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Mansoor Mahmud

Market Potential of V2G for Grid stability

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Author:	Mansoor Mahmud
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ABSTRACT:

Electrification of transport sector is essential to achieve net-zero targets. Globally, transport contributes 12% of carbon emissions and is the number one contributor of emissions in Nordic countries. Adoption of electric vehicles (EVs) reduces the carbon footprint however poses challenges to electricity grid due to high charging load and lack of sufficient infrastructure. Moreover, with high penetration of renewable energy sources with variable production profile and growing demand with high deployment of EVs the power system stability is at risk and if not managed properly can have dire consequences in the form of nationwide blackouts. This report provides a comprehensive insight in the market potential of V2G deeming high deployment of EVs with high penetration of RES in a SMART power system that is imperative for the security of supply of Europe in the aftermath of energy crisis that started as a result of Russia-Ukraine conflict. Nordic countries have the highest deployment of EVs and if these distributed storage batteries are managed smartly it can be valuable assets to enable more renewable energy in the energy mix and can provide flexibility to cater renewable intermittency.

Vehicle-to-Grid (V2G) is an emerging technology that can improve system stability and reliability whilst reducing energy cost and supporting new energy market business models that enables prosumer participation. The main concern of EV owners in participating in V2G is its negative effect on battery life. This report has discussed in detail different types of battery degradation mainly calendar ageing and cyclic ageing. Various battery degradation models are comprehensively studied and integrated in the objective function of the SMART charging. Moreover, this report also provides modelling methods to estimate EV demand for home and public charging using Monte Carlo and gaussian mixture model respectively to include real world charging behaviour of EV owners. The objective function of the modelling equations is formed as a convex problem and to keep the model simple and responsive battery degradation model is run in parallel to calculate cost factor which is fed in the optimization problem and is simulated with SMART charging controller to minimize the electricity cost, recover ownership cost of an EV without compromising user comfort and network thermal limits of the grid with minimal impact on the battery life. Finally, battery degradation is calculated based on the number of cycles used. The model is further developed to include provision of ancillary services and the model is verified using data of two hundred EVs with different plug-in and plug-out times to study economic benefit for user in participating V2G with SMART charging, its impact on grid stability and effect on battery life. From results it is concluded that provision of ancillary services yields more revenue by committing power to grid and has minimal effect of battery. Furthermore, using valley filling EV load can be shifted to off-peak hours when prices are low it reduces electricity cost for users and reduces grid load during peak hours for operators. This report is a part of Best4Grid funded by Nordic Energy Research for the widespread implementation of V2G in Nordic countries.

Keywords: Vehicle-to-grid (V2G), SMART charging, battery degradation modelling, estimation of EV demand, home and public charging, modelling and simulation

1 Contents

1 Introduction

V2G (Vehicle-to-Grid) is an emerging technology capable of utilizing vehicle energy storage capacity for grid services notably during peak hours whilst prioritizing user comfort and low energy cost. Despite availability of technology this is a very challenging scenario that requires a new market structure incentivizing V2G, new regulations for grid and the users, upgrading of infrastructure to support bidirectional power flow, adaptive control and protection schemes, microgrid operation (island mode) for security of supply and to ensure power quality. The most important aspect is the social implementation of this technology because for full economic potential user data would be required to include user comfort in the equation and that means intrusion to their privacy which can be challenging deeming EU privacy laws and regulations. However, trust can be built by ensuring implementing data privacy policies with state-of-the-art data protection technology, and openness about how the user data will be used and protected. Moreover, multiple charging and discharging cycles can be used to maximize economic benefit but at a cost of ageing of the batteries. Despite a dramatic drop in the price of Li-ion batteries, EV vehicles are still comparatively expensive and changing batteries in an EV is costly. This report will study the trade-off between economic benefits, efficiency and devaluation of vehicle (batteries). Nevertheless, challenges bring opportunities for prosumers, aggregators, energy retailers, EV manufacturers, renewable energy sources (RES), and associated businesses. It will also help demand side management (DEM) using variable price signals from the market to even the charging load utilization of surplus energy during off peak hours. Nevertheless, it will accelerate decarbonization journey by encouraging people to invest in V2X technology and customers to buy EVs. We have already seen huge investments from public and private sectors in EVs for instance Tesla Inc has a market cap of 1,5 trillion USD and almost all car companies are now developing high performance and long range EVs. This would have a dramatic effect on the stability of the power system and grid infrastructure with high demands during charging times. If, however coordinated correctly using intelligent energy management system that can communicate with concerned stakeholders this load can be addressed in a cost-effective manner without the need of overloading the infrastructure and without using expensive generators. V2G is part of broader V2X scheme that can connect SMART homes, Electric vehicles, communication with infrastructure to conserve power efficiently with high integration of RES that can be used to its full potential when production is high. The aggregated capacity of EV batteries is connected with grid using smart charger that can reduce charging cost while provide ancillary services – frequency regulation, dispatch improvement, spinning reserve – and balancing power to distribution system operator (DSO) and transmission system operator (TSO) if aggregated capacity is large enough to participate. V2G adds more flexibility in the system to cater variability deeming high penetration of RES and reduces congestion in the network, and is also used to shift load from peak hours to off-peak hours.

