamic pricing from PJM, NYISO, and ISO-NE for 2008	With out battery degradation: $140 - $250/ EV/year With battery degradation: $10-$120/EV/year
[29]/2013 /UK /simulation	V2G availability: 9 Hours. Driving duration per day:10 - 90 minutes	60 kWh. RTE: 100%	No	Electricity price signal on 12 Nov 2013 is considered for all simulation days.	13.6% (£1799.77/5000EVs/5 days) saving in charging cost with V2G when compared to without V2G case.
[61] /2016 /UK /Experimental	V2G availability: 9 Hours	30 kWh. NCA battery	Based on actual degradation from the experiment.	UK energy pricing	$555/EV/year saving from improvement in battery life and not from selling electricity to the grid.

Table (3.2) Comparison between existing V2G arbitrage economic models.

	Office employee	Transportation of waste	Deliveries
Battery capacity (kWh)	38	44	44
Availability (%)	62	62	42
Profit primary control (€/EV/Year)	1027	1141	126
Profit secondary control (€/EV/Year)	2051	2457	900

Table (3.3) Simulation results for Ancillary services in Italian energy market [26].

Source	Country/Year	Type of Service	Type of remuneration	Remuneration
[17]	USA 2003	General frequency regulation	Capacity and energy	$2554/EV/Year
[70]	USA 2013	General frequency regulation	Capacity and energy	$187.68/EV/Year
[72]	France 2013	Primary frequency regulation	Capacity and energy	€193-593/EV/Year
[26]	Italy 2016	Primary frequency regulation	Capacity and energy	€1653.9/EV/year
[26]	Italy 2016	Secondary frequency regulation	Energy	€2642.2/EV/year
[71]	Germany 2013	Secondary frequency regulation	Capacity and energy	€8-180/EV/year
[73]	Netherlands 2017	Secondary frequency regulation	Energy	€120-750/EV/year
[74]	Ecuador 2019	Secondary frequency regulation	Capacity and energy	$319.8/ Aggregator (1000 EVs)/ day

Table (3.4) Comparison of existing frequency regulation ancillary service economic study.

4. V2G Profit

The V2G profit calculation depends on the type of service the EV provides to the grid. When an EV provides an ancillary service, the service depends on the state of the grid like the frequency and voltage. Since the state of the grid controls the amount of energy transfer, the EV cannot be used to its full potential therefore the profit is limited. To evaluate the maximum profit earned by the V2G service, a scenario where an EV can freely participate in the V2G energy arbitrage without considering the state of the grid has to be computed. Here, the EV could discharge excess energy stored in the battery to the grid or charge itself from the grid whenever necessary. The unconstrained participation of the EV in the V2G service helps in understanding the profit, the amount of battery degradation and the energy transferred to the grid. This chapter discusses how these three factors can be quantified and evaluated. This chapter is divided into three sections: methodology, implementation and, result and analysis. The methodology section explains the basic principles used to calculate profit, battery degradation and the amount of energy transferred to the grid. The implementation section discusses how the methodology is implemented. The results of the implementation are discussed and analysed in the last section.

4.1. Methodology

The method used to evaluate the V2G profit takes into account price signals from the German energy market, a fixed driving profile, and a battery degradation model to estimate degradation cost. The block diagram in figure 4.1 visualizes the proposed profit model in this work. The tasks of each block at a high-level is described below.

1. Price signal model: Selects and models the price signal.
2. Driving pattern and V2G profile model: Selects the EV driving profile based on the assumption of driving distance, charging and mobility. It generates the possible V2G profile based on the driving pattern.
3. Battery degradation model: Estimates the battery degradation cost for the selected V2G profile.
4. Profit calculator: Formulates the equations to calculate the profit and evaluates the maximum profit.

Each of these blocks are explained in detail in the following subsections.

4.1.1. Price Signal Model

Electricity prices vary with respect to the energy market and the grid demand. To estimate the profit, the price signal from the past or the real-time price signal or the predicted price for the future can be considered. In this work, the past price signals are considered. However, the real-time price signals from the respective energy market or the predicted electricity prices as depicted by the authors in [75] can also be used. Since the target market for this work is Germany, the price signals from the German day-ahead market are considered. Germany does not have dual tariff prices yet, hence it is assumed that the selling and buying price of electricity is the same at any instant to simulate the dual tariff. The price signal for the year 2019 (from 01-January-2019 to 31-December-2019) is considered and this price signal will be the input to the profit calculator.

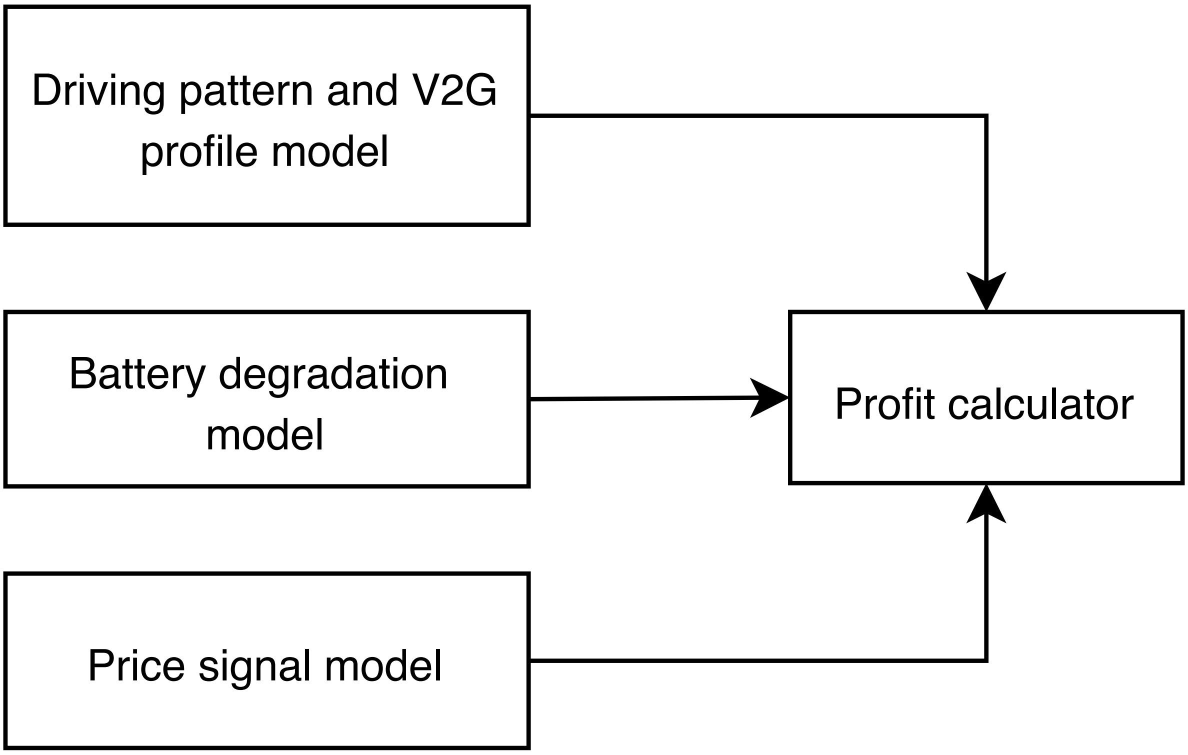


Figure (4.1) Block diagram of V2G profit Model.

4.1.2. EV Driving Pattern

The driving pattern of an EV is unpredictable. Emergencies or unexpected plans always trigger the usage of EV beyond the usual routine. The usual routine of an EV depends on the owner's job and their interest. It is difficult to generalize the driving pattern; However, a predictable driving behaviour is observed in EV owners, who work at an office location five days a week. The EV is fully charged at night, and the vehicle is driven from home to the office in the morning. The vehicle is parked at the office till the evening, driven back home, and charged again at night. The driving pattern chosen for this model is similar to the one put forth by authors in [76] and it is shown in figure 4.2. The EV is charged from 2300 hours to 0700 hours at home, driven to the office for an hour, parked in the office from 0800 hours to 1700 hours, driven back home for an hour and parked at home from 1800 hours to 0700 hours. The driving pattern assumed in this subsection is used to generate the V2G profiles in the next subsection.

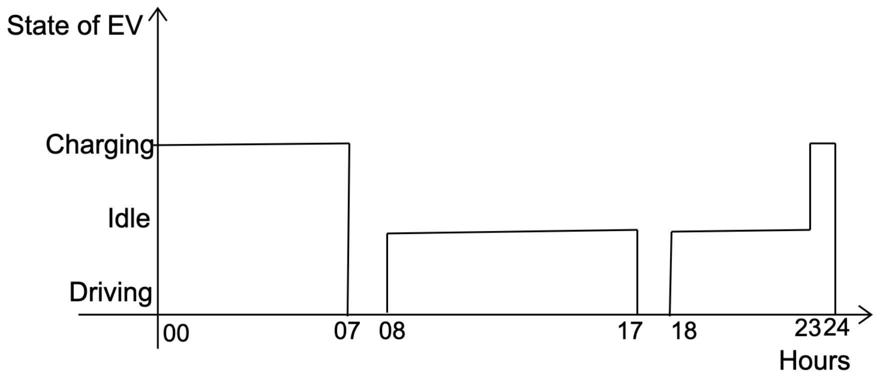


Figure (4.2) EV driving pattern in a day.

4.1.3. V2G Profile

Ideally, an EV can participate in V2G whenever it is connected to the grid. This can happen at home, office, and public charging stations. For the driving pattern considered in the previous section, the EV is connected only to the office building and home charging point, hence V2G can occur either from 0800 hours to 1700 hours at the office or from 1800 hours to 0700 hours at home. The V2G operations lead to additional charge/discharge resulting in battery degradation. It would be complex to model multiple V2G services both at the office and at home . This work shall limit to one V2G transaction per day. The V2G transaction may either happen at the office or at home. Since the electricity demand is higher during the day than in the night, the interval 0800 hours to 1700 hours is chosen for V2G service. The authors in [33] also consider the same time duration for the V2G profit estimation. This implies that V2G transactions can only take place in the office. The time frame in which V2G transaction can take place is referred to as "V2G window" in this work. In the V2G window, the EV can either charge from or discharge to the grid. The maximum charging limit is 100% of the battery capacity and the minimum remaining capacity at any point of time in the battery is 10%. The 10% of the capacity is set as a threshold to fulfill the need for unforeseen and emergency travel. The principle "sell before buy" which was considered in [40] is used in this model. The "sell before buy" principle implies that EV always discharges to the minimum remaining capacity (10%) before charging the battery in the V2G window. The minimum remaining capacity is referred to as "battery discharge threshold". With these assumptions, there are three distinct scenarios on how V2G transfer can occur,

1. No V2G: No charge or discharge event occurs in the V2G window as shown in figure 4.3. This case represents the situation where EV provides no V2G service
2. V2G discharge only: Only one discharge event in the V2G window as shown in figure 4.4. Here, EV can only discharge to the grid but cannot charge from the grid.
3. V2G discharge and charge: A discharge event followed by a charge event in the V2G window as shown in figure 4.5. Here, EV can charge from and discharge to the grid.

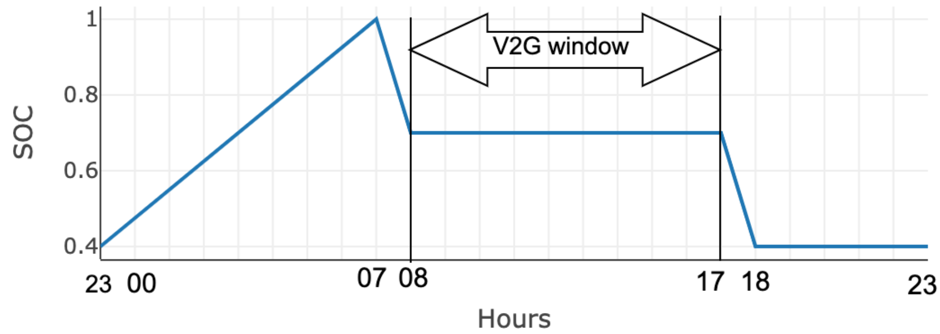


Figure (4.3) SOC profile of an EV with no V2G service.

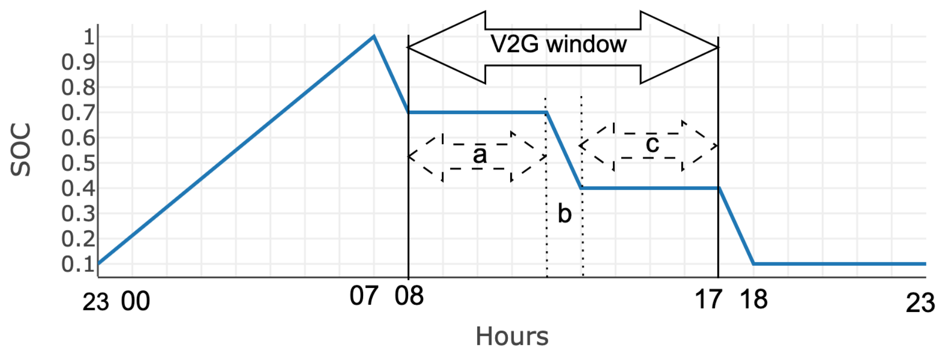


Figure (4.4) SOC profile of an EV with one V2G discharge event in the V2G window.

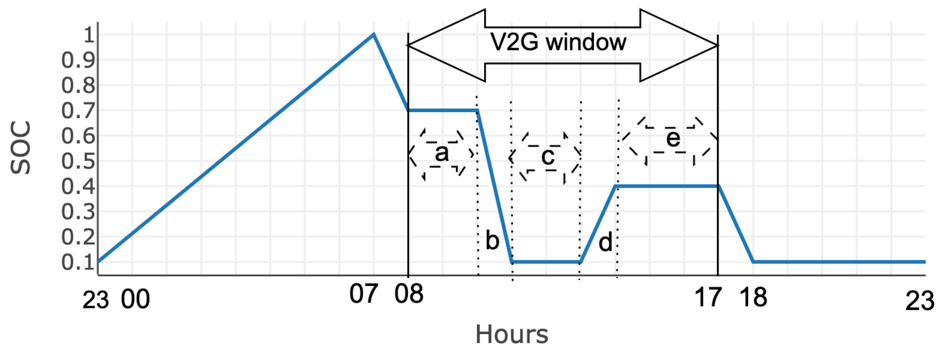


Figure (4.5) SOC profile of an EV with a V2G discharge followed by charge event in the V2G window.

The charging event is required in the third case to make sure the EV has enough battery charge to drive back home. Within these cases, there are multiple V2G paths depending on when the charge or discharge events occur. The EV can immediately discharge to the grid after connecting to the building or be idle for some time and then discharge. There is only one path for the *No V2G* scenario as there are no charge or discharge events. To assess all the possible paths for the other two scenarios, time variables are used to generate different combinations. The *V2G discharge only* scenario has two variables 'a' and 'c' which vary and 'b' is fixed to 1 as the discharge to the grid will always be done within an hour. Figure 4.4 illustrates the timing variables for *V2G discharge only* scenario. For different values of 'a' and 'c' there will be a unique V2G profile. The *V2G discharge and charge* scenario has 3 variables 'a', 'c' and 'e' and two fixed values 'b' and 'd' set to 1. Figure 4.5 illustrates the timing variables for this scenario. There will be a unique V2G profile for different values of 'a', 'c' and 'e'. Since the V2G window is fixed, the sum of all the variables should be equal to the V2G window. The possible number of V2G profiles in each scenario is shown in table 4.1.

These 46 V2G profiles will be given as input to the battery degradation and profit calculation model. The following are the assumptions made during the generation of V2G profile:

1. The driving pattern is fixed (Home to office - 0700 hours to 0800 hours and office to home - 1700 hours to 1800 hours).
2. V2G window is fixed from 0800 hours to 1700 hours. No V2G transaction takes place outside this window.
3. Only a discharge and a charge event can occur in the V2G window.
4. The discharge event occurs before the charge event in the V2G window ("Sell before buy"). The remaining battery capacity should not drop below the fixed threshold (10% of the battery capacity).

Case	**Constraints**	**Possible cases**
No V2G	None	1
V2G discharge	a = 0:8 b = 1 c = 0:8 a+b+c = 9	9
V2G discharge + charge	a = 0:7 b = 1 c = 0:7 d = 1 e = 0:7 a+b+c+d+e = 9	36
Total number of V2G profiles		46

Table (4.1) Number of possible V2G profiles in the V2G window

5. Every charge or discharge event in the V2G window lasts for an hour.

4.1.4. Battery Degradation Model

The battery degradation model estimates the battery degradation cost from V2G transactions and the driving of the EV. To estimate realistic battery degradation costs, the model must meet certain requirements. The battery degradation model should consider the parameters: temperature, SOC, DOD, C-rate, time, and the battery's current degradation. The model should assess incremental degradation due to specific charge or discharge events and allow configuring the parameters for each event. The available battery degradation models are compared in table 3.1. One of the available battery degradation models is chosen from the table based on the following criteria:

1. The battery model should support the most commonly used battery type in the EV market.
2. It should include most of the parameters which affect battery degradation.
3. It should support incremental battery degradation estimation.

Table 4.2 shows the battery technologies used by some of the popular EV manufacturers. It is noticeable that the LMO type battery is the most commonly used. There are two battery degradation models considered in the literature study which support the LMO battery type, the Wang [58] and the Xu model [67]. Wang model does not include the battery SOC for calculating the calendar aging and it excludes DOD to estimate cycle aging. Hence, the Xu model is chosen for modelling battery degradation. This model supports the online estimation of the remaining battery capacity. However, the model has the following limitations; it does not consider C-rate dependency on degradation and the temperature dependency is not valid

Car Model/EV type	Company	Battery Chemistry	Capacity [kWh]
Chevrolet Volt/PHEV	GM	Lithium manganese oxide spinel Polymer (LMO spinel)	16.5
Prius Alpha/PHEV	Toyota	NiMH	1.3
Prius (ZVW35)/PHEV	Toyota	Lithium nickel cobalt aluminum oxide (NCA)	4.4
Leaf/BEV	Nissan	Lithium manganese oxide (LMO)	24
iMiEV/BEV	Mitsubishi	Lithium manganese oxide (LMO)	16
E6/BEV	BYD	Lithium iron phosphate (LFP)	75
Tesla model S/BEV	Tesla	Lithium manganese oxide (LMO)	85
Chevrolet spark/BEV	GM	Nano Lithium iron phosphate (LFP)	21.3
Fiat 500e/BEV	Chrysler	Lithium iron phosphate (LFP)	24
Honda Accord/PHEV	Honda	Lithium manganese oxide (LMO-NMC)	6.7

Table (4.2) Battery technologies and specification used by different EV manufacturers [13].

below 15 degrees. In spite of these two limitations, the model makes a good estimation of battery degradation. The amount of battery degradation estimated by the Xu model is given by equation (4.1) [67].

$$L = 1 - \left(1 - L'\right) e^{-f_d} \tag{4.1}$$

Where:
L: Degraded battery capacity after the charge/discharge event.
L': Current degradation of the battery.
f_d: Degradation components due to calendar(when EV is idle) and cycle aging (during charge or discharge). Sum of the cycle aging and calendar aging. The f_d is calculated as per equation (4.2).

$$\mathrm{f_d(DOD, SOC, T, N, t) = f_{cyc}(DOD, SOCavg, Tavg, N, t) + f_{cal}(t, SOC, T)} \tag{4.2}$$

Where:
f_{cyc} and f_{cal}: Cyclic and calendar aging components respectively. These are computed by the equations (4.3) and (4.4).
During cycle aging, the calendar aging also occurs in parallel. Hence, cycle aging component will also contain calendar aging.

$$\mathrm{f_{cyc}} = \sum_{i=1}^{N} \mathrm{(f_{DOD}(DOD) * f_{SOC}(SOC_{avg}) * f_T(T_{avg}) * n + t * k_t * f_{SOC}(SOC_{avg}) * f_T(T_{avg}))} \tag{4.3}$$

Where:
DOD: Depth of charge for the cycle.
SOC_{avg}- Average SOC during the cycle.
T_{avg}: Average temperature during the cycle.

N: Number of cycles.
t: time duration of the cycle.
n: half or full-cycle factor.
The individual stress factors f_{DOD}, f_{SOC}, and f_T are even by the equations (4.5), (4.6) and (4.7).

$$\mathrm{f_{cal} = k_t * t * f_{SOC}(SOC) * f_T(T)} \tag{4.4}$$

Where:
K_t: Constant coefficient.
t: Time duration for which calendar aging is being calculated.
SOC: SOC at with the battery is idle for the time t.
T: Temperature of the battery during the calendar aging.

$$\mathrm{f_{DOD}(DOD) = \left(k_{DOD1}DOD^{k_{DOD2}} + k_{DOD3}\right)^{-1}} \tag{4.5}$$

Where:
k_{DOD1}, k_{DOD2} and k_{DOD3} are the constant coefficients.

$$\mathrm{f_{SOC}(SOC) = e^{k_{SOC}(SOC - SOC_{ref})}} \tag{4.6}$$

Where:
k_{SOC}: Constant coefficient.
SOC_{ref}: Reference SOC, also a constant

$$\mathrm{f_T(T) = e^{k_T*(T - T_{ref})*\frac{T_{ref}}{T}}} \tag{4.7}$$

k_T: constant coefficient.
T_{ref}: Reference Temperature also a constant.