This research work - Best4Grid - is a part of Nordic Grand solutions funded by Nordic Energy Research for the widespread implementation of Vehicle-to-everything (V2X) technology in Nordic countries covering technical solutions, legislative and regulatory framework, a review of existing and new business models, and its social impact. Nordic energy research is a Nordic Institute for joint energy research and research-based policy development under Nordic Council of Ministers. Nordic countries have ambitious targets of becoming carbon neutral by 2030 by relying on sustainable energy resources. Electrification of transport is one of the key challenges that will reduce carbon footprint significantly. The scope of the report is to study opportunities and challenges of implementing V2G, analyze effects on efficiency deeming ageing of batteries, control schemes for onboard energy management system (EMS), develop new business models and recommend market regulations supporting V2G deeming data privacy, user comfort and social aspects, and to provide a framework for different stakeholders to operate. The study will include estimation of EV demand, EV demand management, impact of EV charging on the grid and services that can be offered to grid. This report will cover in depth study of the above points, and furnish analysis and recommendations based on simulations.

2 Opportunities and Challenges

Global EV sales has increased exponentially in last one decade. In 2012, a hundred and twenty thousand 120.000 EVs were sold globally. Over 250.000 electric cars were sold every week in 2023. In 2022, 14% of all new vehicles are electric. China and Europe are leading the path of adopting EVs and accounted for more than 85% of global sales in 2021. European EV sales in 2021 has increased by two-third to 2.3 million year-on-year basis (IEA, Global EV outlook 2022 and 2023). In 2024, EV sales reached to 17 million worldwide compared to 14 million in 2023 accounting for more than one in five cars sold. When it comes to market share of EVs China is leading with 45%, Europe with 25% and US slightly over 11% (IEA 2024).

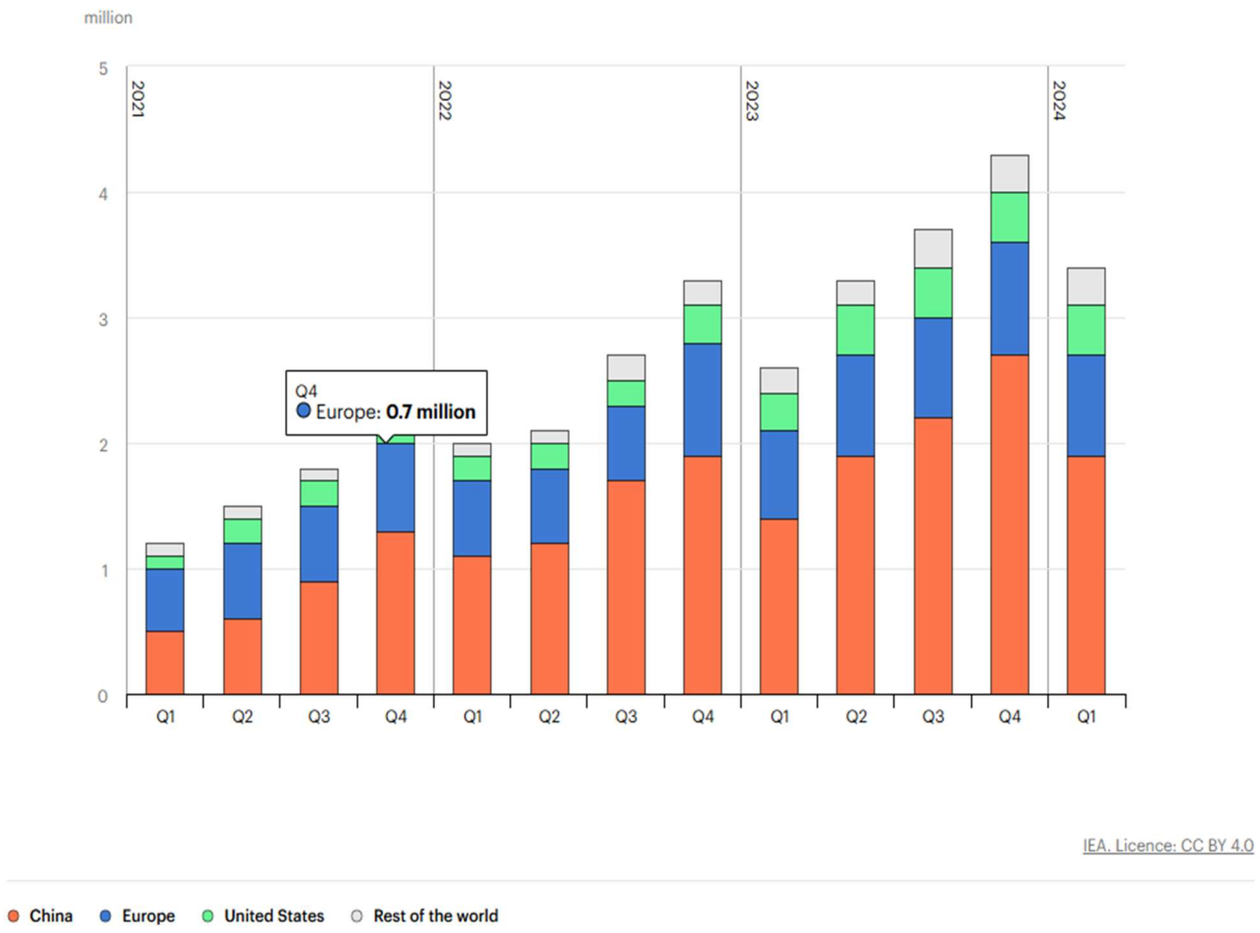


Figure 1: Global EV sale since 2021

Sources

IEA analysis based on data from on EV Volumes, China Passenger Car Association and the European Automobile Manufacturers' Association.

Increase in sales is mainly due to improved vehicle performance, long range, fast charging capability and infrastructure but also because of lower prices due to competition among EV manufacturers, lower battery prices and incentivised policy. In contrast, EV sales in growing economies is slow with 15% cars sold in Vietnam are EVs, 10% in Thailand and 2% in India. This is mainly due to lack of supporting policy, incentives in purchasing new EV and lack of charging infrastructure. With this growth every other car sold in 2035 will be either an electric or hybrid vehicle deeming current policies on climate. Industrial incentives by global players for instance US IRA, the EU Net Zero Industry Act, China's 14th Five-year plan and India's PLI is accelerating transition to EVs that will avoid 12 mb/d of oil. Investment of USD 500 billion is announced in battery technology and EVs during 2022 to 2023, 40% of which has already been committed. Major global car manufacturers – Tesla, Volkswagen, Volvo - have already committed investments in EVs and have set net-zero targets. With such growth more than 40 million EVs would be sold by 2030. High investments in EV battery technology have led to a total manufacturing capacity of 2.2 terawatt-hours globally which is more than current global demand. However, the batteries demand in EV sectors is likely to increase up to seven times by 2035. The EV growth in China is also because of cheaper price of EV compared to its combustion engine counterpart. In EU and US the price of an EV is still 10% to 50% expensive than its combustion engine counterpart. However, with high production the price will decline and more affordable models will be available in future. For instance, Tesla Model 3 price with a range of 220 miles is comparatively same as its counterpart combustion engine sedans in United States however same model 3 is more expensive in Europe due to high manufacturing cost and high taxes. Nevertheless, Tesla has recently announced price cuts in US, China and Germany because of the competition from other EV manufacturers notably from Chinese EV manufacturer BYD, and German car manufacturer Volkswagen (He, 2024).

To meet high EV influx a supporting charging infrastructure will be required. High capacity fast charging stations are more in demand to enable long distance travel of EVs and electric trucks. Number of public charging stations have increased by 40% in 2023 globally but to meet EVs deployment targets it should increase by at least six times by 2035. Danfoss and Volvo have recently developed a 24-hour e-truck to be utilised for their transport needs in Denmark. This fleet is equipped with on-board charging equipment that can save extra cost of charging. Godenergi has developed and deployed charging stations for the fleet that will be installed on key points. Heavy trucks according to IEA accounts for 1,776 Mt CO2 in 2020 (*Volvo and Danfoss Introduce First 24-*

hour E-truck Fleet, n.d.). With heavy duty electric vehicles like buses and trucks more charging infrastructure would be required to enable transition. The electric truck sales increased by 35% compared with 2022 and projected increase in electric truck sales is thirty times deeming stringent emission policies by EU and US. This implies the charging capacity can jump up to twenty folds by 2035 which could have serious implications on existing power system and a need to expand electrical grids with more flexible energy sources is imperative because of the high penetration renewable energy resources (RES) in next decade. To ensure security of supply with lower prices of energy while ensuring system stability and reliability a supporting policy with in depth analysis and a collaborative work between public, private and academia is needed (IEA, 2024).

In a report 'EU competitiveness: Look ahead' by Mario Draghi – former ECB president – analyzed different challenges EU face in achieving a sustainable and competitive economy compared to its trade partners US and China. Affordable, clean and reliable power is the driving force for economic growth and competitiveness however it is challenging due geopolitical conflicts resulting in high energy cost. In 2023, EU energy mix consists of 45% renewable, 20% from nuclear and 32.5% comes from fossil fuels with gas as the main fuel with 14.7% share. As EU energy market is an interconnected single market based on marginal price – the expensive generator in the energy mix decides the price of the electricity on the basis of merit order principle. In 2022, 63% of the time the price was set by gas powered power plants despite 20% share in the energy mix. Therefore, high energy price is mainly observed due to less efficient plants being most expensive and gas plants setting up the price (Draghi, 2023).