The authors in the Xu model modelled the equations based on the experimental observation. First, the individual stress factors were varied keeping the others constant. The relationship between the stress factors and aging was formulated using curve fitting techniques. The constant coefficients were derived from these curve fitting techniques. Finally, these relationships were combined to form the battery degradation model. The model was validated with experiments and the mathematical relationship and the constant coefficients were verified. The constant coefficients derived for the model are listed in table 4.3. The parameter 'n' used in the equation (4.3) specifies whether the battery charge/discharge cycle was a half or a full cycle. For example, if the battery is discharged by 40% and is followed by a charge event of 40%, this case corresponds to a full cycle of 40% DOD. Due to irregular charge/discharge cycles in real-life, it is difficult to identify the full and half cycles. A rain-flow count algorithm [77] is used to detect the number of half and full cycles [67]. For example, consider the SOC profile in figure 4.6. The rain-flow algorithm detects two full cycles of amplitude 0.9 and 0.3. It also gives the cycle mean values of 0.55 and 0.25 respectively for each cycle. For the battery degradation model, cycle amplitude will be the DOD and the cycle mean value will be the SOC_{avg}. For this example, there are two cycle aging components; the first one with DOD = 0.9, SOC_{avg} = 0.55, t = 10 hours and n=1 and the second with DOD = 0.3, SOC_{avg} = 0.25, t = 2 hours and n=1. There are four calendar aging components, one with SOC = 0.7, t = 2 hours, the second with SOC = 0.1, t = 2 Hours, the third with SOC = 0.4, t = 3 hours and the fourth with SOC = 0.1 and t = 5 hours. The temperature will be set according to the battery temperature at that point.

Coefficient	**Value**
k_{DOD1}	140000
k_{DOD2}	-0.501
k_{DOD3}	-0.0000123
k_{SOC}	1.04
SOC_{ref}	0.5
k_T	0.00693
T_{ref}	25°
k_t	0.000000000414

Table (4.3) Constant coefficients of the Xu battery degradation model [67].

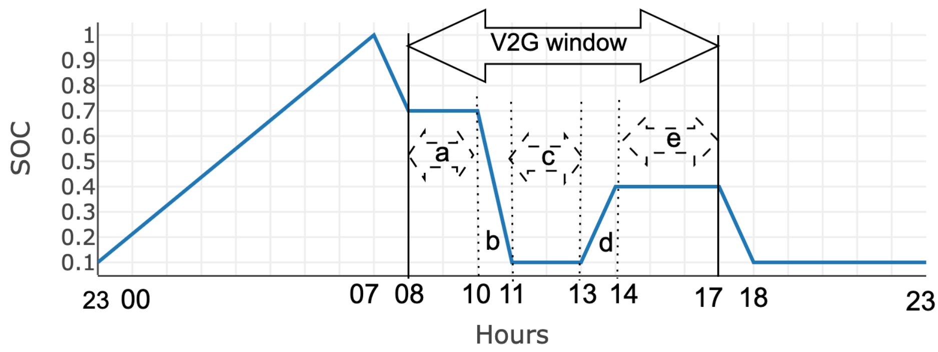


Figure (4.6) Example of an EV SOC profile to calculate battery degradation.

4.1.4.1. Limitations Of The Battery Degradation Model

The selected battery model has two limitations due to the factors it considers for modelling the battery. The C-rate dependency is neglected and the temperature dependency is not valid below 15° Celsius. In addition to these limitations, there is another limitation that is due to the coefficients used in the degradation calculation. The coefficients slightly vary based on the operating region of the battery [78]. The coefficients have to be tuned according to the experimental results. Since the experiments are not conducted as part of this work, the coefficients are assumed to be constant. The battery degradation formulae are derived from the experimental results and these experiments are conducted to simulate the EV battery usage in real-life. Due to a large number of test scenarios and time required to conduct these tests, accelerated tests are employed to formulate the relationship between the parameters and the coefficients of battery degradation. During the experiments, the battery undergoes a symmetric charge and discharge cycle. But, in real-life battery charging and discharging is not symmetric. For example, to estimate battery degradation due to discharge of 60% of battery capacity, the battery is first charged to 100% of its capacity, discharged to 60%, and then charged to 100%. The experiment is repeated multiple times to determine the average battery degradation. In real life, if 60% of the battery is used by EV in a day, then 30% of the battery may be used in the morning and the remaining 30% in the evening. The battery may be charged to increase up to 40% in the evening and the remaining 20% at night. Since the experiment and the real-life scenarios do not match exactly, a slight deviation is expected in the output.

4.1.5. Profit Calculation

Profit is the financial gain, which is the difference between the amount earned and the amount spent. Revenue is the income generated by the sale of goods or services. In V2G service, the revenue earned is the amount paid to the EV owner for the electric energy discharged (sold) to the grid. Profit is the difference between the revenue and the cost incurred by the EV owner for charging the EV battery and battery degradation. Profit from V2G can be calculated in two ways, one without considering the battery degradation and other considering the battery degradation. Both the profit calculations are necessary to understand the impact of battery degradation on the profit.

4.1.5.1. Profit without battery degradation

The profit without battery degradation is given by equation (4.8).

$$\mathrm{profit_{without\_deg}} = \mathrm{revenue_{v2g}} - (\mathrm{cost_{v2g}} - \mathrm{cost_{no\_v2g}}) \tag{4.8}$$

Where:
$revenue_{v2g}$: Revenue to the EV owner when EV provides the V2G service.
$cost_{v2g}$: Total cost of charging the EV battery per day, when EV provides the V2G service. This cost includes the charging cost of the battery charge used for driving and the V2G service.
$cost_{no\_v2g}$: Total cost to the EV owner per day when the EV does not provide V2G service. This cost only includes the charge used for driving.
$cost_{v2g} - cost_{no\_v2g}$ computes the cost incurred to the EV owner, which is purely used for the V2G service. The generated $revenue_{v2g}$ is given by the equation (4.9).

$$\mathrm{revenue_{v2g}} = \sum_{n=1}^{N} \left(\frac{\Delta \mathrm{SOC\_dis}}{\mathrm{N}}\right) * \mathrm{price\_signal(n)} * \mathrm{Battery\_capacity} * \mathrm{discharge\_eff} \tag{4.9}$$

Where:
ΔSOC_dis: Percentage of EV battery capacity discharged to the grid in the V2G window.

N: Number of hours of discharge.
price_signal: Selling price of the electricity for the corresponding hour.
discharge_eff: Battery discharge efficiency.
battery_capacity: Total capacity of the battery.
The value of N in equation (4.9) is 1. This is due to the assumption that the discharge event in the V2G window lasts only for an hour. The charging cost is calculated as per the equation (4.10).

$$\text{cost} = \sum_{m=1}^{M}\sum_{n=1}^{N_m}\left(\frac{\Delta\text{SOC\_charge}}{N_m}\right) * \text{price\_signal}(n) * \frac{\text{Battery\_capacity}}{\text{charge\_eff}} \tag{4.10}$$

Where:
ΔSOC_charge: Percentage of EV battery capacity charged from the grid to the EV for the corresponding charge event.
M: Number of charge events.
N_m: Duration of charge in hours corresponding to a charge event m.
price_signal: Buying price of the electricity for the corresponding hour.
charge_eff: Battery charge efficiency which is the square root of the round trip efficiency.
battery_capacity: Total capacity of the battery.
The value of *M* in the equation (4.10) is one when there is no charge event in the V2G window. This denotes the charging cost is only due to the night charging. The value of M is two when there is a charge event in the V2G window.

4.1.5.2. Profit with battery degradation

Profit with degradation takes into account the battery degradation cost along with the charging cost. The equation (4.11) calculates the V2G profit with degradation.

$$\begin{aligned}\text{profit}_{\text{with\_deg}} = \text{revenue}_{\text{v2g}} - (\text{cost}_{\text{v2g}} - \text{cost}_{\text{no\_v2g}}) - \\ (\text{battery\_deg\_cost}_{\text{v2g}} - \text{battery\_deg\_cost}_{\text{no\_v2g}})\end{aligned} \tag{4.11}$$

The equation (4.11) can be rewritten as (4.12).

$$\text{profit}_{\text{with\_deg}} = \text{profit}_{\text{without\_deg}} - (\text{battery\_deg\_cost}_{\text{v2g}} - \text{battery\_deg\_cost}_{\text{no\_v2g}}) \tag{4.12}$$

Where:
$revenue_{v2g}$: Revenue to the EV owner when EV participates in the V2G service.
$battery\_deg\_cost_{v2g}$: Battery degradation cost per day, when the EV offers V2G service. This includes the battery degradation due to the driving, charging of the EV and V2G service.
$battery\_deg\_cost_{no\_v2g}$: Battery degradation cost per day, when EV does not participate in the V2G service. The degradation cost here is only due to the night charging and driving. Therefore, $battery\_deg\_cost_{v2g} - battery\_deg\_cost_{no\_v2g}$ computes the battery degradation cost, which is purely due to the V2G service. The battery degradation cost is calculated as per the equation (4.13).

$$\text{battery\_deg\_cost} = \text{battery\_replacement\_cost} * \frac{\text{battery\_degradation}}{0.2} \tag{4.13}$$

Where:
battery_replacement_cost: Cost of replacing the degraded battery with a new one.
battery_degradation: Amount of degradation given by the battery degradation model for a V2G profile.
The *battery_degradation* can take values from 0 to 0.2. The factor 0.2 is used because the commercial EV batteries End Of Life (EOL) is reached when the battery loses 20% of it's initial capacity [63].

4.1.6. Profit Model

Profit model is created to evaluate the profit due to V2G service. Input parameters to the profit model are:

1. Price signal for the year 2019 (€/kWh).
2. Battery capacity (kWh).
3. Round trip efficiency.
4. Battery replacement cost (€).
5. EV driving distance (km)
6. Maximum charge capacity (% of the battery capacity)
7. Battery discharge threshold (% of the battery capacity)
8. V2G possibility on weekends (True or False)

The above parameters are chosen such that they can be set to represent the real-life scenarios. The model is divided into four sub models as per their tasks as discussed earlier in this chapter.

1. Price signal model
2. Driving pattern and V2G profile model
3. Battery degradation model
4. Profit calculator

The price signal for a number of days is given as input to the price signal model. The *price signal model* extracts the single day price each of one hour resolution. If the V2G possibility on weekends is false, then the price signals for weekends are removed. The *driving pattern and V2G profile* model creates the driving pattern as mentioned earlier in this chapter. Based on the driving pattern, different V2G profiles are created as per the timings in table 4.1. The V2G profile also contains SOC of the EV battery as shown in figure 4.5. The term V2G profile and SOC profile is used interchangeably as they are the same. These SOC profiles are given as input to the *profit calculator*. Based on the SOC profile, the *profit calculator model* separates the charge and discharge events and calculates the amount of energy transferred during each event. The energy transferred is calculated based on the inputs: EV driving distance, SOC of the battery, and battery discharge threshold. The *profit calculator* takes a SOC profile and calculates the profit without degradation using the equation (4.8). The *profit calculator* requests the *battery degradation model* to give the amount of battery degradation for a specific SOC profile. The *battery degradation model* calculates the battery degradation according to the SOC profile and gives the amount of degradation to the *profit calculator*. Now, the *profit calculator* calculates the profit with degradation using the equation (4.11). The algorithm 1 shows the steps to calculate the V2G profit.

Algorithm 1 Algorithm to calculate V2G profit per day with battery degradation

```
procedure PROFIT
    Initialize the input parameters.
    Derive the price signal for a day from the input price signal.
    Generate the driving pattern.
    Generate V2G profile for the driving pattern based on the driving distance.
    Select a V2G profile for which the profit has to be calculated.
    Calculate the revenue_v2g, cost_v2g and cost_no_v2g for this profile.
    Calculate the amount of battery degradation for the selected profile assuming new
  battery (L'= 0).
    Calculate profit without degradation as per the equation (4.8).
    Calculate the battery degradation cost as per the equation (4.13).
    Calculate profit with degradation as per the equation (4.11).
```

There are 46 ways by which the V2G service can be offered for a single day as illustrated in figure 4.8. The profit calculated for the same day will differ based on the SOC profile selected. There are three different approaches to select one SOC profile for a day out of the 46 SOC profiles. Based on these approaches, the profit, battery degradation and the amount of charge transferred to the grid would vary. The approaches for selecting the SOC profile for the EV on a particular day are:

1. Selecting the SOC profile based on the price signal so that the V2G discharge occurs when the selling price is maximum and the charging occurs when the buying price is minimum in the V2G window.

2. Selecting the SOC profile which leads to a minimum battery degradation.

3. Selecting the SOC profile to balance the price signal and battery degradation.

The profit model will calculate the profit for all the above cases. The procedure for calculating the profit for all three cases is explained in the implementation section.

4.2. Implementation

This sections deals with the implementation of the profit model discussed in the methodology section. The Profit model is implemented in Matlab with the following input parameters:

1. Price signal: German day-ahead price 2019
2. Battery capacity: 24KWh
3. Usable capacity: 22KWh

4. Battery round trip efficiency: 85%, resulting in charge and discharge efficiency of 92.19% each
5. Battery replacement cost: 6000 €
6. SOC used for driving: 30% of the battery capacity
7. Maximum charge capacity: 100%
8. Battery discharge threshold: 10%
9. V2G possibility on weekends: Yes

The implementation of each of the blocks discussed in the methodology section are explained in detail in the following subsections.

4.2.1. Price Signal Modelling

The price signal for the year 2019 from Jan 1 to Dec 31 taken from [79] is processed in Matlab. The procedure to download the price signals is described in the section A.1. Each day or 24 hour cycle is assumed to start at 2300 hours and ends the next day at 2300 hours. EV starts charging at 2300 hours every day and this is considered as the starting point. The trend of electricity price over the year 2019 is illustrated in figure 4.7. From the figure, it is clear that the price of the electricity at night is low, it increases at the start of the day and decreases in the afternoon. The price again increases in the evening and then decreases at night. This is the general trend over the period of a year, but the electricity price varies dynamically every day. For the profit evaluation, the price signal for each day is given as input to the profit calculator.

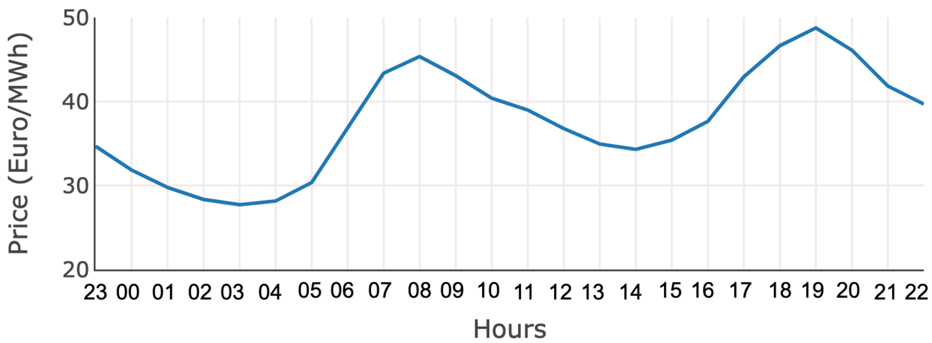


Figure (4.7) Hourly electricity price trend in Germany for the year 2019.

4.2.2. EV Driving Pattern And V2G Profile

The EV driving pattern and V2G profile model is implemented in Matlab with the input parameters as mentioned earlier. Based on the combination of the time variables in table 4.1, the Matlab program generates the SOC profiles. The V2G profiles generated are shown in figure 4.8. Subfigure 'a' shows the possible V2G paths when there is only one discharge event in the V2G window and no charge event. Subfigures 'b' to 'i' show the different paths based on the time of charge in the V2G window. Profile 1 in subfigure 'i' depicts the no V2G case. The driving distance for each of the profiles can be calculated as follows:

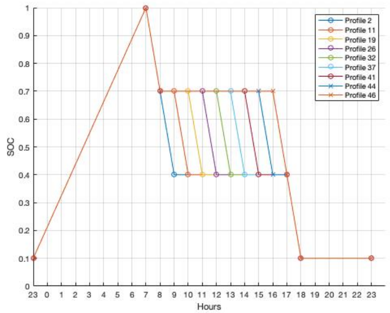
1. Energy consumed per trip: 30% of SOC (ΔSOC = 0.3)
   = ΔSOC * Capacity(kWh)* discharge efficiency
   = 6.0845 kWh
2. Vehicle consumption = 160.934 km/30kWh [80]
3. Distance travelled = 32.64 km

4.2.3. Battery Degradation Model

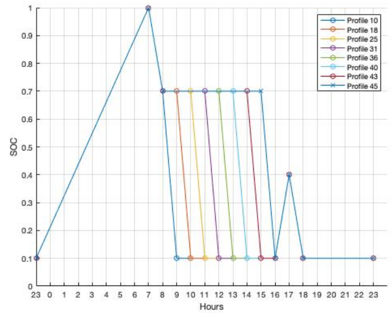
The battery degradation model is also implemented in Matlab with the input as the SOC profiles generated in the *EV driving pattern and V2G profile* block. The Matlab function will first parse the SOC profile to identify the calendar and cycle aging components. After identifying these components, Matlab function separates calendar and cycle aging components and prepares input parameter arrays (containing SOC, DOD, T, t and N) which are input to the battery degradation function. The rain-flow counting algorithm built-in Matlab is used to calculate the parameters for cycle aging. The rain-flow algorithm is used to identify the charge and discharge cycles, to make the calculations similar to the experiments conducted during the creation of the battery degradation model. The rain-flow algorithm gives the DOD and $SOCavg$ values for the equation (4.3). For a new battery, the calculation of battery degradation is simple. The value of L' in the equation (4.1) is zero. If the battery is already rain flow, then L' would be the current battery degradation. The *battery degradation model* stores the battery degradation till the previous day (L') and uses that for the battery degradation calculation for the present day (L). The amount battery degradation per day for all the V2G profiles is shown in the plot in figure 4.9. Profile 1 causes the highest degradation when compared to other profiles and profile 2 causes the lowest degradation. The battery type considered in this work is LMO, and it is highly sensitive to high temperature and SOC [55]. Storing energy at high temperatures and at high SOC will cause more degradation than discharging the battery to a lower SOC and maintaining this lower SOC. In profiles 2-46, the battery is discharged to a lower SOC in the V2G window when compared to profile 1. Hence, the degradation when EV participates in V2G service (profiles 2-46) is less than when EV does not provide V2G service (profile 1). The authors in [61] made a similar observation that the life of the battery can be extended by participating in the V2G service. The profiles 2, 11, 19, 26, 32, 41, 44, and 46 cause less battery degradation compared to other profiles as they do not have a charging event in the V2G window that causes additional cycling.