Since, Russia-Ukraine conflict the energy prices have dramatically increased because of the sanctions imposed on Russia by EU and US that led shortage of supply and reliance on LNG from spot market. High LNG prices was due to liquification, transport and additional cost of new infrastructure but also because of competition with other buyers. Russian gas imports to EU has decreased from 40% in 2021 to 8% in 2023. Norway, US, UK and Qatar are the new main suppliers of LNG to EU (*Where Does the EU's Gas Come From?*, 2019). Share of gas intensive industries in EU is limited – almost 4% of EU's GDP – yet its impact on electricity prices as discussed previously affects the whole economy.

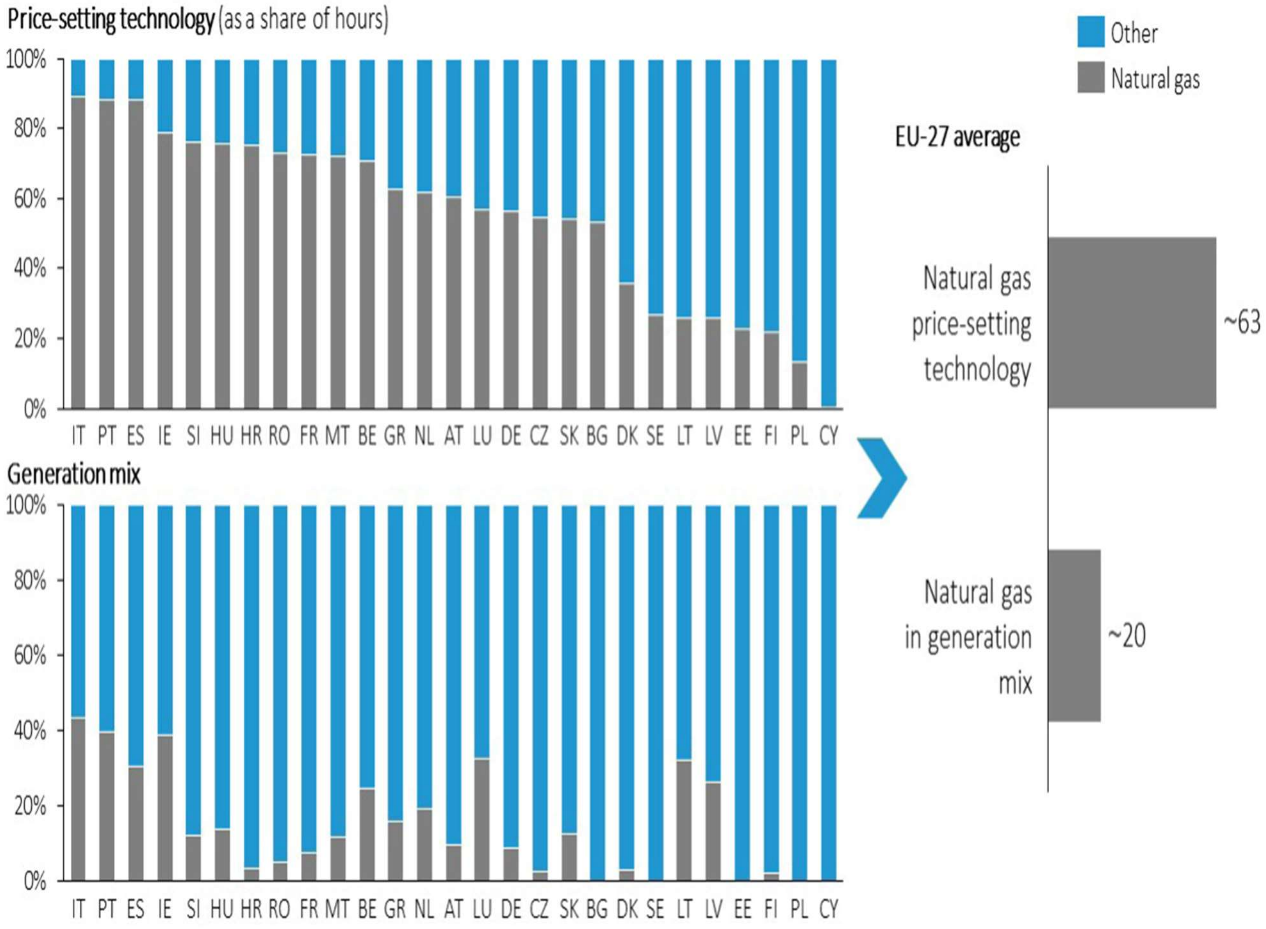
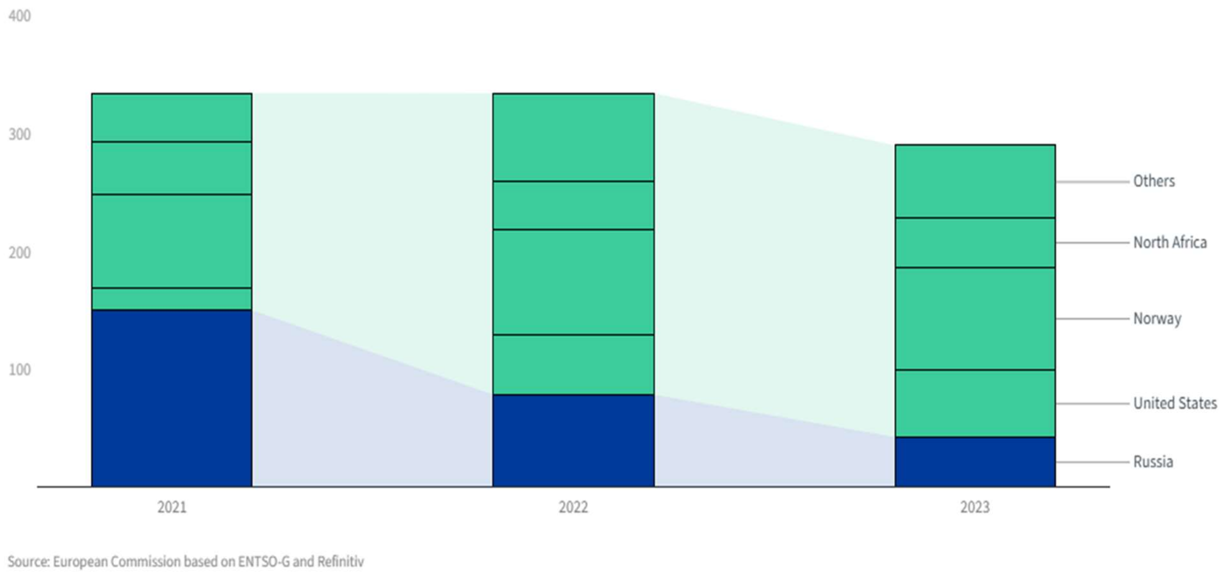