4.2.4. Profit Calculation

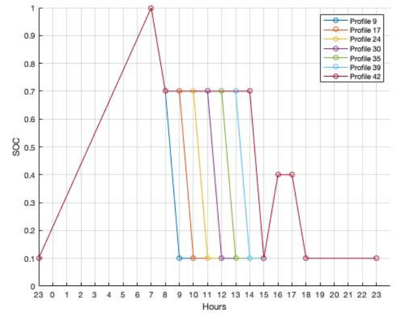
The profit calculation block is also implemented in Matlab. The first part of profit calculation is pre-processing. Pre-processing will identify the following: charge and discharge events in the



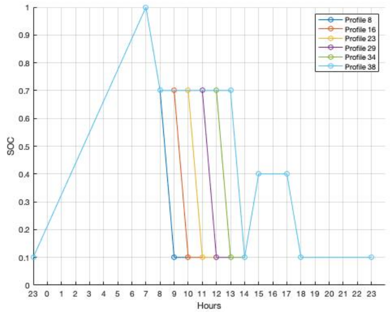
(a) V2G profiles with only one discharge event and No charge event in the V2G window



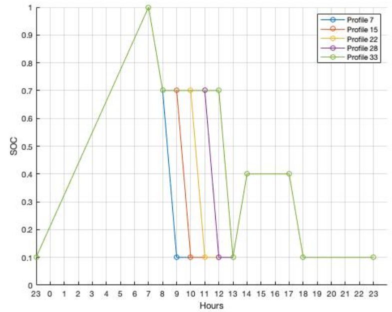
(b) V2G profiles with charging event just before the departure in the V2G window



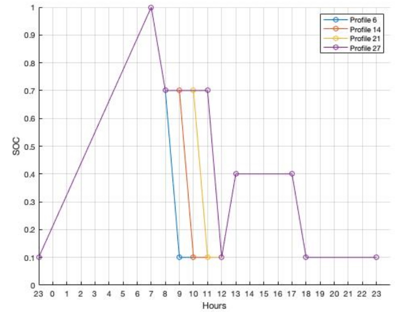
(c) V2G profiles with charging event one hour before the departure in the V2G window



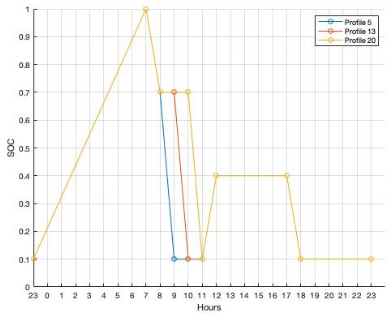
(d) V2G profiles with charging event two hours before the departure in the V2G window



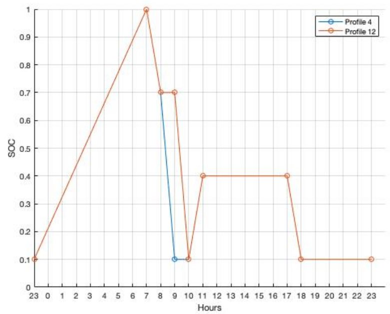
(e) V2G profiles with charging event three hours before the departure in the V2G window



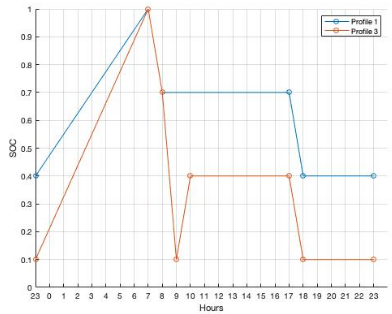
(f) V2G profiles with charging event four hours before the departure in the V2G window



(g) V2G profiles with charging event five hours before the departure in the V2G window



(h) V2G profiles with charging event six hours before the departure in the V2G window



(i) V2G profile with charging event seven hours before the departure in the V2G window and profile 1 with no V2G

Figure (4.8) V2G profiles generated based on different timings of V2G arbitrage

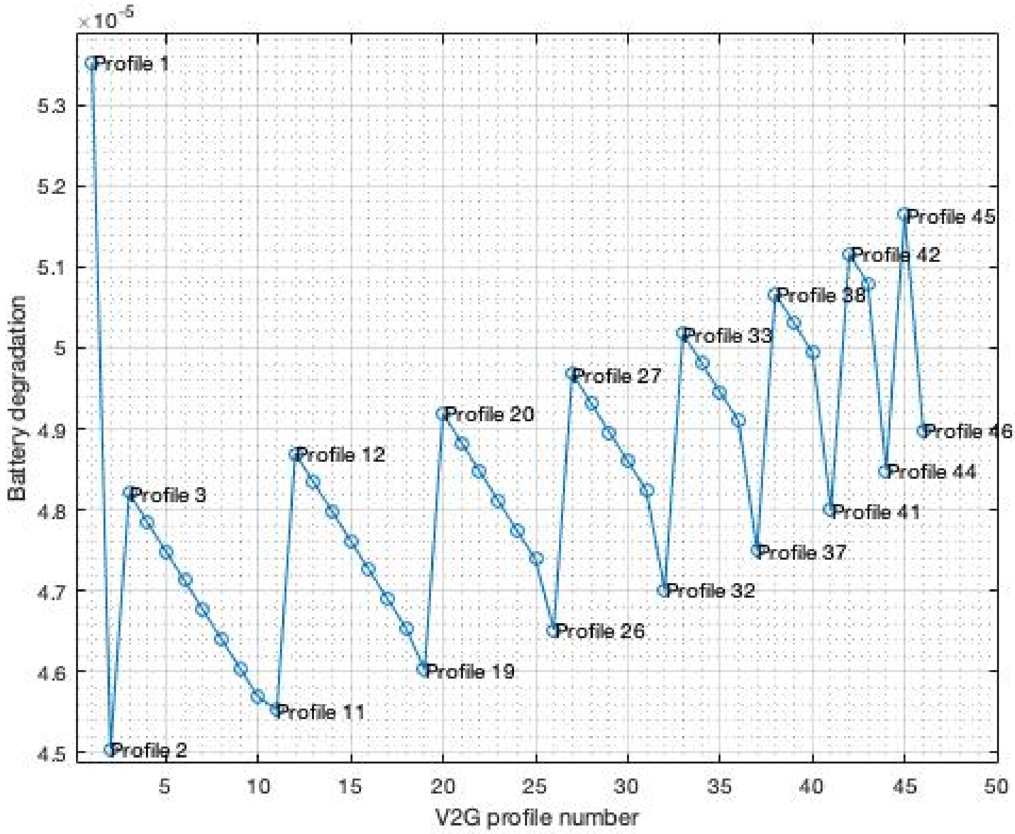


Figure (4.9) Amount of battery degradation for different SOC profiles. Profile 1 corresponds to no V2G case. Profile 2-46 correspond to different V2G cases.

V2G profile, the duration of these events, and the amount of energy transferred. The charge and discharge events are identified using the built-in Matlab function *diff* (differentiate function). The V2G profile is differentiated with respect to time. Whenever the output of differentiation is positive, there is a charging event and when it is negative, there is a discharging event. The profit calculation model calculates both profit considering degradation and without. The implementation of these are explained in the following subsections.

4.2.4.1. Profit without degradation

The pre-processing function calculates the ΔSOC_dis, ΔSOC_charge and corresponding values of N, M and N_m for the equation (4.9) and (4.10). For every V2G profile, the pre-processing is performed and the profit without degradation is calculated using the equation (4.8). This is repeated for all the days and the V2G profile which gives the highest profit is selected. The profit per day is added to give the total profit at the end of duration considered for estimation. The algorithm 2 explains the steps followed to calculate the profit without degradation. The $Number\_of\_profiles$ is set to 46 and $Number\_of\_days$ is set to 365 to evaluate annual profit.

Algorithm 2 Profit without battery degradation

```
procedure PROFIT(price_signal)
    Initialize the input parameters.
    Generate the driving pattern.
    Generate the V2G profiles for the driving pattern based on the driving distance.
    for Number_of_profiles do
        Calculate the amount of energy charged and discharged from the EV battery.
    for Number_of_days do
        for Number_of_profiles do
            Calculate profit as per the equation (4.8).
    for Number_of_days do
        Select the profile which gives highest profit.
    Sum the profit each day to get the total profit.
```

4.2.4.2. Profit with degradation

Profit with degradation depends on the way the V2G profiles are selected as discussed earlier. The Matlab program implements three different cases based on the approaches for selecting the V2G profile.

1. Based on the price signal: The V2G profile is selected based on the price signal to maximize profit. The electric energy is discharged to the grid when the price signals are high and the EV is charged when the price signals are low. The profit is evaluated as shown in the algorithm 3.

2. Minimum battery degradation: The V2G profile that results in minimum battery degradation is selected for all the days. The profit in this case is evaluated as per the algorithm 4.

3. Balanced profit calculation: The V2G profile is selected so that there is a balance between the price signal and the battery degradation. The algorithm 5 explains the procedure for this calculation.

The profit calculated with the balanced profit calculation approach results in the best possible profit. This can be explained with the help of an example shown in table 4.4. The table shows the profit calculation for Jan 19, 2019 for the three different profiles selected based on the above three approaches. The degradation cost is calculated by subtracting battery degradation cost without V2G service from the battery degradation cost with V2G service. The profit without degradation is highest for the price based profile selection, but the degradation cost is more. The profit calculated in the minimum degradation case is less for both, profit without degradation and profit with degradation. In the balanced case, the profile is selected to increase profit and decrease the battery degradation cost; hence, the profit with degradation is highest.

Algorithm 3 Profit with battery degradation based on price signal

```
1: procedure PROFIT(price_signal)
2:     Initialize the input parameters.
3:     Generate the V2G profiles.
4:     for Number_of_days do
5:         for Number_of_profiles do
6:             Calculate profit as per the equation (4.8).
7:     for Number_of_days do
8:         Select the profile that gives the highest profit from step 6.
9:         Calculate the battery degradation for this profile considering previous degradation.
10:    Calculate the degradation cost from V2G using equation(4.13).  ▷ battery_deg_cost_v2g
11:    Sum the profit obtained for each day in step 8.                ▷ profit_without_deg
12:    for Number_of_days do
13:        Calculate the battery degradation without V2G.
14:    Calculate the battery degradation cost using equation (4.13).   ▷ battery_deg_cost_no_v2g
15:    Recalculate the profit as per the equation (4.12).             ▷ profit_with_deg
```

Algorithm 4 Profit with battery degradation based on minimum degradation

```
1: procedure PROFIT(price_signal)
2:     Initialize the input parameters.
3:     Generate the V2G profiles.
4:     for Number_of_profiles do
5:         Calculate the amount of battery degradation.
6:     Select the profile which causes minimum degradation from step 5.
7:     for Number_of_days do
8:         Calculate profit as per the equation (4.8) for the profile selected in step 6.
9:         Calculate the battery degradation considering the previous degradation.
10:    Calculate the degradation cost from V2G using equation(4.13).  ▷ battery_deg_cost_v2g
11:    Sum the profit obtained for each day in step 8.                ▷ profit_without_deg
12:    for Number_of_days do
13:        Calculate the battery degradation without V2G.
14:    Calculate the battery degradation cost using equation (4.13).   ▷ battery_deg_cost_no_v2g
15:    Recalculate the profit as per the equation (4.12).             ▷ profit_with_deg
```

Algorithm 5 Profit with battery degradation balanced case

1: **procedure** PROFIT(*price_signal*)
2: Initialize the input parameters.
3: Generate the V2G profiles.
4: **for** *Number_of_profiles* **do**
5: Calculate the amount of battery degradation.
6: Calculate the degradation cost as per the equation equation (4.13).
7: **for** *Number_of_days* **do**
8: **for** *Number_of_profiles* **do**
9: Calculate profit as per the equation (4.11) with the battery degradation costs calculated in step 6.
10: **for** *Number_of_days* **do**
11: Select the profile which gives the highest profit in step 9.
12: Calculate profit as per the equation (4.8) for this profile.
13: Calculate the battery degradation with this profile considering the previous degradation.
14: Calculate the degradation cost from V2G using equation(4.13). ▷ $battery\_deg\_cost_{v2g}$
15: Sum the profit for each day obtained in step 12. ▷ $profit_{without\_deg}$
16: **for** *Number_of_days* **do**
17: Calculate the battery degradation without V2G.
18: Calculate the battery degradation cost using equation (4.13). ▷ $battery\_deg\_cost_{no\_v2g}$
19: Recalculate the profit as per the equation (4.12). ▷ $profit_{with\_deg}$

	Profit without degradation(€)	**Degradation cost(€)**	**Profit with degradation(€)**
Profile 2 (Minimum degradation)	-0.15489	-0.25423	0.09933
Profile 23 (price)	0.08646	-0.1622	0.24875
Profile 19 (balanced)	0.05033	-0.22472	0.27505

Table (4.4) Example of profit calculation in balanced case. The Profit with degradation is obtained by subtracting degradation cost from the profit without degradation.

4.3. Result And Analysis

4.3.1. Result

The profit model is executed assuming the specification of an EV similar to the 2016 Nissan leaf (24kWh) model. The parameters used for the execution of the model are shown in table 4.5. The results of the profit evaluation are tabulated in table 4.6. This result includes the V2G service on weekends. In real-life scenarios during weekends, EVs are disconnected from the grid. With the assumption of V2G services not available on weekends, the model recalculates the profit. Table 4.6 shows the profit for 261 weekdays in 2019. There is a significant difference in the profits and the amount of energy transferred in both cases. Figure 4.10 depicts the number of times a V2G profile is selected in the profit model simulation for 2019. Out of 365 days in 2019, for the price based V2G profile selection, 85 days have profiles with only discharge event, 252 days have profiles with one discharge and one charge event and 28 days have no V2G service. In the balanced case, 183 days have only discharge event and 182 days have one discharge and one charge event. There are no days on which there is no V2G service. In the case of minimum degradation, profile 2 is chosen for all days. As expected, the balanced profit calculation approach gives the highest profit and has fewer days where there is no V2G service is offered compared to the other two cases.

4.3.2. Sensitivity Analysis

An EV is defined by various specifications like capacity, efficiency and energy consumption. There are plenty of EV manufacturers in the market with different battery specifications. It is necessary to consider these factors and analyze their contribution to determine the sensitivity of V2G profit. This section deals with the detailed sensitivity analysis of V2G profit with respect to the capacity, battery efficiency, battery replacement cost, and driving distance. The one-at-a-time sensitivity analysis technique [81] is used in this work. In order to find the individual sensitivity, all the other factors except one are varied. The base assumptions for the sensitivity analysis are listed in table 4.5. The sensitivity analysis is done for two cases

1. Profit without degradation

Parameter	Value
Battery capacity (kWh)	24
Usable capacity (kWh)	22
Round trip efficiency (%)	85
Battery replacement cost (€)	6000
V2G on Weekends	Yes
Number of days	365
Consumption (km/kWh)	5.3644
Energy consumed for a single trip (% of battery capacity)	30
Driving distance for a single trip - home to office (km)	32.63

Table (4.5) Input parameters to the profit evaluation model model

Case	Profit (€/EV/year)	Total V2G discharged (kWh)
Profit without degradation	43.158247	3584
Profit with degradation based on price signal	109.550238	3584
Profit with degradation based on Minimum battery degradation	110.941761	2220.98
Profit with degradation based on balance between price signal and the battery degradation	123.285335	3328.4

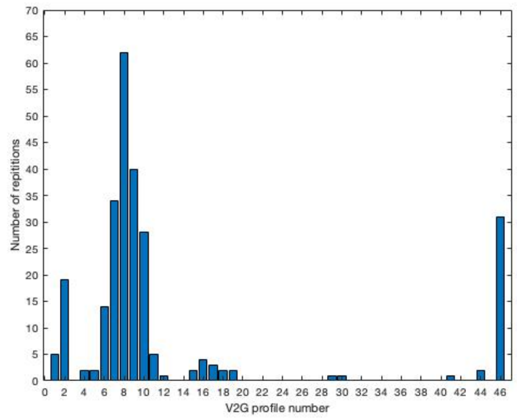
Table (4.6) Annual profit evaluation with EV providing V2G service everyday (365 days)

Case	Profit (€/EV/year)	Total V2G discharged (kWh)
Profit without degradation	34.71	2750.37
Profit with degradation based on price signal	86.80	2750.37
Profit with degradation based on Minimum battery degradation	86.02	1588.15
Profit with degradation based on balance between price signal and the battery degradation	93.45	2458.29

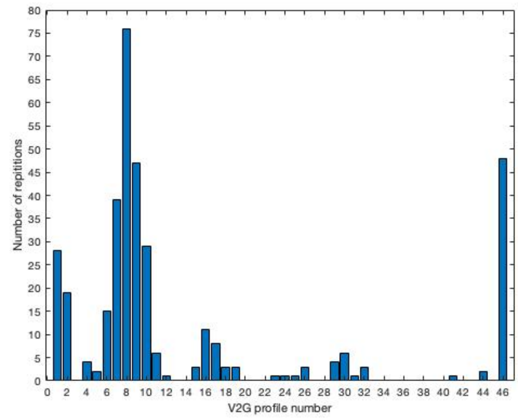
Table (4.7) Annual profit estimation with EV providing V2G service only on week days (261 days)

2. Profit with degradation.

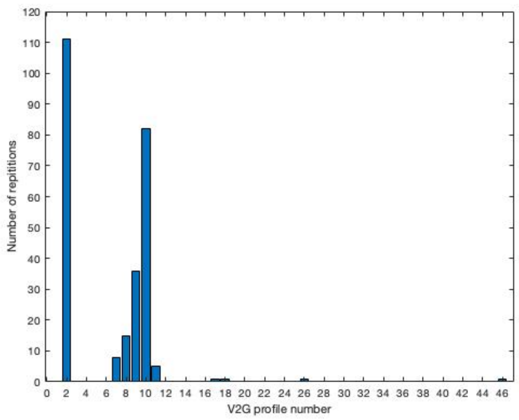
From the results discussed in the previous subsection, it is evident that profit with degradation



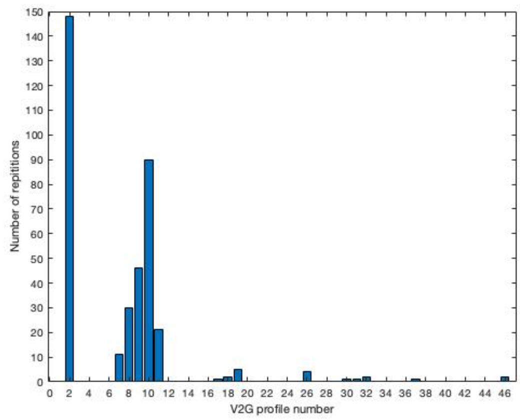
(a) Price based V2G profile selection excluding weekends (261 days)



(b) Price based V2G profile selection including weekends (365 days)



(c) Balanced V2G profile selection excluding weekends (261 days)



(d) Balanced V2G profile selection including weekends (365 days)

Figure (4.10) Number of repetitions of each V2G profile in the profit model simulation for 2019.

that is based on the balanced profit calculation provides the highest profit. Hence, for sensitivity analysis only this case is considered. Henceforth, profit with degradation will represent the profit with degradation based on the balanced profit calculation.

4.3.2.1. Efficiency of the battery

The sensitivity plot of V2G profit with respect to the round trip efficiency of the battery is shown in figure 4.11. It is observed that as efficiency increases, the profit increases. The conclusion is obvious because as the efficiency increases, the energy loss decreases. From the sensitivity plot it can be derived that, for every one percent increase in the round trip efficiency, there is an increase of €1.8 in profit without degradation and €1.62 in profit with degradation.

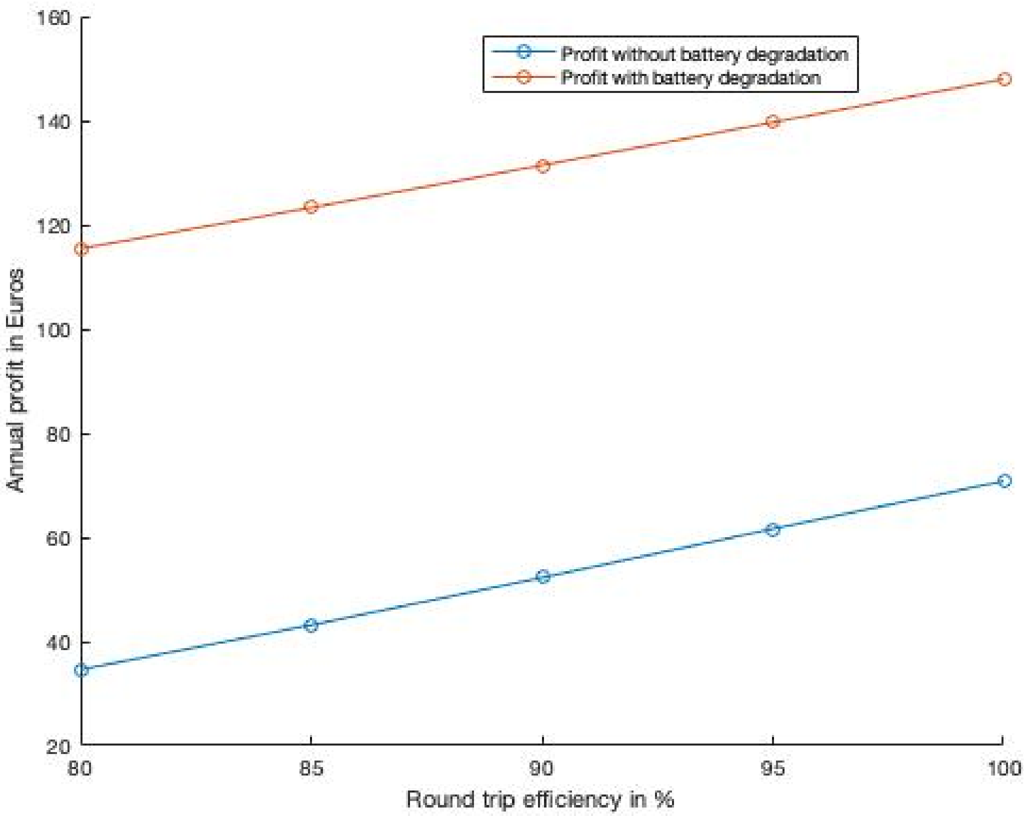


Figure (4.11) Variation in profit with respect to battery round trip efficiency.

4.3.2.2. Battery Replacement Cost

The sensitivity plot of V2G profit with respect to battery replacement cost is shown in figure 4.12. It is perceivable from the figure that profit without degradation does not depend on battery replacement cost. However, the profit with degradation increases as battery replacement cost increases. This is because of the factors: the chosen battery type, the chosen battery degradation model and the chosen V2G profile results in less degradation with V2G service in comparison with no V2G service. Hence, the battery degradation cost in the case of no V2G will be more than with V2G. From the plot in figure 4.12, for every €1000 increase in battery replacement cost, the profit with degradation increases by €13.62.