Figure 2: Natural gas as price setting vs its share in energy mix (Draghi, 2023)



Source: European Commission based on ENTSO-G and Refinitiv

Figure 3: EU energy imports since Ukraine-Russia conflict (IEA 2024)

Another observation is the energy mix of member states for instance energy prices in Italy were among the highest compared to Sweden. It can be concluded that a diverse energy mix can bring energy prices down and can be resilient to price shocks. Furthermore, demand side management (DSM) and integration of distribution energy resources (DER) can greatly reduce the need of using expensive generators. As renewable energy resources have added more uncertainty in the power system unscheduled use of expensive generators increases the price significantly. Additional capacity payments also affect the economic dispatch adversely but are essential for the stability of the system. Flexible power system capable of reacting to power fluctuations with sufficient energy storage systems can increase RES share in energy mix, reduce reliance on fossil fuel power plants and unscheduled dispatch at higher prices.

Physical bottlenecks on power system is preventing the EU energy market to operate as an ideal single market that can reduce electricity prices and can save EUR 34 billion a year by controlling the price volatility utilizing cost-effective energy sources (ACER's Final Assessment of the EU Wholesale Electricity Market Design, 2022). Congestion charges in EU TSO can increase significantly due to lack of transmission capacity in utilizing cheaper generating resources. To avoid congestion high infrastructure investment in recommended by the EU to tap full potential of renewable and to lower electricity prices. Electricity networks needs to be more resilient, smart and decentralized, capable of supporting bi-directional power flow and integrating RES. Grids are likely to have more congestion considering RES are located away from areas of high demand for instance offshore wind farms. Moreover, statistically wind energy is more available during night time in winters compared to solar power available during day time in summers. Diverse deployment of wind and solar farms across Europe can reduce intermittency. The intermittent nature could cause higher prices due redispatch and because of utilizing most expensive generators at sport price if RES production varies and can increase overall price to EUR 100 billion. Also, due to limitations of grid infrastructure an estimated of 310TWh of RES could be curtailed by 2040 (THOMASSEN et al., 2024). Moreover, electricity demand is expected to grow 20% faster in next ten years and investment in clean energy has already exceeded USD 3 trillion that is more than the spending in Oil & Gas and is committed in renewable energy resources, energy storage systems and electricity grids (IEA (2024), World Energy Investment).