4.3.2.3. Battery Capacity

Battery capacity is one of the most commonly used parameters to compare EVs. It affects the V2G profit as more amount of energy is available for V2G transfer with increased battery capacity. The sensitivity plot of V2G profit with respect to battery capacity is shown in figure 4.13. The V2G profit is highly sensitive to capacity. For every 1kWh increase in battery

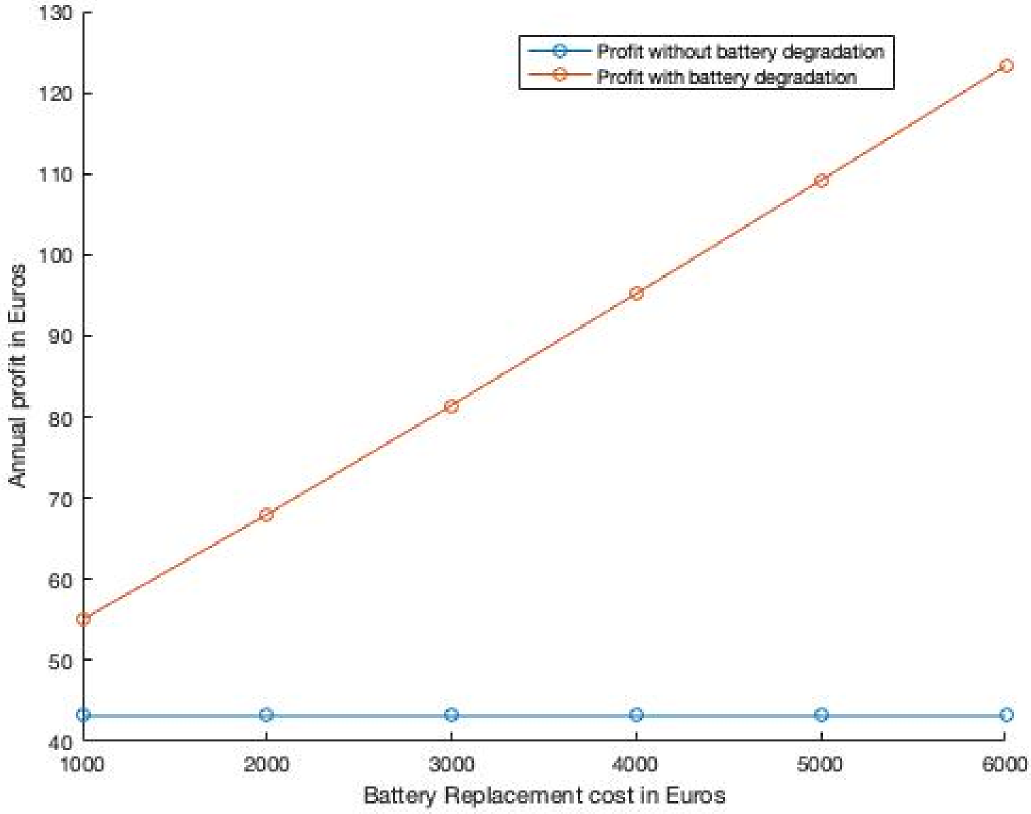


Figure (4.12) Variation in profit with respect to battery replacement cost.

capacity, profit without degradation increases by €1.961 and profit with degradation increases by €1.85.

4.3.2.4. Driving Distance

The sensitivity of V2G profit with respect to the driving distance is shown in figure 4.14. The total driving distance per day is twice the distance driven per trip. As the driving distance reduces, the amount of energy that can be used for V2G transfer increases. Hence, the profit increases with decreasing driving distance. For every 1km decrease in driving distance per trip, the profit without degradation increases by €1.011 and profit with degradation increases by €6.64.

4.3.2.5. Combined Sensitivity Analysis

The above sensitivity analysis is done by keeping all the parameters constant except one. In order to find the combined effect of all the parameters and to explore the minimum and maximum values of profit, a combined sensitivity analysis is performed. The qualitative

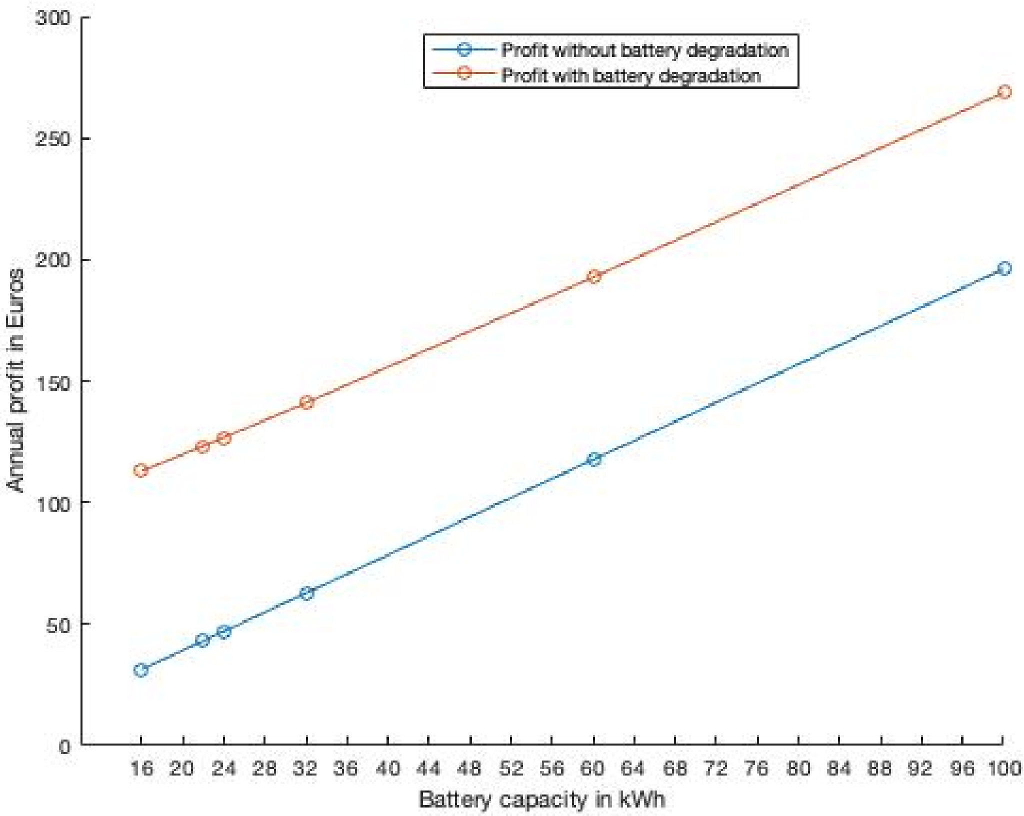


Figure (4.13) Variation in profit with respect to battery capacity.

(scatter plot) Random Sampling Method[81] is used for the combined sensitivity analysis. 216 different combinations of input parameters: capacity, efficiency, and driving distance are selected, and the corresponding profit is calculated using the profit model. The plot of the output against the input parameters shows the parameter sensitivity. The capacity is varied from 16 kWh to 100 kWh and the efficiency is varied from 85% to 100% and the driving distance in terms of DOD is varied from 5% to 30%. Figure 4.15 shows the variation of profit without considering the battery degradation and figure 4.16 shows the variation of profit with degradation. A maximum annual profit of €502.50 with 29,485 kWh energy transferred at 17.04 €/MWh is computed without considering the battery degradation. This profit corresponds to driving DOD = 0.05, efficiency = 1, and battery capacity = 100 kWh. Considering the battery degradation, a profit of €723.9343 and an energy transfer of 30,665 kWh per year at 23.6 €/MWh can be achieved for the same input parameters. A minimum profit of €31.38 per year with is earned without considering the degradation, with driving DOD = 0.3, efficiency = 0.85, and battery capacity = 16kWh. With degradation, the minimum profit earned is €113.00 per year, for the same input. In this case, the energy transferred is 2314.47 kWh. The sensitivity of energy transferred per year with respect to the parameters is

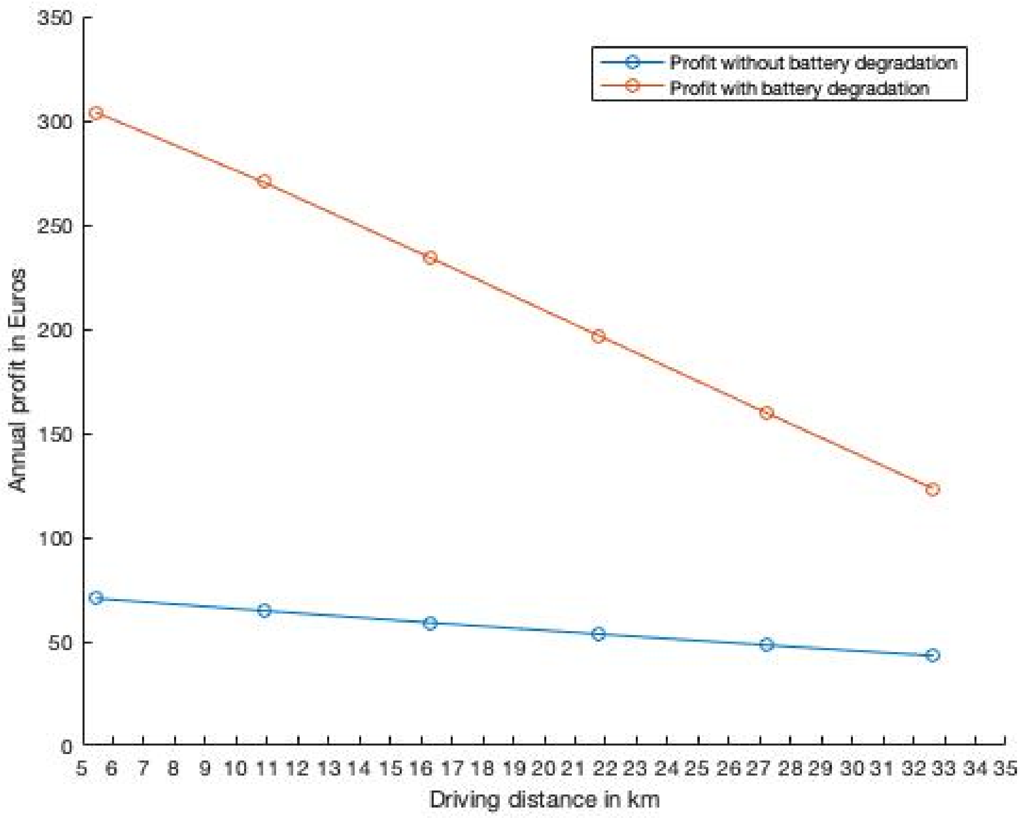


Figure (4.14) Variation in profit with respect to driving distance

shown in figure 4.17.

4.3.3. Best Case

The sensitivity analysis shows that lower driving distance, higher efficiency, and higher capacity values results in higher profit. The maximum battery capacity available currently in the market is 100kWh (Tesla model X 2019). 100% battery efficiency implies zero loss in energy transfer hence, for the best case 95% efficiency is assumed. With 100 kWh battery and 0.05 % DOD per trip , with an energy consumption of 100 miles/30 kWh, the total daily driving distance would be around 54 km. Table 4.8 shows the best possible profit along with the values of the input parameters. A profit of €442.64 with 28,216.96 kWh per year at 15.68 €/MW can be achieved per year without considering battery degradation. A profit of €662.37 is estimated with 29,761.836 kWh of energy transferred per year to the grid at 22.25 cents/kWh considering the battery degradation.

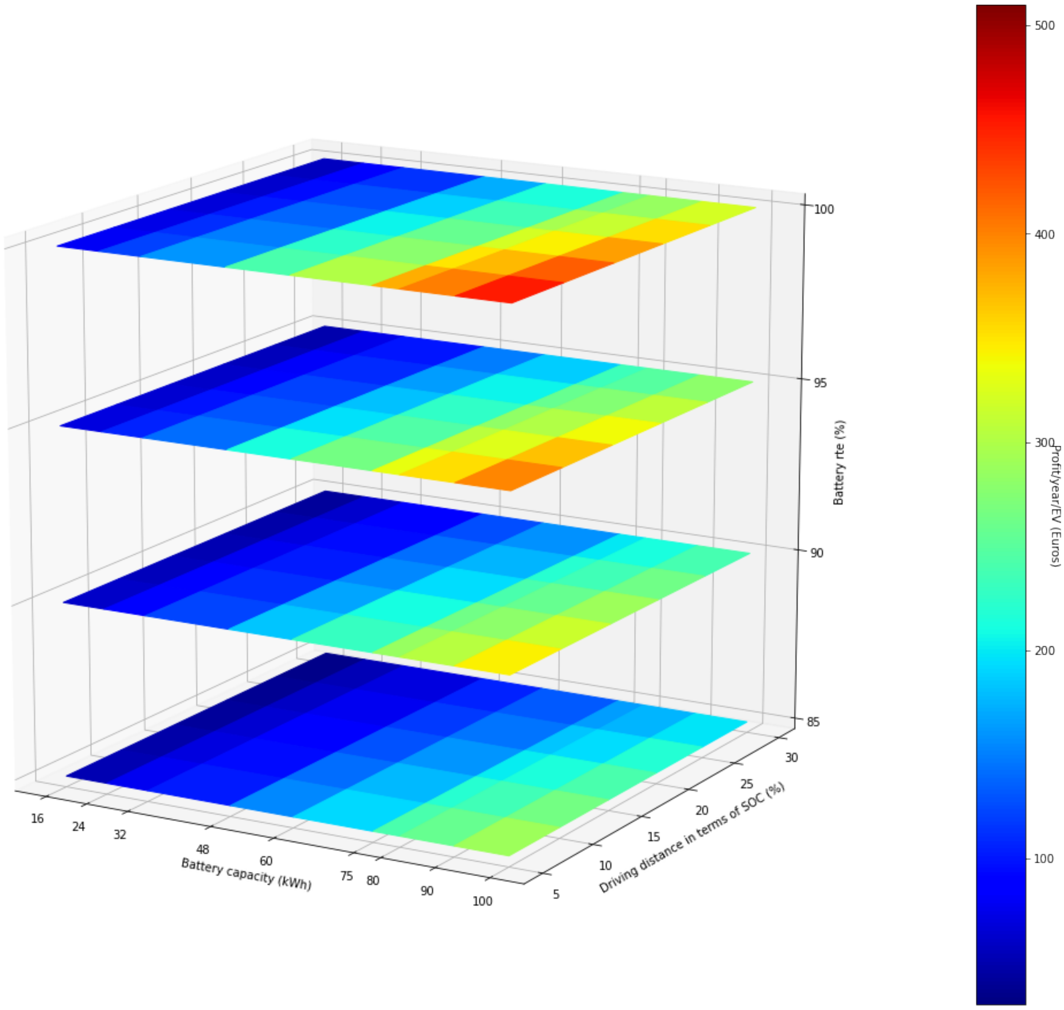


Figure (4.15) Variation of profit without considering battery degradation with respect to RTE, battery capacity and driving distance

4.3.4. Break-Even Analysis

4.3.4.1. Profit without degradation

The break-even point will give the condition when the V2G service becomes profitable for the EV. The basic rule of any profit calculation is that the selling price should be greater than the buying price. In this case, the selling price will be the electricity price signal at the instant of V2G discharge and buying price is the electricity price signal when the EV is being charged. It is assumed that the price signal shall be constant whenever the EV is charged and discharged. Hence there are only two price signals, selling (P_{sell}) and buying (P_{buy}). With this assumption, the equation (4.8) can be modified as (4.14).

$$\text{profit} = \text{K1} * \text{P}_{\text{sell}} - ((\text{K2} * \text{P}_{\text{buy}} + \text{K3} * \text{P}_{\text{buy}}) - \text{K4} * \text{P}_{\text{buy}}) \tag{4.14}$$

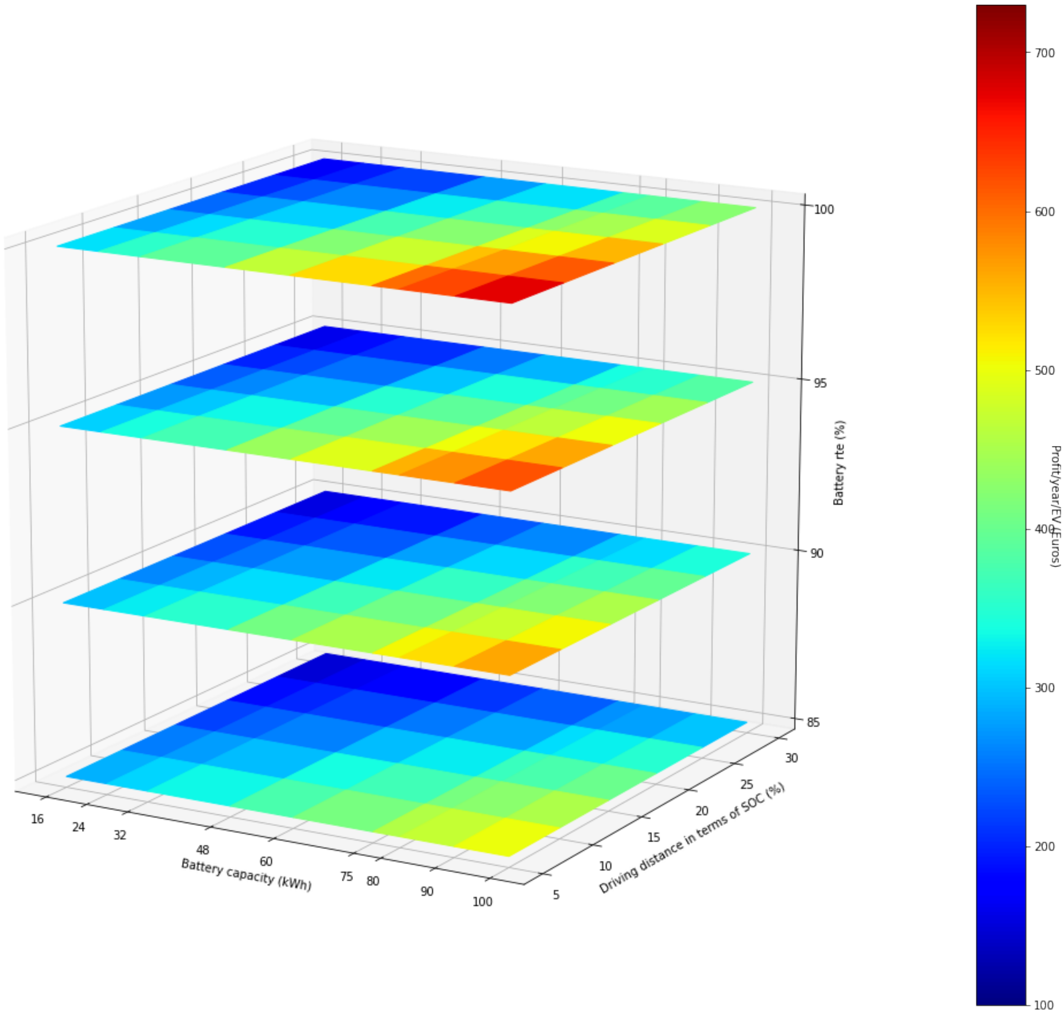


Figure (4.16) Variation of profit considering battery degradation degradation with respect to RTE, battery capacity and driving distance

Where:
$K1$: Energy discharged (sold) to the grid.
$K2$: Energy charged (bought) at night from the grid, for a day where EV participates in V2G.
$K3$: Energy charged (bought) from the grid in the V2G window.
$K4$: Energy charged (bought) at night from the the grid, for a day where EV does not participate in V2G.
The Parameters $K1$, $K2$, $K3$, and $K4$ differ based on the SOC profile. For the profile in figure 4.4, where only one discharge event is allowed the parameters can be defined as

$$\mathrm{K1} = (1 - (2 * \Delta\mathrm{SOC\_driving}) - \mathrm{Battery\_threshold}) * \mathrm{Battery\_capacity} * \mathrm{discharge\_eff} \tag{4.15}$$

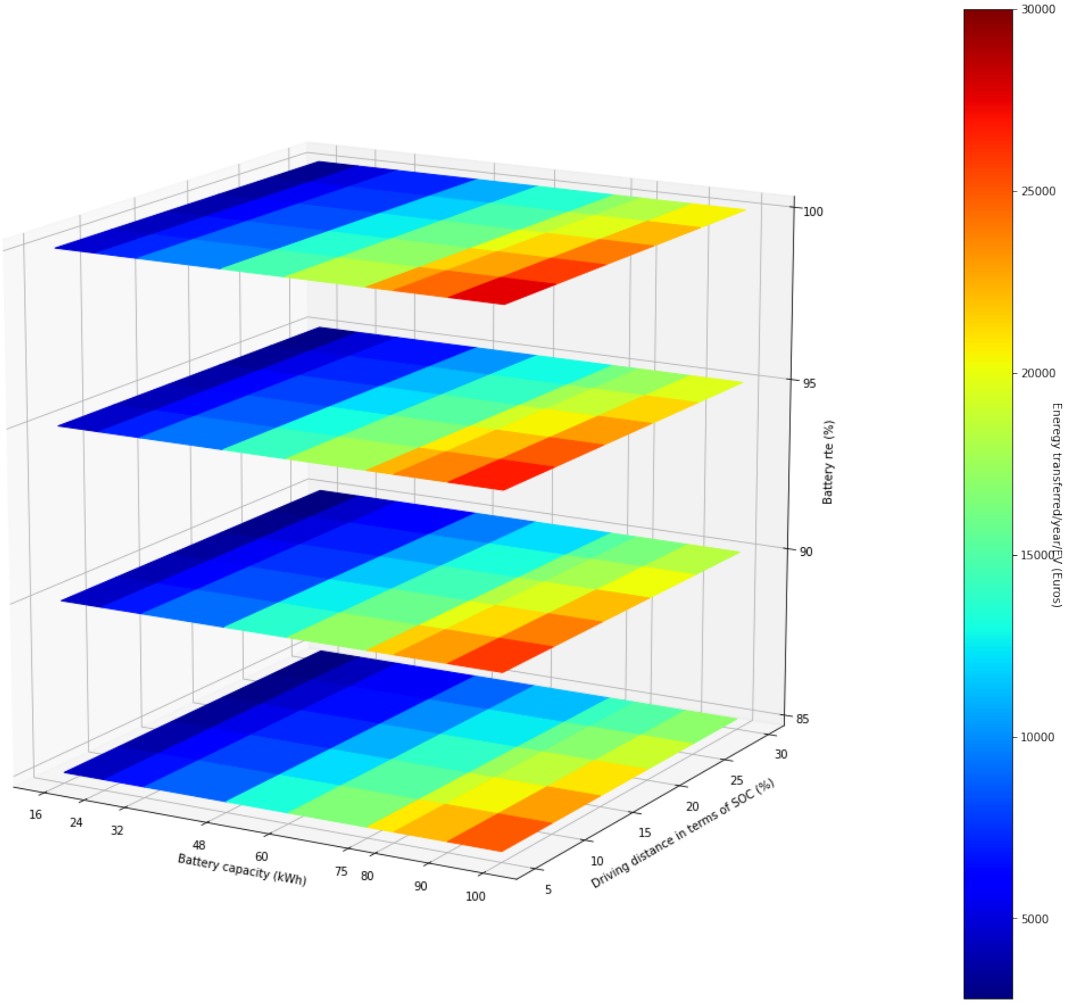


Figure (4.17) Variation of total energy transferred with respect to RTE, battery capacity and driving distance

$$\text{K2} = \frac{(1 - \text{Battery\_threshold}) * \text{Battery\_capacity}}{\text{charge\_eff}} \tag{4.16}$$

$$\text{K3} = 0 \tag{4.17}$$

$$\text{K4} = \frac{(2 * \Delta\text{SOC\_driving}) * \text{Battery\_capacity}}{\text{charge\_eff}} \tag{4.18}$$

Where:
ΔSOC_driving: SOC used for driving.
Battery_threshold: Minimum SOC to be maintained at any point of time (kWh).
Battery_capacity: Capacity of the battery (kWh).

Input	Value
Battery capacity (kWh)	100
Usable capacity (kWh)	100
Round trip efficiency (%)	95
Battery replacement cost (€)	6000
V2G on Weekends	yes
Number of days	365
EV Consumption (km/kWh)	5.3644
Energy consumed for a single trip (\% of battery capacity)	0.05
Driving distance for a single trip - home to office (kM)	26.1376535
Output	**Value**
Profit without degradation (€)	442.642165
Total V2G discharge (kWh)	28216.96
Profit with degradation based on balance between price signal and the battery degradation (€/EV/year)	662.372052
Total V2G discharged (kWh)	29761.83

Table (4.8) Best case V2G profit (Annual profit)

discharge_eff and *charge_eff*: Battery discharge and charge efficiency.
On substituting K1, K2, K3 and K4 in the equation (4.14), equating the profit to zero and simplifying the equation the equality (4.19) is obtained.

$$\frac{\text{P\_sell}}{\text{P\_buy}} = \frac{1}{\text{RTE}} \tag{4.19}$$

Where:
RTE: Round trip efficiency. Product of *discharge_eff* and *charge_eff*.
For the profile in figure 4.5, where one discharge and one charge event is allowed the parameters can be defined as

$$\text{K1} = (1 - (\Delta\text{SOC\_driving}) - \text{Battery\_threshold}) * \text{Battery\_capacity} * \text{discharge\_eff} \tag{4.20}$$

$$\text{K2} = \frac{(1 - \text{Battery\_threshold}) * \text{Battery\_capacity}}{\text{charge\_eff}} \tag{4.21}$$

$$\text{K3} = \frac{\Delta\text{SOC\_driving} * \text{Battery\_capacity}}{\text{charge\_eff}} \tag{4.22}$$

$$\text{K4} = \frac{(2 * \Delta\text{SOC\_driving}) * \text{Battery\_capacity}}{\text{charge\_eff}} \tag{4.23}$$

Where:
$\Delta SOC\_driving$: SOC used for driving.
$Battery\_threshold$: Minimum SOC to be maintained at any point of time.
$Battery\_capacity$: Capacity of the battery.
$discharge\_eff$ and $charge\_eff$: Battery discharge and charge efficiency.
On substituting K1, K2, K3 and K4 in the equation (4.14), equating the profit equal to zero and simplifying the equation, the equality (4.24) is obtained.

$$\frac{\text{P\_sell}}{\text{P\_buy}} = \frac{1}{\text{RTE}} \tag{4.24}$$

Where:
RTE: Round trip efficiency.
For both the SOC profiles in figure 4.4 and 4.5 break-even point is the same. Hence, the break even point depends only on the Round trip efficiency of the battery. This is true only for profit without degradation. If the round trip efficiency is 1, then the break-even point is when the selling price and buying price are equal. In all other cases, the break-even point is determined by the RTE. The ratio of selling and buying price for the break-even case for different round trip efficiencies are shown in table 4.9

Round trip efficiency	Break even selling price to buying price ratio
0.8	1.25
0.85	1.1764
0.9	1.111
0.95	1.053
1	1

Table (4.9) Break-even selling price to buying price ratio with respect to round trip efficiency.

4.3.4.2. Battery degradation

The battery type and the battery degradation model considered in this work results in less degradation when compared to no V2G case. Already V2G is profitable because it increases battery life. Hence the break-even analysis is not conducted.

5. V2G As An Ancillary Service

The ancillary market for frequency regulation in Germany consists of three types of services: primary control reserve, secondary control reserve, and tertiary control reserve. The remuneration for an ancillary service provider depends on the type of service offered. As discussed earlier, the service providers must fulfil the timing and power requirements to participate in the bidding process. An individual EV cannot fulfil the power requirements of the ancillary market. For example, the minimum capacity required for a service provider to be an FCR is 1MW. An EV cannot fulfil this requirement. Hence, an "aggregator" is assumed to present between the grid and EV. The aggregator combines several EVs so that the power requirements of FCR, aFRR and mFRR are met. In this section, a methodology is formulated to evaluate the profit for an EV when it participates via an aggregator in the frequency regulation services. It is assumed that the Aggregator has enough power in addition to the EV considered for calculation, to place a bid and provide service. The aggregator shall not charge any remuneration for it's service and infrastructure. Hence, the profit earned from the FCR, aFRR and mFRR go to the EV owner directly. This chapter is divided into three sections: methodology, simulation, and results. The approach and the equations used to calculate the profit are discussed in the methodology section. The implementation of the methodology and the results are discussed in the simulation and result section respectively.

5.1. Methodology

The approach followed to calculate the profit for the frequency regulation ancillary service is similar to the one used for calculating the profit for the V2G service in the previous chapter. The price signals are modelled first, and assumptions are made to represent the real-world use cases. The equations are derived to calculate the revenue, cost, and profit. Each of these is explained in detail in the following subsections.

5.1.1. Price Signal

In order to make the profit calculation more realistic the price signals are taken from the Regelleistung website [47]. This website contains the capacity and energy payment price signals for the ancillary services in the German energy market. The procedure to download the price signals is described in section A.2. The EV is available for the same duration as assumed in the previous chapter. The ancillary service window is assumed to be from 0800 hours to 1700 hours. The FCR gets paid for only capacity, and the capacity payment price is constant for a day. There is no separate payment for positive and negative frequency control in FCR. aFRR and mFRR get paid for both capacity and energy. The aFRR and mFRR have

6 different bidding slots of 4 hours each and the positive and negative frequency control services are offered as a separate bid. An ancillary service provider has to bid separately for positive and negative frequency regulation except for FCR. However, the same ancillary service provider can provide both positive and negative aFRR and mFRR simultaneously. This is possible because grid imbalance is either positive or negative, and never both at the same time. Due to the assumption of ancillary service window from 0800 hours to 1700 hours, EV can participate in aFRR and mFRR service only for the two slots out of the six slots in a day. Figure 5.1 depicts the different bidding slots for FCR, aFRR and mFRR. It also compares the bidding slot timing with the EV driving profile. There are 17 price signals to be considered for calculation for this work. One price signal for FCR and eight each for aFRR and mFRR. The following are the 17 price signals

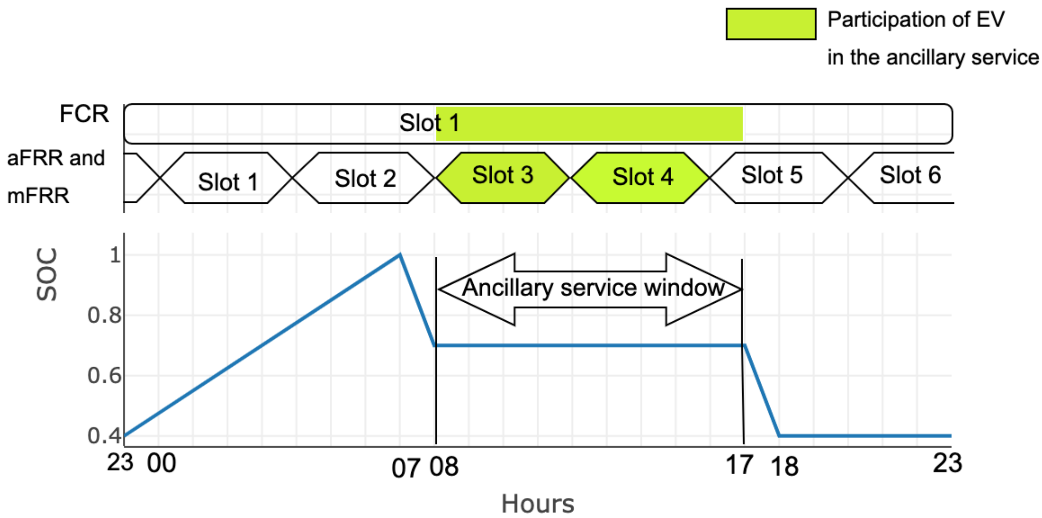


Figure (5.1) Participation of EV in FCR, aFRR and mFRR bidding slots

1. *FCR_capacity*: FCR capacity payment price signal
2. *aFRR_capacity_pos*_08_12: aFRR positive capacity payment price signal 0800 - 1200 hours
3. *aFRR_capacity_neg*_08_12: aFRR negative capacity payment price signal 0800 - 1200 hours
4. *aFRR_capacity_pos*_12_16: aFRR positive capacity payment price signal 1200 - 1600 hours
5. *aFRR_capacity_neg*_12_16: aFRR negative capacity payment price signal 1200 - 1600 hours
6. *mFRR_capacity_pos*_08_12: mFRR positive capacity payment price signal 0800 - 1200 hours
7. *mFRR_capacity_neg*_08_12: mFRR negative capacity payment price signal 0800 - 1200 hours

8. *mFRR_capacity_pos*_12_16: mFRR positive capacity payment price signal 1200 - 1600 hours
9. *mFRR_capacity_neg*_12_16: mFRR negative capacity payment price signal 1200 - 1600 hours
10. *aFRR_energy_pos*_08_12: aFRR positive energy payment price signal 0800 - 1200 hours
11. *aFRR_energy_neg*_08_12: aFRR negative energy payment price signal 0800 - 1200 hours
12. *aFRR_energy_pos*_12_16: aFRR positive energy payment price signal 1200 - 1600 hours
13. *aFRR_energy_neg*_12_16: aFRR negative energy payment price signal 1200 - 1600 hours
14. *mFRR_energy_pos*_08_12: mFRR positive energy payment price signal 0800 - 1200 hours
15. *mFRR_energy_neg*_08_12: mFRR negative energy payment price signal 0800 - 1200 hours
16. *mFRR_energy_pos*_12_16: mFRR positive energy payment price signal 1200 - 1600 hours
17. *mFRR_energy_neg*_12_16: mFRR negative energy payment price signal 1200 - 1600 hours

The price signal data for FCR is available from July 1 to December 31 2019 and the data for aFRR and mFRR are available from 1 January, 2019 to 31 December 2019. Table 5.1 compares the average values of the price signal. From the table it is noticeable that the average value of mFRR is greater than the average value of aFRR.

Price signal	**Average value**	**Unit**
FCR_capacity	208.4281	€/MW
aFRR_cap_neg_08_12	11.8839	€/MW
aFRR_cap_pos_08_12	17.296	€/MW
aFRR_cap_neg_12_16	16.2892	€/MW
aFRR_cap_pos_12_16	13.6699	€/MW
mFRR_cap_neg_08_12	6.9688	€/MW
mFRR_cap_pos_08_12	19.9804	€/MW
mFRR_cap_neg_12_16	12.8595	€/MW
mFRR_cap_pos_12_16	35.2074	€/MW
aFRR_en_neg_08_12	360.8207	€/MWh
aFRR_en_pos_08_12	708.1368	€/MWh
aFRR_en_neg_12_16	455.6295	€/MWh
aFRR_en_pos_12_16	584.6979	€/MWh
mFRR_en_neg_08_12	1593.5	€/MWh
mFRR_en_pos_08_12	1097.3	€/MWh
mFRR_en_neg_12_16	1490.0	€/MWh
mFRR_en_pos_12_16	986.6863	€/MWh

Table (5.1) Comparison between the average values of frequency control ancillary service price signal.

5.1.2. Scenarios

The base case for profit calculation is the No V2G case, where the EV does not provide any ancillary service. The profit from FCR, aFRR and mFRR are calculated considering the base case as a reference. These service providers are activated based on the frequency of the grid, and the profit earned depends on the duration of the regulation. Since the fluctuations in grid frequency are complex to model, simulations resort to a "dispatch-to-contract" ratio. This is the ratio of actual power delivered to the grid to the total amount of power contracted [17]. The equation (5.1) is used to calculate the dispatch-to-contract ratio.

$$R_{d-c} = \frac{E_{disp}}{P_{offered} * T_{offered}} \tag{5.1}$$

Where:
E_{disp}: Total energy dispatched by the service provider in the offer period in MWh.
$P_{offered}$: Contracted power capacity in MW.
$T_{offered}$: Duration of the contract in hours.

This ratio is calculated based on the history of the market. For example, a service provider secures a contract to offer 1 MW ($P_{offered}$) for 24 Hours ($T_{offered}$), and provides 6 MWh of energy (E_{disp}) to the grid. In this case the R_{d-c} is 0.25 or 25%. The ratio is set equal to 10% in the economic feasibility analysis done in the existing literature by [17], [70] and [82]. Unfortunately, there is no data available for the German electricity market to calculate the dispatch-to-contract ratio. The assumption for this ratio limits the profit calculation as the battery's full potential is not used. However, in real-life, the services are not used continuously and activated based on the grid frequency. Two scenarios are considered for each of the services based on the value of the dispatch-to-contract ratio. For FCR, the following two scenarios are considered:

1. Scenario 1: Dispatch-to-contract ratio set equal to 100%. 100% dispatch-to-contract ratio gives the maximum usage as the actual power transferred is equal to the contracted power.

2. Scenario 2: dispatch-to-contract ratio set equal to 10%.

For aFRR and mFRR, the following two scenarios are considered:

1. Scenario 1: dispatch-to-contract ratio set equal to 50%. This is due to the assumption that positive and negative regulation activation are symmetric. For example, assume an EV makes a power offer for 1kW for both positive and negative regulation for 8 hours. This implies that the EV should be able to provide 8 hours of positive or negative regulation continuously. If the activation is symmetric, then the EV would provide 4 hours each of positive and negative regulation. EV would be providing the regulation service for 8 hours but, for each positive and negative regulation the dispatch-to-contract ratio would be 50%.
2. Scenario 2: dispatch-to-contract ratio set equal to 10%.

In the second scenario, the dispatch-to-contract ratio set to 10% per contract (per bid), and it is separate for positive and negative regulation service.

5.1.3. Profit Model

The profit model takes the price signal as input. The driving pattern of the EV assumed for the evaluation is shown in figure 5.2. Based on the type of service the profit model chooses the appropriate remuneration scheme. The model calculates the possible power offer for the EV battery. This depends on the initial SOC of the battery and the expected final SOC, which is required for the EV to return home. An ideal aggregator is assumed to be present, which will always win the bid and takes care of the additional power required to meet the grid requirements. Based on the scenarios, the profit model generates the SOC profile for the EV. The SOC profile is given to the battery degradation model to calculate the amount of battery degradation. The profit is calculated by subtracting the battery degradation cost from the revenue.

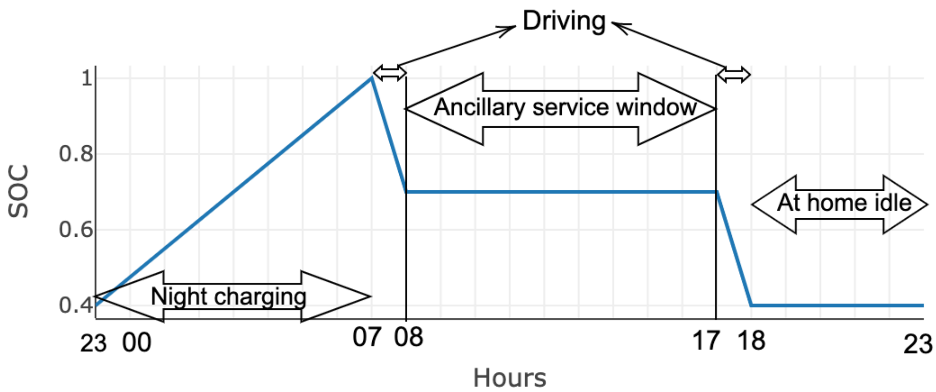


Figure (5.2) EV driving pattern considered for ancillary service profit estimation

The power offer and remuneration to the EV depends on the service (FCR or aFRR or mFRR). The equations to calculate the profit for each of these are explained in the simulation section separately.

The assumptions made for the profit model are summarized below.

1. The EV participates in the ancillary service from 0800 hours to 1700 hours.
2. EV does not participate in FCR, aFRR and mFRR simultaneously. The profit for each of these are calculated independently.
3. EV offers positive and negative regulation simultaneously. The final profit includes the revenue due to both positive and negative regulation.
4. Positive and negative regulation occur symmetrically. This implies for every positive regulation activation there is a corresponding negative regulation activation.

5. The aggregator is ideal and handles the shortage of power offer to meet the market requirements.

6. The infrastructure cost for the aggregator is not considered.

5.2. Simulation Of Primary Frequency Regulation

For an EV to provide primary frequency regulation service it must satisfy the following basic rules

1. Guarantee to provide the stated power capacity throughout the offer period.

2. On activation, provide the stated power capacity uninterrupted for 15 minutes [50].

3. Provide both positive and negative frequency control.

4. The power injected or absorbed to or from the grid should be proportional to the frequency deviation.

The FCR price signals of already won bids for the year 2019 is taken from the Regelleistung website. Since FCR service gets paid only for the capacity, the revenue earned by an EV providing FCR service is given by the equation (5.2).

$$\text{revenue} = \text{P}_{\text{offered}} * \text{Capacity\_payment} * \text{Availability} \tag{5.2}$$

Where:
$P_{offered}$: Power in MW the EV can provide for the frequency regulation.
Capacity_payment: Payment that the aggregator has won in the bid .Taken for the Regelleistung website.
Availability: Ratio of time duration for which EV is available for the service to the offer period.
All three parameters in the equation (5.2) are dependent on other factors and are calculated as follows.

1. $P_{offered}$ is the power capacity that the EV can offer. This depends on the starting battery SOC of the EV when it starts providing the service (SOC_{start}) and the minimum battery SOC to be retained by the EV at the end of the service (SOC_{end}). The SOC_{end} is not the SOC of the EV at the end of the primary regulation service, but the minimum value of the SOC to be maintained by the EV. At the end of the service the EV can have a SOC greater than the SOC_{end}, but not less. The available power for FCR service is given by the equation (5.3).

$$\text{energy\_available} = \min(1 - \text{SOC}_{\text{start}}, \text{SOC}_{\text{start}} - \text{SOC}_{\text{end}}) * \text{Battery\_capacity} \tag{5.3}$$

Where:
The *Battery_capacity*: Capacity of the battery in kWh.