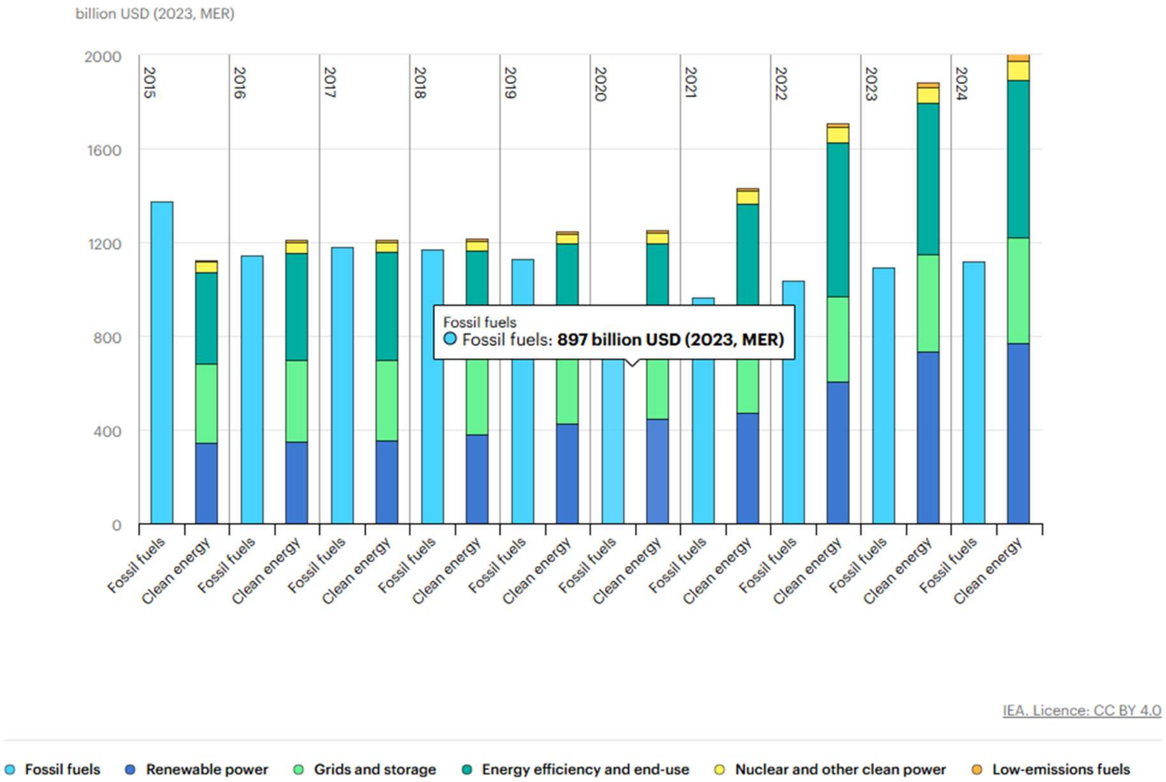


Figure 4: Global investment in clean energy and fossil fuels, 2015-2024 (IEA (2024), World Energy Investment)

As per ‘Grid Delay Scenario’ published by IEA integration of RES and to meet net-zero targets it is essential to expand grid capacity that can cope with high electricity demand for electric vehicles (EVs), hydrogen production through electrolysis, heating and cooling systems, and to enable economic viability of energy storage systems. An estimated investment of EUR 500 billion is required in next ten years to tap full potential of RES in upgrading grid infrastructure. However, these projects require long planning and permitting process deeming EU regulations are delaying these projects.

Share of share of fossil fuels vs wind & solar in grid delay scenario

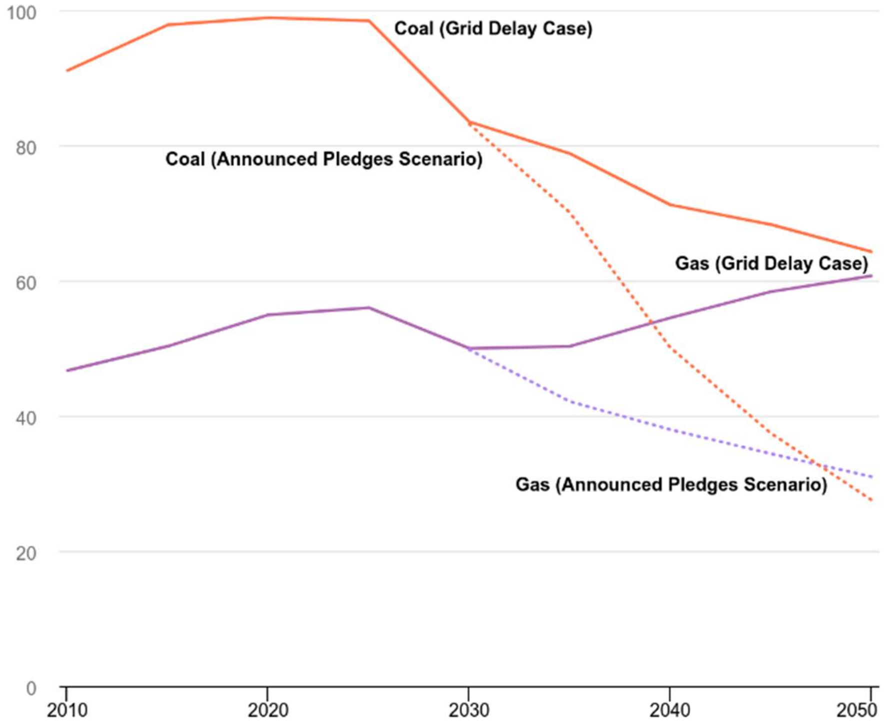


Figure 5: Grid Delay and Pledge Scenarios (IEA (2023), Electricity Grids and Secure Energy Transitions, IEA, Paris)

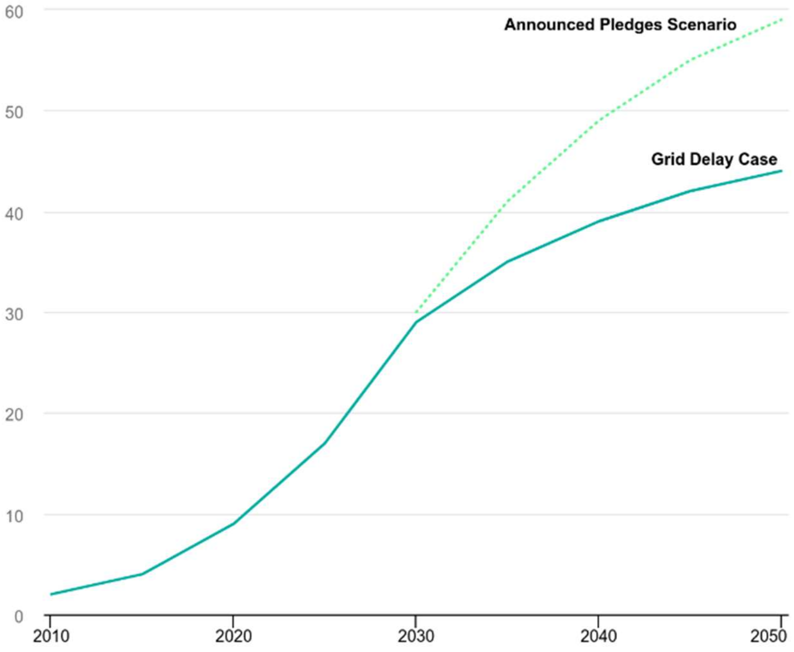


Figure 6: Share of RES (wind & solar) in energy mix in the Grid delay case vs announced pledges

In EU action plan for grids published in November 2023, it is studied that 40% of Europe's distribution grids are more than 40 years old and a substantial investment is required for upgrade that will enable SMART power systems capable of integrating DER and high demand of EVs. Also, transmission networks between different member states can save up to EUR 9 billion annually (*EU Action Plan for Grids*, 2023).

Due to slow growth and development in upgrading grid infrastructure for more than ten years an annual investment of more than USD 600 billion is needed to upgrade grids notably distribution grids to meet net-zero targets considering high penetration of distribution energy resources (DER). IEA (2023).