The minimum of two values is chosen to provide symmetric positive and negative frequency regulation. To make a bid, the vehicle should be able to provide the $P\_offered$ for the time it is available. The power offered by the EV is given by the equation (5.4).

$$\text{P\_offered} = \text{energy\_available} * \text{discharge\_eff}/\text{T\_available} \tag{5.4}$$

Where:
$T\_available$: Time duration for which the EV is connected to the grid and available for service in hours.
$discharge\_eff$: Battery discharge efficiency.
The discharge efficiency is considered instead of round trip efficiency because during the negative control (charging of the battery) the battery can take more than the offered power. But, during positive control (discharging) battery can give less than the actual charge that is present inside the battery due to the discharge efficiency. A similar method is used to calculate the power offered by the authors in [44].

2. $Availability$ is the ratio of time duration for which EV is available for service ($T\_available$) to the offer period. The $T\_available$ depends on the driving profile of the EV. The offer period is the time slot for which the aggregator has won the bid. For FCR it is 24 hours.

3. $Capacity\_payment$ depends on the energy market and it is the bid won by the aggregator. This is the FCR_capacity price signal listed in table 5.1.

The profit is calculated by subtracting the cost from the revenue calculated by the equation (5.2). If the operating and infrastructure cost of the aggregator is ignored, then the cost consists of two components: charging cost and battery degradation cost. The battery degradation cost is calculated as per the equation (5.5).

$$\begin{aligned}\text{Bat\_degradation\_cost} = \text{degradation\_cost\_with\_regulation} - \\ \text{degradation\_cost\_without\_regulation}\end{aligned} \tag{5.5}$$

Where:
$degradation\_cost\_with\_regulation$: Battery degradation cost due to the driving profile which includes primary regulation.
$degradation\_cost\_without\_regulation$: Battery degradation cost due to the driving profile without primary regulation.

5.2.1. Input

The inputs to the profit calculation model are listed below.

1. Battery capacity: 24 kWh
2. Battery round trip efficiency: 85%, resulting in charge and discharge efficiency 92.1% each
3. Battery Replacement cost: €6000
4. Driving distance: 32.448 km

5. Battery SOC used for driving: 30%
6. Maximum charge capacity: 100%
7. Battery discharge threshold: 10%
8. SOC_{start}: 70%
9. SOC_{end}: 40%
10. *T_available*: 9 hours
11. Capacity payment: Price from the bids already won for primary frequency regulation from July 1 to December 31 2019 for the German energy market [47].

5.2.2. Profit Calculation Scenario 1

Scenario 1, with dispatch-to-contract ratio set to 100% would result in continuous service throughout the *T_available* period. The direction of the regulation would alternate every 15 minutes and the frequency of the grid would be as shown in figure 5.4. The FHigh and FLow are the frequency limits for which the primary control reserve activates its full potential. This is a hypothetical frequency signal to understand the activation of FCR. The

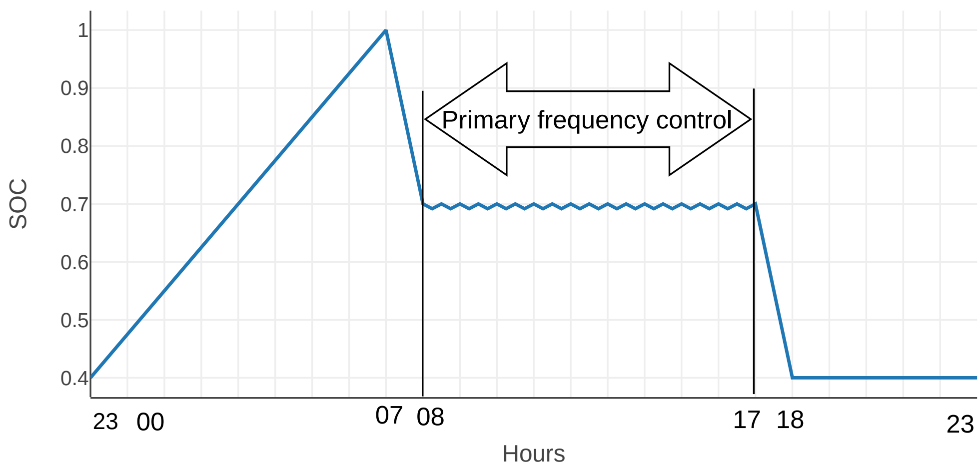


Figure (5.3) Variation in EV battery SOC participating as a FCR service with dispatch-to-contract ratio 100%

EV battery SOC profile for this case is as shown in figure 5.3.The battery degradation model selected earlier in this thesis is used to calculate the battery degradation. The degradation cost without frequency regulation is calculated for the SOC profiles shown in figure 4.3. The degradation cost with frequency regulation is calculated for the SOC profile shown in figure 5.3. The EV needs no additional charge for providing the regulation service because the charge lost during positive regulation is gained back during negative regulation. The charging cost due to frequency regulation service is zero. Only one of the possible cases for

100% dispatch-to-contract ratio is explained in detail here. However, there are other cases which may occur based on the time of activation of the service. The remaining cases are depicted in the appendix subsection A.3. The results of the simulation are tabulated in table 5.2.

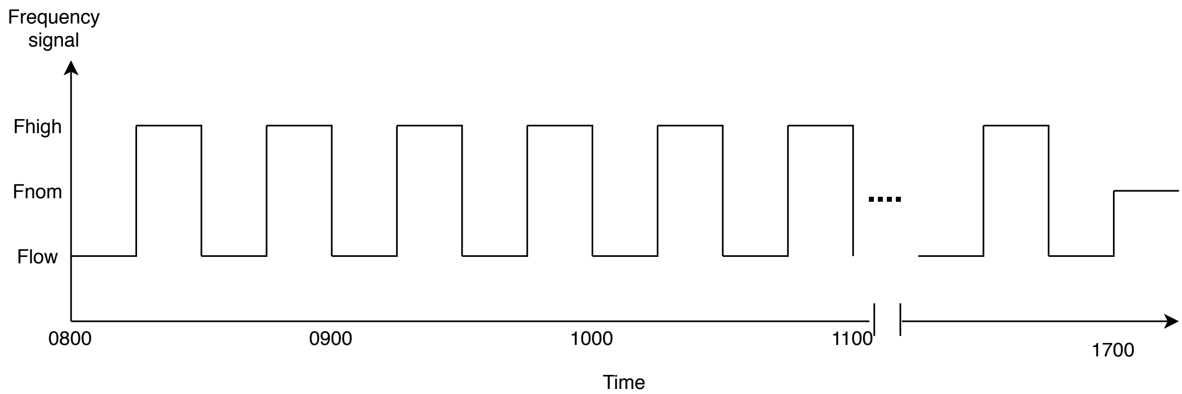


Figure (5.4) Hypothetical frequency deviation for FCR with dispatch-to-contract ratio 100%

5.2.3. Profit Calculation Scenario 2

Scenario 2, with a dispatch-to-contract ratio set to 10%, would result in two positive and two negative regulation activations, each lasting for 15 minutes. The each regulation lasting for 15 minutes would result in dispatch-to-contract ratio of 11%. The 15 mins interval is chosen as it is the minimum duration for which the activation lasts. The corresponding hypothetical grid frequency would be as shown in figure 5.6. The resulting SOC profile in response to this frequency signal is shown in figure 5.5. The battery degradation model calculates the battery degradation cost for the two cases with and without providing frequency regulation. The charging cost for providing frequency regulation is zero, as the positive and negative regulation is symmetrical. Only one of the possible cases for 10% dispatch-to-contract ratio is explained in detail here. However, there are other cases which may occur based on the time on activation of the service. The remaining cases are depicted in the appendix subsection A.3. The results of the simulation are tabulated in table 5.2.

5.2.4. Results

The results of the simulation for primary frequency control are tabulated in table 5.2. The table compares the result of simulation with 100% and 10% dispatch-to-contract ratio. The revenue generated for both 100% and 10% dispatch-to-contract ratio is the same as the FCR gets paid only for the capacity and not the energy provided. But, the battery degradation cost is different for both the cases. The battery degradation cost in both cases is high because the symmetric dispatch causes the SOC to be maintained at a higher value and causes more calendar aging. The additional cycling, when compared to no regulation case, causes more cycle aging. The increased calendar and cycle aging is evident from the SOC profiles with

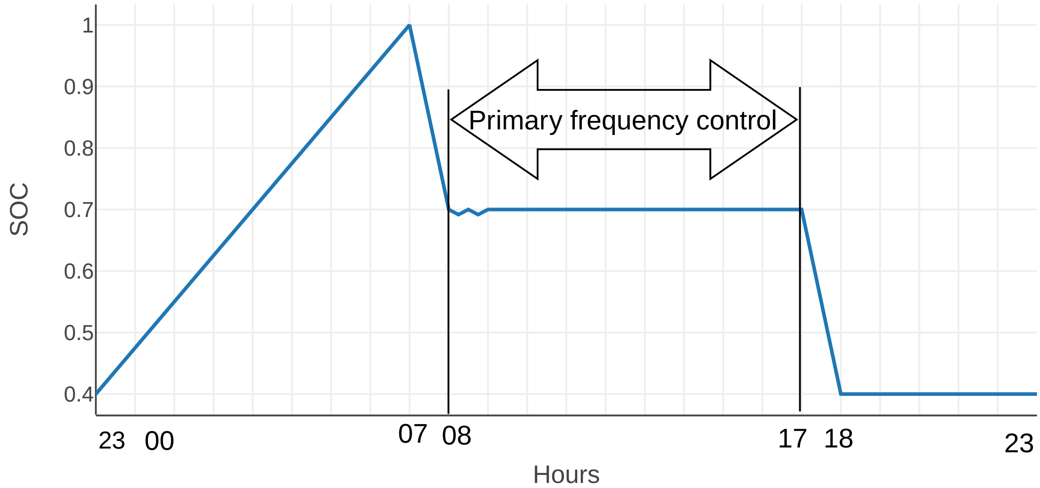


Figure (5.5) Variation in EV battery SOC participating as a FCR with dispatch-to-contract ratio 10%.

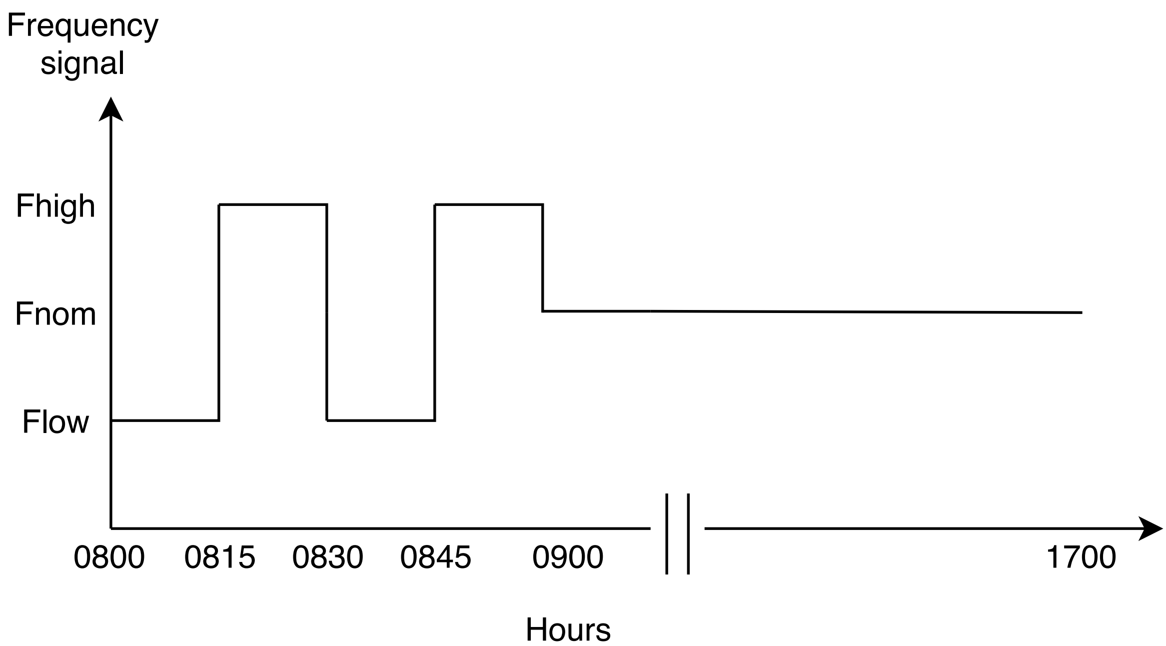


Figure (5.6) Hypothetical frequency deviation for FCR with dispatch-to-contract ratio 10%.

the regulation in figure 5.3 and 5.5, when compared with SOC profiles without regulation in figure 4.3. All three SOC profiles have an average SOC of approximately 70% in the Ancillary service window. Because of the high battery degradation cost, FCR service is not profitable if

Parameter	FCR simulation for 100% dispatch-to-contract ratio.	FCR simulation for 10% dispatch-to-contract ratio.
Battery capacity (kWh)	24	24
energy_available (kWh)	7.2	7.2
P_{offered} (kW)	0.7375	0.7375
Availability (%)	37.5	37.5
Simulation period	184 days (July 1 - Dec31 2019)	184 days (July 1 - Dec31 2019)
revenue (€/EV/year)	10.60	10.60
Battery degradation cost (€/EV/year)	113.667 to 30.9250	12.650 to 7.94
Profit (€/EV/year)	-103.06 to -20.325	-2.05 to 2.66

Table (5.2) Simulation results for FCR with dispatch-to-contract ration 100% and 10%.

a symmetrical dispatch of positive and negative regulation is considered. This observation holds true for all the primary frequency regulation cases illustrated in appendix section A.3.

5.3. Simulation Of Secondary And Tertiary Frequency Regulation

For an EV to provide secondary and tertiary frequency regulation service, it must satisfy the following basic rules

1. Guarantee to provide the stated power capacity throughout the offer period.
2. On activation, should be capable of providing the stated power capacity uninterrupted for 60 minutes [51].
3. Provide either positive and negative frequency control based on the bid placed.

The secondary and tertiary control reserve gets paid for both the capacity and the energy provided. The revenue earned by a secondary and tertiary frequency control service provider is given by the equation (5.6).

$$\text{revenue} = \text{revenue\_capacity} + \text{revenue\_energy} \tag{5.6}$$

Where:
revenue_capacity: Revenue earned from the capacity payment in €.
revenue_energy: Revenue earned from the energy payment in €.
EV can offer both positive and negative regulation simultaneously as an aFRR or mFRR. This is possible because the grid frequency can either be positive or negative at any point in time and never both. The revenue due to capacity payment is the sum of positive and negative regulation. The energy payment is the sum of all the energy payments for both positive and

negative frequency regulation. With this the equation (5.6) can be expanded as (5.7).

$$\text{revenue} = \text{revenue}_{\text{pos\_capacity}} + \text{revenue}_{\text{neg\_capacity}} + \text{revenue}_{\text{pos\_energy}} + \text{revenue}_{\text{neg\_energy}} \tag{5.7}$$

Where:
$revenue_{pos\_capacity}$ and $revenue_{neg\_capacity}$ are calculated as per the equation (5.2).
$revenue_{pos\_energy}$ and $revenue_{neg\_energy}$: Revenue generated from the energy transferred. These are calculated as a product of energy price and the amount of energy transferred, as per equation (5.8).

$$\text{revenue}_{\text{energy}} = \text{energy\_price} * \text{energy\_transferred} \tag{5.8}$$

Where:
energy_price: Energy payment, this would be one of the 8 energy price signals for aFRR and mFRR, listed in table 5.1 based on the bid slot. The revenue due to the capacity payment is calculated as per the equation (5.2). The parameters in this equation are calculated differently when compared to FCR. The parameters are calculated as follows.

1. $P_{offered}$ The power offered is different for positive and negative regulation for aFRR and mFRR unlike FCR. The available energy for positive and negative power reserve is also different and is calculated as per equation (5.9) and (5.10) respectively.

$$\text{energy\_available}_{\text{pos}} = (\text{SOC}_{\text{start}} - \text{SOC}_{\text{end}}) * \text{Battery\_capacity} \tag{5.9}$$

$$\text{energy\_available}_{\text{neg}} = (1 - \text{SOC}_{\text{start}}) * \text{Battery\_capacity} \tag{5.10}$$

   Where:
   The *Battery_capacity*: Capacity of the battery in kWh.
   SOC_{start}: SOC of the battery at the beginning of the service.
   SOC_{end}: Minimum battery SOC to be retained by the EV at the end of the service.
   The power offered for positive regulation is calculated using the equation (5.11) and negative regulation is given by the equation (5.12)

$$\text{P\_offered}_{\text{pos}} = \frac{\text{energy\_available}_{\text{pos}} * \text{discharge\_eff}}{\text{T\_available}} \tag{5.11}$$

$$\text{P\_offered}_{\text{neg}} = \frac{\text{energy\_available}_{\text{neg}}}{\text{T\_available} * \text{charge\_eff}} \tag{5.12}$$

   Where:
   T_available: Time duration for which the EV is connected to the grid and available for service in hours.
   discharge_eff: Battery discharge efficiency.
   charge_eff: Battery charge efficiency.

2. *Availability*: Is the ratio of time duration for which EV is available for service (*T_available*) to the offer period. The offer period for each bid in aFRR and mFRR is 4 hours.

3. *Capacity_payment*: depends on type of service and the time slot. One of the 8 capacity price signal from the table 5.1 is considered depending on the type of service aFRR or mFRR and positive or negative regulation.

As the infrastructure and maintenance costs are ignored, the cost to the EV is the sum of charging costs and battery degradation costs. The battery degradation cost is calculated as per the equation (5.5). The charging cost is zero as the positive and negative regulation activation is symmetric.

5.3.1. Input

The inputs to the profit calculation model, where EV participates as an aFRR and mFRR are listed below.

1. Battery capacity: 24 kWh
2. Battery round trip efficiency: 85%, resulting in charge and discharge efficiency 92.1% each
3. Battery Replacement cost: €6000
4. Driving distance: 32.448 km
5. Battery SOC used for driving: 30%
6. Maximum charge capacity: 100%
7. Battery discharge threshold: 10%
8. SOC_{start}: 70%
9. SOC_{end}: 40%
10. *T_available*: 8 hours, the aggregator is assumed to bid for two slots from 0800 hours - 1200 hours and 1200 hours - 1600 hours.
11. Capacity payment: capacity price from the bids already won for aFRR and mFRR from January 1 to December 31 2019 for the German energy. market [47].
12. Energy payment: Energy price from the bids already won for aFRR and mFRR from January 1 to December 31 2019 for the German energy. market [47].

5.3.2. Profit Calculation Scenario 1

In scenario 1, the dispatch-to-contract ratio set to 50%. This implies that the aFRR and mFRR services are provided throughout the ancillary service window. For secondary and tertiary ancillary services, the law mandates that the reserves should be capable of providing the service for 60 minutes. Assuming symmetric positive and negative regulation activation, this would result in change in the direction of regulation every 60 minutes. The hypothetical frequency of the grid in such a case is shown in figure 5.7. The SOC profile of the EV battery providing aFRR or mFRR in this scenario would be as shown in figure 5.8. The battery degradation model calculates the battery degradation cost for this SOC profile. The charging cost for this SOC profile is zero because of the symmetric dispatch of positive and negative regulation. The profit is calculated by subtracting the battery degradation cost from the revenue. Only one of the possible cases for 50% dispatch-to-contract ratio is explained in detail here. However, there are other cases which may occur based on the time of activation of the service. The remaining cases are depicted in the appendix subsection A.3. The results of the simulation are tabulated in table 5.3

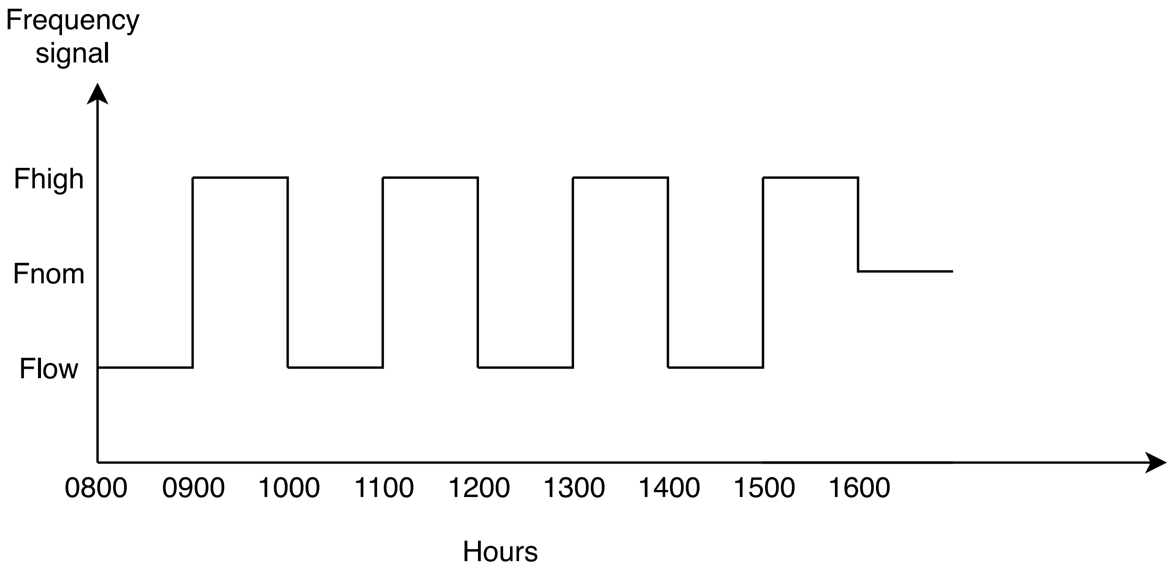


Figure (5.7) Hypothetical frequency deviation for aFRR and mFRR with dispatch-to-contract ratio 50%

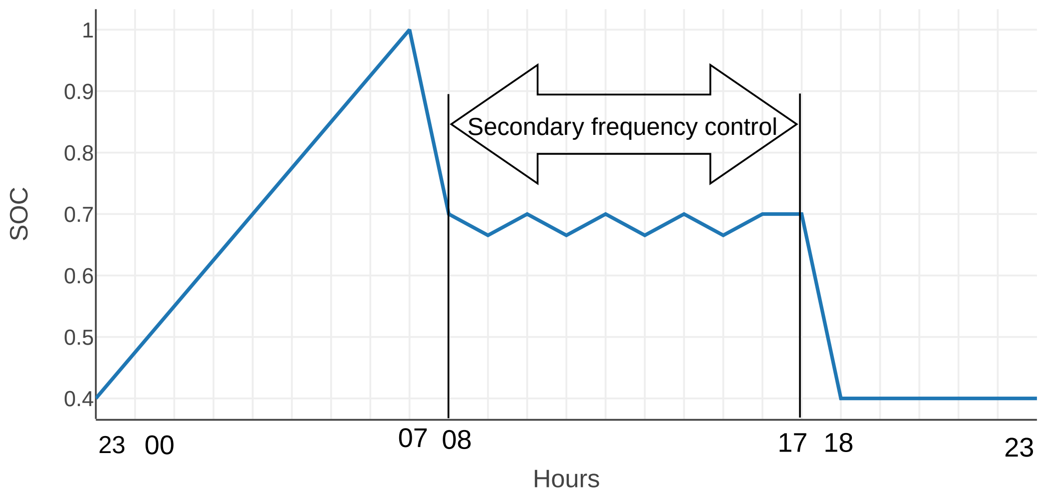


Figure (5.8) Variation in EV battery SOC participating as an aFRR or mFRR with dispatch-to-contract ratio 50%.

5.3.3. Profit Calculation Scenario 2

In scenario 2, the dispatch-to-contract ratio set as 10%. This would result in one positive and one negative activation in the bidding slot 0800 hours to 1200 hours, and one positive and one negative activation in the bidding slot 1200 hours to 1600 hours. In order to satisfy the 10% dispatch-to-contract ratio, the duration of each of these activations will not be 60 minutes. It would be 24 minutes each. The law mandates that the service provider should be capable of providing the service for at least 60 minutes, but the actual service period can be lower than that. The grid frequency in such a case would be as illustrated in figure 5.9. The EV battery in such a scenario will have the SOC profile as shown in figure 5.10. The battery degradation model calculates the battery degradation cost with and without regulation. The battery degradation due regulation service is given by the equation 5.5. The profit is calculated by subtracting the battery degradation cost for the revenue. Only one of the possible cases for 10% dispatch-to-contract ratio is explained in detail here. However, there are other cases which may occur based on the time on activation of the service. The remaining cases are depicted in the appendix subsection A.3. The results of the simulation are tabulated in table 5.3.

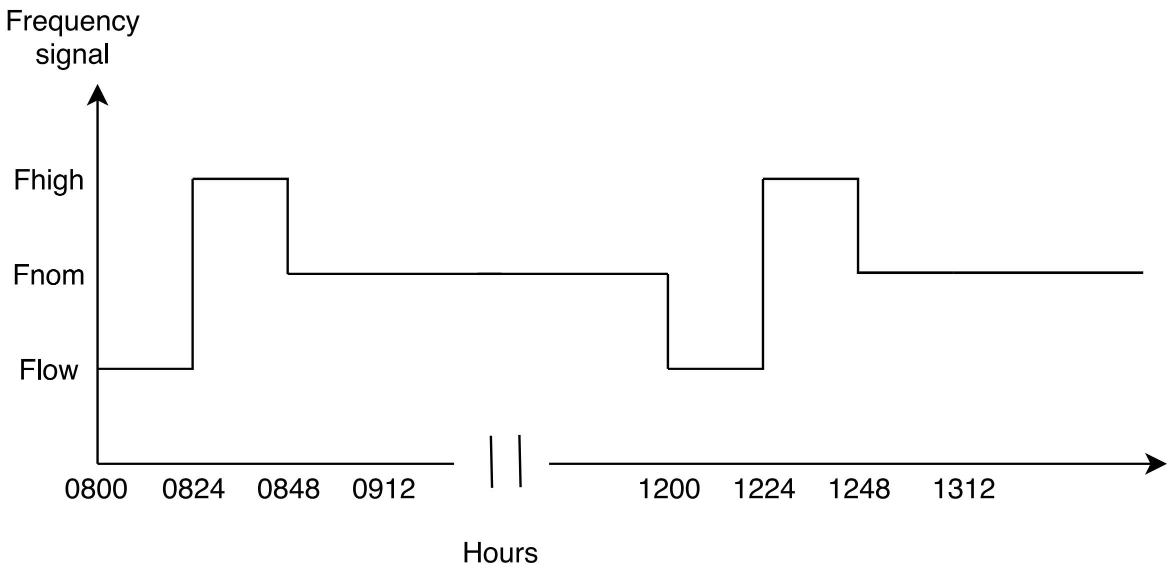


Figure (5.9) Hypothetical frequency deviation for aFRR and mFRR with dispatch-to-contract ratio 10%.

5.3.4. Results

The results of the simulation for aFRR and mFRR are tabulated in table 5.3. The table compares aFRR and mFRR service with 10% and 50% dispatch-to-contract ratio. It can be inferred from the results that, mFRR is more profitable than the aFRR service. This is expected as the the average price of mFRR is greater than the aFRR service. The aFRR and mFRR

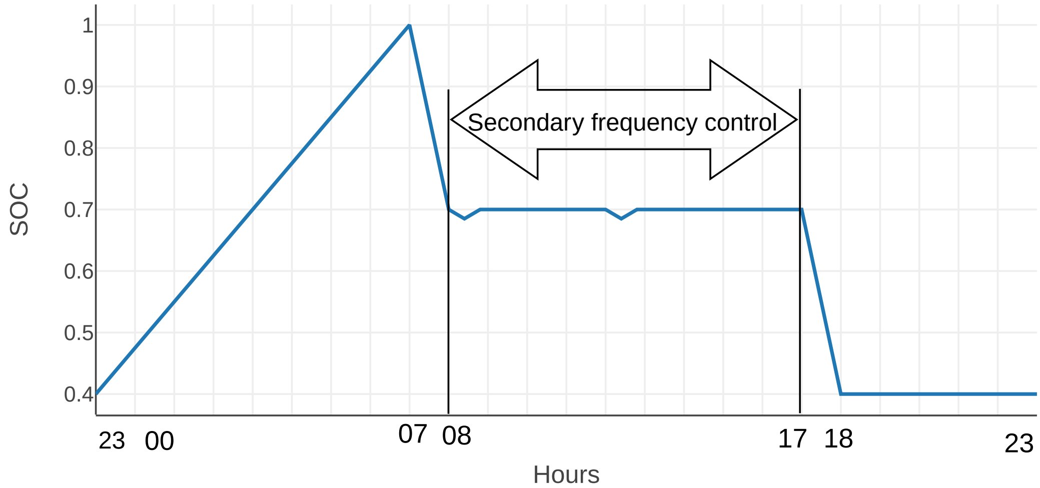


Figure (5.10) Variation in EV battery SOC participating as an aFRR or mFRR with dispatch-to-contract ratio 10%.

cause more battery degradation than the no regulation case. This is because of the SOC profiles of aFFR and mFRR are similar to no regulation case, with additional cycle aging. This additional cycling can be visualized in all the SOC profiles of aFRR and mFRR in the appendix section A.3. Despite the battery degradation cost, aFRR and mFRR are profitable assuming symmetric activation of positive and negative regulation.

Parameter	aFRR simulation for 50% dispatch-to-contract ratio.	aFRR simulation for 10% dispatch-to-contract ratio	mFRR simulation for 50% dispatch-to-contract ratio	mFRR simulation for 10% dispatch-to-contract ratio
Battery capacity (kWh)	24	24	24	24
power_available positive (kWh)	7.2	7.2	7.2	7.2
power_available negative (kWh)	7.2	7.2	7.2	7.2
P_offered positive (kW)	0.82975	0.82975	0.82975	0.82975
P_offered negative (kW)	0.97618	0.97618	0.97618	0.97618
Availability (%) in the offer period	100	100	100	100
Simulation period	365 days (Jan 1 - Dec 31 2019)	365 days (Jan 1 - Dec 31 2019)	365 days (Jan 1 - Dec 31 2019)	365 days (Jan 1 - Dec 31 2019)
Energy dispatched (kWh) for positive regulation per day	3.319	0.6638	3.319	0.6638
Energy dispatched (kWh) for negative regulation per day	3.9047	0.7809	3.9047	0.7809
Total contracted energy (kWh) for positive regulation per day	6.638	6.638	6.638	6.638
Total contracted energy (kWh) for negative regulation per day	7.809	7.809	7.809	7.809
revenue (€/EV/Year)	2749.25	565.38	6943.20	1407.66
Battery degradation cost (€/EV/Year)	125.0488 to 84.453	34.634 to 31.3586	125.0488 to 84.453	34.634 to 31.3586
Profit (€/EV/Year)	2624.20 to 2664.797	530.746 to 534.0214	6818.15 to 6858.747	1373.026 to 1376.30

Table (5.3) Simulation results for aFRR and mFRR with dispatch-to-contract ration 50% and 10%.

6. Discussion

This chapter discusses the results obtained in this work and compares it with the available literature. With the free energy arbitrage for 365 days - 9 hours per day, and considering battery degradation, a maximum profit of €662.37 per year is estimated and a total energy of 29,761.83 kWh per year at 22.25 €/MW is transferred. This value is evaluated for an EV with battery capacity 100 kWh, RTE 95% and total driving distance per day of 54 km. Without considering the battery degradation, a profit of €442.64 with 28216.96 kWh per year at 15.68 €/MW is estimated for the same case. The range of expected profit from free energy arbitrage is between €113.00 to €662.37 per year and the amount of energy transferred varies from 2,314.47 to 29,761.83 kWh per year. Table 6.1 compares the results obtained in this work with the existing literature. There is no direct comparison between the results, as the price signals and the EV specifications are different in each estimation. However, the V2G service is evaluated to be profitable substantiating the assertion of the existing literature.

There is a significant difference in the two profit estimations: profit without battery degradation and profit with battery degradation. The profit without degradation is less than the profit with degradation. This is because V2G service causes less battery degradation compared to the case when EV does not provide the service. The additional saving in the case of profit with degradation is due to the battery life extension that leads to a lower battery replacement cost over a period of time.

The profit due to V2G service is found to be highly sensitive to the three parameters, RTE, capacity and driving distance. The sensitivity analysis shows that for every one percent increase in the RTE, the profit increases by €1.62. With 1 kWh increase in the battery capacity, the profit increases by €1.85. With 1 km decrease in single trip driving distance (2 km decrease in total), the profit increases by €6.64.

The frequency control ancillary service profit model with 10% dispatch-to-contract ratio estimates an annual profit of -€2.05 to €2.66 for FCR, €530.746 to €534.021 for aFRR and €1373.026 to €1376.3 for mFRR. Based on the results of the profit model, aFRR and mFRR services are profitable but FCR service results in a loss. This is because FCR service only gets paid for the capacity but aFRR and mFRR services get paid for both capacity and energy. Moreover, energy payment for aFRR and mFRR services is high compared to capacity payment for the FCR service. Table 6.2 compares the results obtained in this work with that of the existing work. The results obtained in this work do not align entirely with the existing literature. The authors in [26] estimated primary frequency regulation service to be profitable in the Italian energy market. The authors in [72] assessed primary frequency regulation service to be profitable in the French electricity market. This thesis evaluates primary frequency regulation service as non-profitable in the German energy market. The authors in [72] ignored the battery degradation cost and they considered a different remuneration scheme. The authors in [26] also overlooked the battery degradation cost and they considered a higher remuneration for the profit calculation. This is the first ever profit evaluation performed for an EV providing frequency regulation ancillary services, which complies with the latest German energy market regulations. Hence the discrepancy is expected in the results obtained in this work compared to the existing literature.

Comparing the results of the chapter 4 with chapter 5 of this thesis, it is perceivable that unconstrained and free V2G service causes less battery degradation when compared to frequency regulation ancillary services. The reason for this is, the ancillary services cause short cycles of charge/discharge because of the symmetric frequency regulation activation. Short cycles not only increase the cycle aging but also maintain the SOC of the battery at a higher value and consequently result in increased calendar aging. However, this observation holds true only for the symmetric activation of the frequency regulation.

Source /Year /Country /model type	Driving pattern and V2G availability	EV specific characteristics	Battery degradation	Pricing scheme	Profit
[33] /2011 /USA /simulation	V2G availability: 8AM to 5 PM. Driving distance per day: 32 miles	Tesla Model 70D 70kWh battery. RTE: 80%	10.42 cents/kWh	Fixed night charging cost 5.95 cents/kWh. Dynamic pricing during day from ERCOT RTM.	$338.56 per EV per year
[40] /2008 /USA /simulation	V2G availability: 5PM to 7AM.	16kWh. LPF battery. RTE: 85%	4.2 cents/kWh	Considers dynamic pricing from PJM, NYISO, and ISO-NE for 2008	With out battery degradation: $140 - $250 per EV per year With battery degradation: $10-$120 per EV per year
[29]/2013 /UK /simulation	V2G availability: 9 Hours. Driving duration per day:10 - 90 minutes	60 kWh. RTE: 100%	No	Electricity price signal on 12 Nov 2013 is considered for all simulation days.	13.6% (£1799.77/5000EVs/5 days) saving in charging cost with V2G when compared to without V2G case.
[61] /2016 /UK /Experimental	V2G availability: 9 Hours	30 kWh. NCA battery	Based on actual degradation from the experiment.	UK energy pricing	$555 per EV per year saving from improvement in battery life and not from selling electricity to the grid.
This work /2019 /Germany /Simulation	V2G availability: 9 Hours. Driving distance: 32.63 km	24 kWh LMO battery. RTE:85%	Xu model [67]	German day ahead pricing signal for 2019	Without battery degradation: €43.158/Year/EV. With battery degradation: €123.28/Year/EV

Table (6.1) Comparison of profit estimated in this work with existing economic models for free energy arbitrage.

Source	Country/Year	Type of Service	Type of remuneration	Remuneration
[17]	USA 2003	General frequency regulation	Capacity and energy	$2554/EV/Year
[70]	USA 2013	General frequency regulation	Capacity and energy	$187.68/EV/Year
[72]	France 2013	Primary frequency regulation	Capacity and energy	€193-593/EV/Year
[26]	Italy 2016	Primary frequency regulation	Capacity and energy	€1653.9/EV/year
This work	Germany 2019	Primary frequency regulation	Capacity	-€2.05 to €2.66/EV/184 days
[26]	Italy 2016	Secondary frequency regulation	Energy	€2642.2/EV/year
[71]	Germany 2013	Secondary frequency regulation	Capacity and energy	€8-180/EV/year
[73]	Netherlands 2017	Secondary frequency regulation	Energy	€120-750/EV/year
[74]	Ecuador 2019	Secondary frequency regulation	Capacity and energy	$319.8/Aggregator (1000 EVs)/day
This work	Germany 2019	Secondary frequency regulation	Capacity and energy	€530.746-534.0214/EV/year
This work	Germany 2019	Tertiary frequency regulation	Capacity and energy	€1373.026-1376.30/EV/year

Table (6.2) Comparison of profit estimated in this work with existing economic models for frequency control ancillary service.

7. Conclusion And Future Work

7.1. Conclusion

This thesis aims at evaluating the EV owners' profit by participating in V2G services in the German energy market. A profit calculation model is developed, which takes the price signals from the German electricity market and evaluates the profit for the given EV battery specification. This model includes an online battery degradation model to estimate battery degradation costs due to the V2G service. The profit is evaluated for two cases; one where EV can participate in V2G energy arbitrage freely without any restrictions from the energy market or grid and the other, where the EV participates in frequency control ancillary service.

In the first case, the EV owner controls the buying and selling of energy based on the German day-ahead market's electricity price signal. The profit evaluated for this case is very significant, thereby making V2G services beneficial to the EV owner. The profit earned is not only from selling electricity to the grid but also from the savings in battery replacement cost. The LMO battery considered in this model is highly sensitive to high temperature and high SOC. Providing V2G service, EV maintains a low SOC compared to when it is not. Hence, battery degradation is less in the case of EV participating in the V2G service than otherwise. This implies that V2G service can improve the lifetime of the EV battery. However, this observation cannot be generalized for all battery types as the amount of degradation depends massively on the battery chemistry. The sensitivity analysis results show that the profit increases as the capacity of the battery and the round trip efficiency increases and the profit increases as the driving distance per day decreases.

In the second case, the profit is calculated for the participation of an EV in the frequency regulation ancillary service. The price signals from already won bids of the German ancillary services for the year 2019 are considered. The primary frequency regulation service is found to be non-profitable, whereas the secondary and tertiary frequency regulation services are found to be profitable. Though secondary and tertiary regulation services reduce the battery life, the monetary benefit outweighs the battery degradation cost, making these services profitable. The tertiary regulation service is more beneficial than the secondary regulation service because it provides a higher remuneration.

The profitability of the V2G grid service from EV owners' perspective depends on factors like remuneration, battery degradation, and charging and discharging criteria. The profit evaluated changes as one of these factors changes. Without considering these factors, it is not possible to state if V2G is profitable or not. Considering the German electricity price signals for the year 2019 and an EV with battery type LMO, this work evaluates that providing a price-based and unconstrained V2G service is profitable for the EV owners. In addition to that, the participation of EV in secondary and tertiary frequency regulation services in the German ancillary service market is also beneficial to EV owners.

7.2. Future Work

The present work can be improved further by relaxing the assumptions made during the profit estimation. The current work assumes that the EV provides the V2G service only for 9 hours a day. The V2G service is assumed to be available only at the office location and not at home. Only one discharge and charge event is assumed to be possible in the V2G window. These assumptions can be relaxed by formulating profit estimation as an optimization problem. However, having multiple charge and discharge events would lead to more battery degradation. The profit model can be made agnostic to the battery type by including the battery degradation models for battery technologies like NCA, NMC, and LPF. The battery replacement cost is assumed to be fixed at €6000. However, this value will change based on the battery manufacturer and the battery capacity. In real-life, it is necessary to include the infrastructure cost required for V2G. However, this work neglects the infrastructure cost and maintenance cost required for V2G services. The profit from frequency ancillary services is calculated with the fixed dispatch-to-contract ratio. The profit will be more realistic if this ratio is taken from the energy market's history. However, at the time of this work, this ratio was not available for the German energy market and the ratio is set to 10%. This work considers symmetric activation of frequency regulation service. To asses the exhaustive profitability of frequency regulation ancillary service, considering the asymmetric activation of frequency regulation is necessary. The battery degradation model considered in this work has two limitations; first, it does not consider C-rate dependency on degradation; second, the temperature dependency is not valid below 15 degrees. In the future, if these limitations are overcome, the battery degradation estimation can be improved.

A. Appendix

A.1. Extracting Day-ahead price signals for the German energy market

The German day-ahead prices are taken from the website `https://transparency.entsoe.eu/`. The price signals can be extracted using the following steps:

- Select "Transmission"->"Day-ahead Prices" in the web-page.
- Select "Germany" in the area checkbox menu.
- Select region as "BZN | DE-LU".
- Configure the date for which the price signals are to be extracted.
- Download the data by exporting it to one of the listed data format by logging into the website.

The snap of the UI of the website to download the day ahead price for Jan 1, 2019 is shown in figure A.1 .

A.2. Extracting ancillary service price signals for German energy market

The price signals for FCR, aFRR and mFRR are taken from the website `https://www.regelleistung.net/ext/?lang=en`. The price signals can be extracted using the following steps:

- Select the option "Data center" on the web-page.
- In the drop down menu select "Overview results aFRR/mFRR 2018-07-12".
- Select either "PRL" or "SRL" or "MRL" for FCR, aFRR and mFRR respectively.
- Select the duration for which the data is to be extracted.
- Download in XLSX format.

The snap of the UI of the website to download the ancillary service price signals for the month of July 2019 is shown in figure A.2.

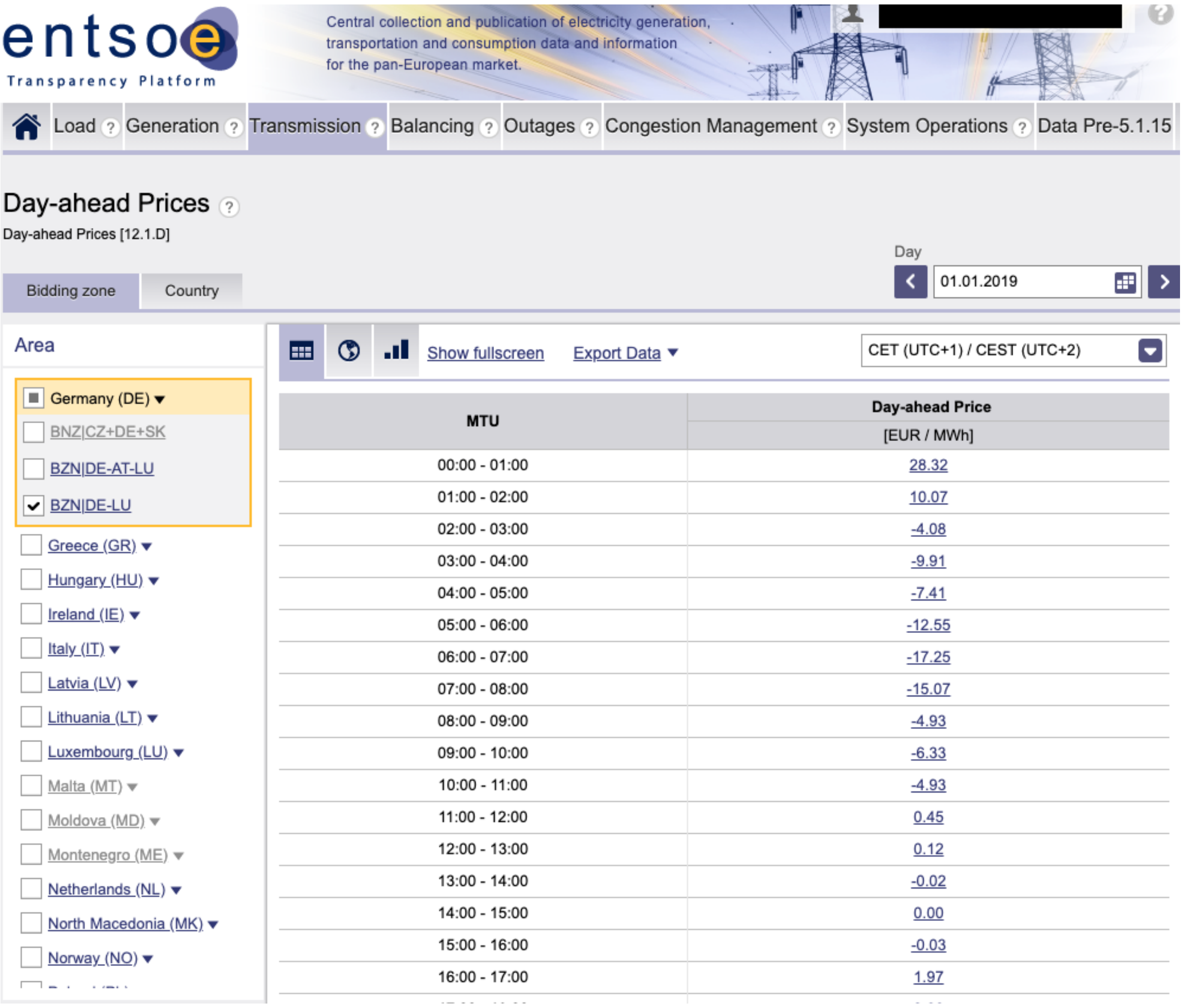


Figure (A.1) Example of extracting Day-ahead price signal for Jan 1,2019 [79].

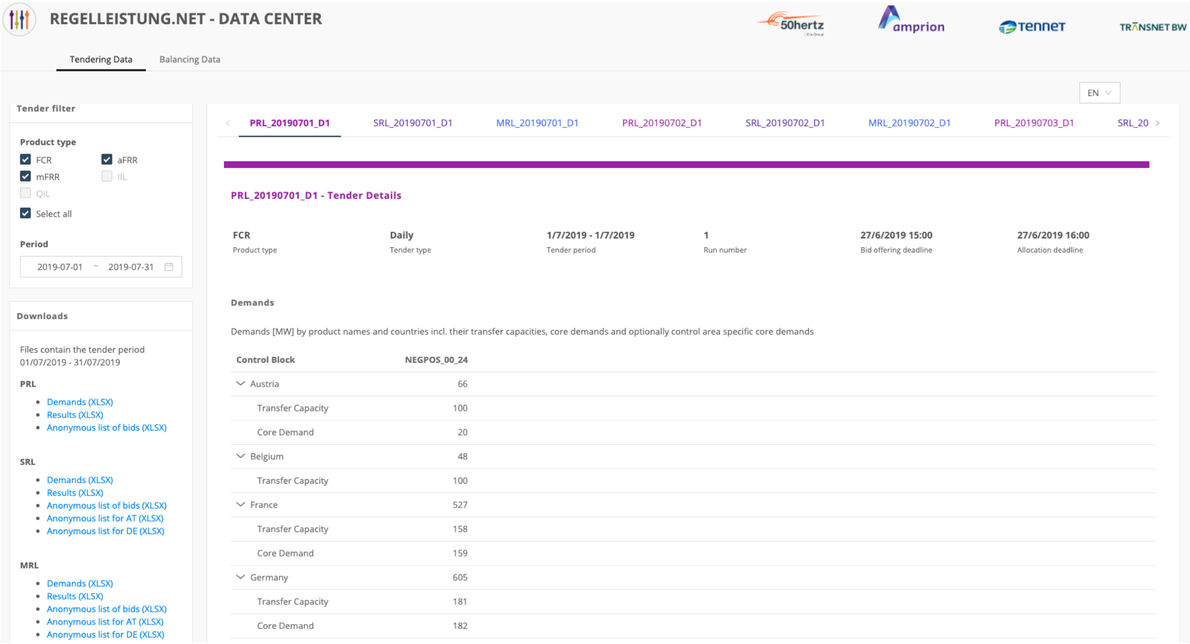
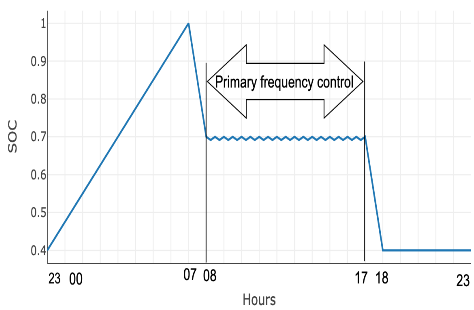
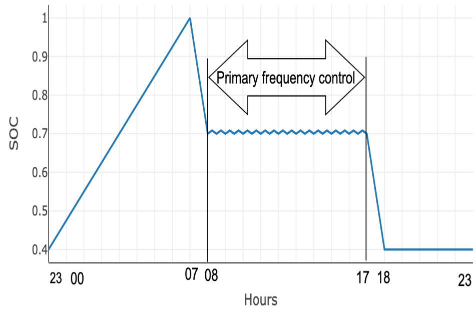
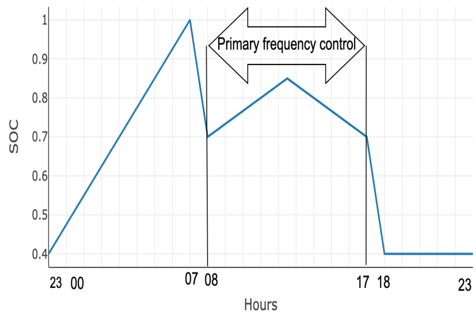
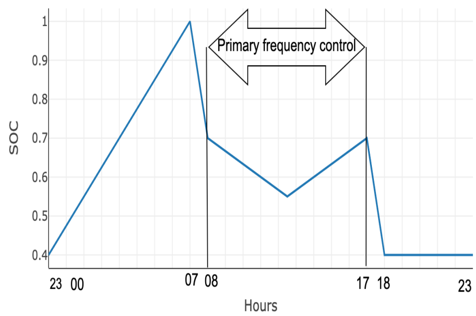


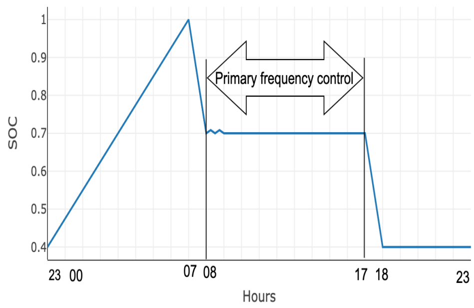
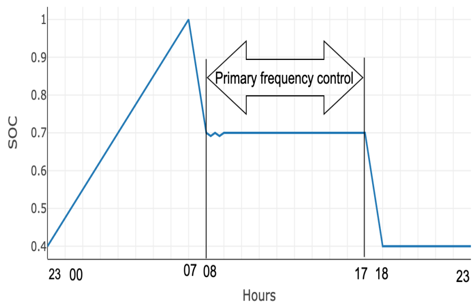
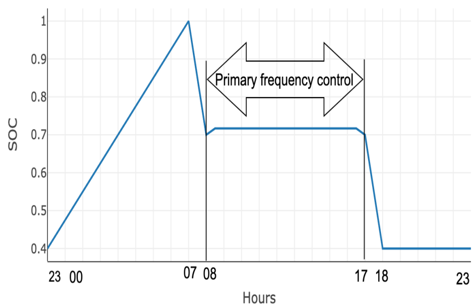
Figure (A.2) Example of extracting ancillary service price signal for July 2019 [47].

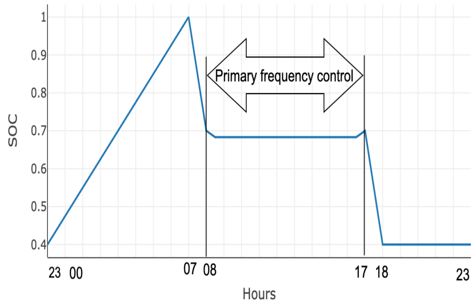
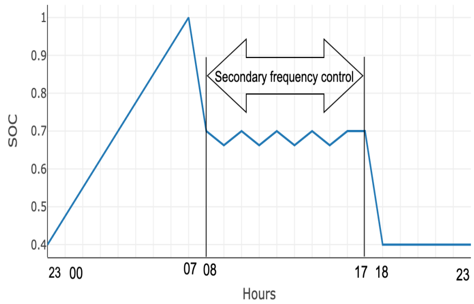
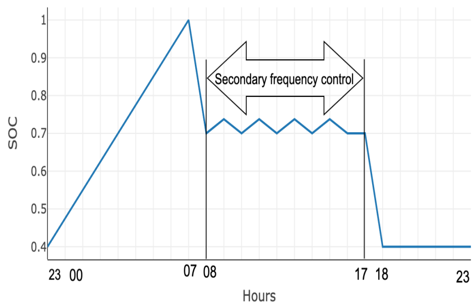
A.3. Frequency regulation ancillary service remaining cases

The chapter 5 considers only two scenarios for each of the ancillary services. The remaining scenarios are discussed here and the battery degradation cost for each of these profiles and the corresponding profit are calculated.

Primary frequency regulation ancillary service	
	**Case description**: 100% dispatch-to-contract ratio with the positive frequency regulation at the beginning of the ancillary window. The positive and negative regulation alternates every 15 minutes. Revenue (€/EV/year): 10.6 Battery degradation cost (€/EV/year): 111.907 Profit (€/EV/year): -101.3

	**Case description**: 100% dispatch-to-contract ratio with the negative frequency regulation at the beginning of the ancillary window. The positive and negative regulation alternates every 15 minutes. Revenue (€/EV/year): 10.6 Battery degradation cost (€/EV/year): 113.667 Profit (€/EV/year): -103.6
	**Case description**: 100% dispatch-to-contract ratio starting with negative regulation. The negative regulation occurs continuously for the first half of the ancillary window, followed by positive regulation. Revenue (€/EV/year): 10.6 Battery degradation cost (€/EV/year): 51.3538 Profit (€/EV/year): -40.7538
	**Case description**: 100% dispatch-to-contract ratio starting with positive regulation. The positive regulation occurs continuously for the first half of the ancillary window, followed by negative regulation. Revenue (€/EV/year): 10.6 Battery degradation cost (€/EV/year): 30.9250 Profit (€/EV/year): -20.325

	**Case description**: 10% dispatch-to-contract ratio with the positive frequency regulation at the beginning of the ancillary window. The positive and negative regulation alternates every 15 minutes till 10% dispatch-to-contract ratio is met. Revenue (€/EV/year): 10.6 Battery degradation cost (€/EV/year): 12.650 Profit (€/EV/year): -2.05
	**Case description**: 10% dispatch-to-contract ratio with the negative frequency regulation at the beginning of the ancillary window. The positive and negative regulation alternates every 15 minutes till 10% dispatch-to-contract ratio is met. Revenue (€/EV/year): 10.6 Battery degradation cost (€/EV/year): 12.455 Profit (€/EV/year): -1.855
	**Case description**: 10% dispatch-to-contract ratio with the negative frequency regulation at the beginning of the ancillary window. The positive regulation occurs at the end of the ancillary window. There is an idle period of 8 hours between the two regulations. Revenue (€/EV/year): 10.6 Battery degradation cost (€/EV/year): 11.064 Profit (€/EV/year): -0.464

	**Case description**: 10% dispatch-to-contract ratio with the positive frequency regulation at the beginning of the ancillary window. The negative regulation occurs at the end of the ancillary window. There is an idle period of 8 hours between the two regulations. Revenue (€/EV/year): 10.6 Battery degradation cost (€/EV/year): 7.94 Profit (€/EV/year): 2.66
Secondary and tertiary frequency regulation ancillary service	
	**Case description**: 50% dispatch-to-contract ratio with the positive frequency regulation at the beginning of the service period (bidding slot). The positive and negative regulation alternates every 60 minutes. **aFRR** Revenue (€/EV/year): 2749.25 Battery degradation cost (€/EV/year): 114.2742 Profit (€/EV/year): 2634.98 **mFRR** Revenue (€/EV/year): 6943.20 Battery degradation cost (€/EV/year): 114.2742 Profit (€/EV/year): 6828.93
	**Case description**: 50% dispatch-to-contract ratio with the negative frequency regulation at the beginning of the service period (bidding slot. The positive and negative regulation alternates every 60 minutes. **aFRR** Revenue (€/EV/year): 2749.25 Battery degradation cost (€/EV/year): 125.0488 Profit (€/EV/year): 2624.20 **mFRR** Revenue (€/EV/year): 6943.20 Battery degradation cost (€/EV/year): 125.0488 Profit (€/EV/year): 6818.15

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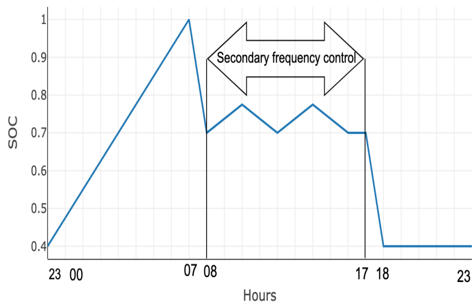

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<td>
Case description: 50% dispatch-to-contract ratio starting with negative regulation. The negative regulation occurs continuously for the first half of the service period (bidding slot), followed by positive regulation.

aFRR
Revenue (€/EV/year): 2749.25
Battery degradation cost (€/EV/year): 104.03
Profit (€/EV/year): 2645.22
mFRR
Revenue (€/EV/year): 6943.20
Battery degradation cost (€/EV/year): 104.03
Profit (€/EV/year): 6839.17
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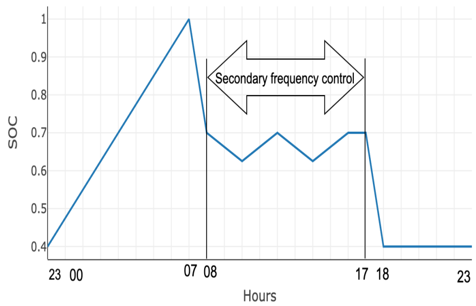

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<td>
Case description: 50% dispatch-to-contract ratio starting with positive regulation. The positive regulation occurs continuously for the first half of the service period (bidding slot), followed by negative regulation.

aFRR
Revenue (€/EV/year): 2749.25
Battery degradation cost (€/EV/year): 84.453
Profit (€/EV/year): 2664.797
mFRR
Revenue (€/EV/year): 6943.20
Battery degradation cost (€/EV/year): 84.453
Profit (€/EV/year): 6858.747
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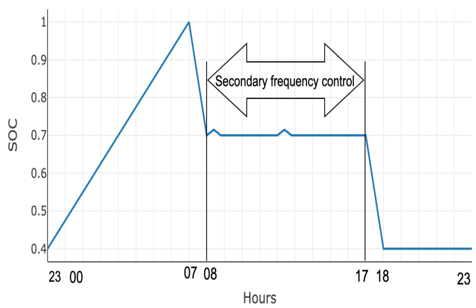

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Case description: 10% dispatch-to-contract ratio starting with negative regulation in the service period (bidding slot). The negative regulation occurs first followed by a positive regulation.

aFRR
Revenue (€/EV/year): 565.38
Battery degradation cost (€/EV/year): 34.634
Profit (€/EV/year): 530.746
mFRR
Revenue (€/EV/year): 1407.66
Battery degradation cost (€/EV/year): 34.634
Profit (€/EV/year): 1373.026
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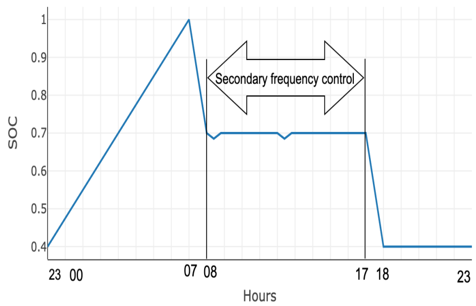
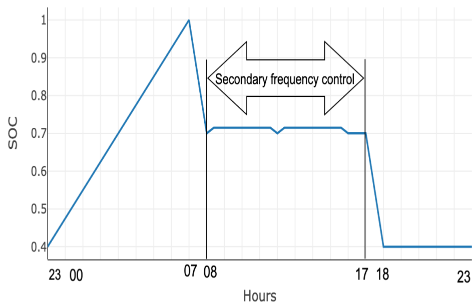
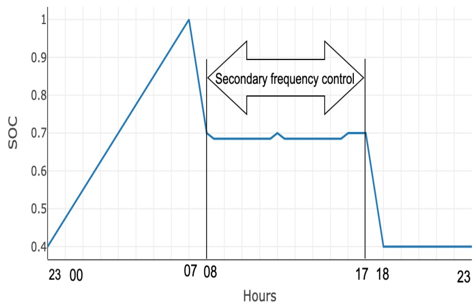
 	**Case description**: 10% dispatch-to-contract ratio starting with positive regulation in the service period (bidding slot). The positive regulation occurs first followed by a negative regulation. **aFRR** Revenue (€/EV/year): 565.38 Battery degradation cost (€/EV/year): 33.612 Profit (€/EV/year): 531.768 **mFRR** Revenue (€/EV/year): 1407.66 Battery degradation cost (€/EV/year): 33.612 Profit (€/EV/year): 1374.04
 	**Case description**: 10% dispatch-to-contract ratio starting with negative regulation regulation in the service period (bidding slot). The positive regulation occurs at the end of the service period. There is an idle period of 3.2 hours between the positive and negative regulation. **aFRR** Revenue (€/EV/year): 565.38 Battery degradation cost (€/EV/year): 36.9228 Profit (€/EV/year): 528.4572 **mFRR** Revenue (€/EV/year): 1407.66 Battery degradation cost (€/EV/year): 36.9228 Profit (€/EV/year): 1370.73



Case description: 10% dispatch-to-contract ratio starting with positive regulation regulation in the service period (bidding slot). The negative regulation occurs at the end of the service period. There is an idle period of 3.2 hours between the positive and negative regulation.

aFRR
Revenue (€/EV/year): 565.38
Battery degradation cost (€/EV/year): 31.3586
Profit (€/EV/year): 534.0214
mFRR
Revenue (€/EV/year): 1407.66
Battery degradation cost (€/EV/year): 31.3586
Profit (€/EV/year): 1376.30

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Stuttgart, 29 June, 2020 Prasad P Malya