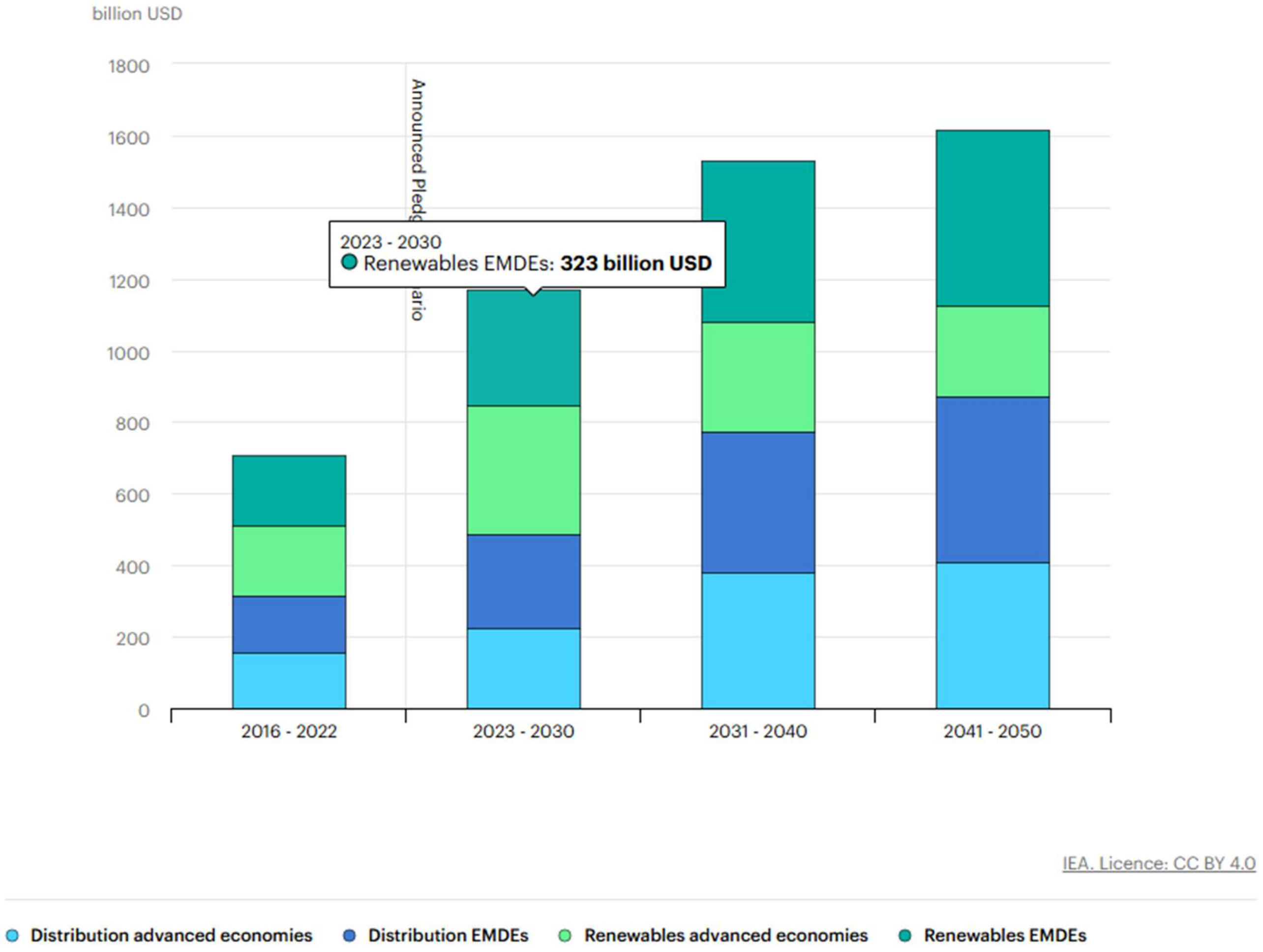


Figure 7: IEA (2023), Average annual investment in grids and renewables by regional grouping in the Announced Pledges Scenario, 2011-2050, IEA, Paris

Long planning and approval processes, and excessive regulations is hurdle in accelerating decarbonization. In comparison a RES project takes one to five years from planning to completion whereas a grid infrastructure takes five to fifteen years. Similarly, an EV charging infrastructure take up to two years. There is a need for a broader consensus among all stakeholders to improve planning process by incorporating inputs government, private sector, regulatory bodies and transport to enable fast growth in distribution energy resources, RES and supporting grid infrastructure including domestic and public bidirectional charging stations. This will increase EV adoption and V2G implementation. In this regard, EU member states have agreed to remove unnecessary red tap notably for projects of common interest (PCIs) that can accelerate energy transition (Projects of Common Interest | www.acer.europa.eu, n.d.) (IEA, 2023).

EV sales is expected to reach 40 million worldwide by 2030 and can be an asset to grid and electricity market other than transportation if integrated in SMART power system. Almost 90% of the time the electric vehicles (EVs) are idle and parked either at work place or at home. This aggregated battery storage is a huge potential for V2G applications that can eliminate network congestion, power spikes, efficient use of RES, network support by providing voltage and frequency support and for demand-side-management.

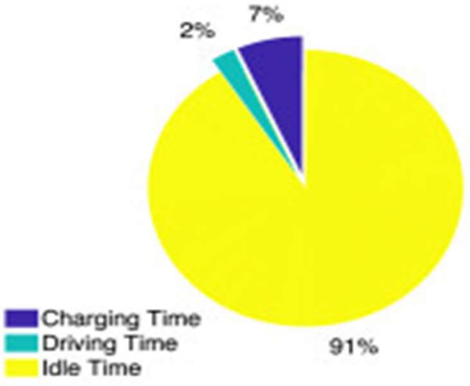


Figure 8: Average EV idle, charging and traveling time

In 2023, EVs consumed more than 130TWh of electricity equivalent to 0.5% of global energy consumption. This demand is expected to increase to 6-8% of global electricity consumption by 2035 (IEA (2024), Global EV Outlook 2024). Addition of EVs in the system will increase the energy demand and if not managed efficiently can cause price volatility notably during peak hours but also grid instability. However, these additional storage capacity of EVs if connected with grid can support TSO and DSO in eliminating power fluctuations, can provide ancillary services to grid and reduce the need of using expensive fossil fuel plants. The need for additional infrastructure spending on grids can also be reduced by implementing V2G technology. However, business case for V2X is difficult to convey to EV owners deeming its effect on battery life, range anxiety and user comfort. A win-win situation in which the economic incentive is significant enough to cover battery degradation without affecting user comfort can be viable. A recent report 'Willingness to Participate in Vehicle-to-Everything (V2X) in Sweden' presented interesting results on EVs owner's perception and drivers to participate in V2X (Khezri et al., 2024). Most of the EV owners, according to this research are still unaware of the benefits of V2G. The owners would like to have control in V2G with an override option, expect compensation covering battery degradation cost and saving in energy bill. Distribution system operators (DSO) have far more benefits of using V2G for instance demand side management, avoid network congestion, provision of ancillary services, peak shaving, utilizing surplus renewable energy by valley filling and associated cost savings. Another conclusion is if the charging and discharging control does not affect the owners negatively – affecting the warranty, damage to EV hardware etc. – they are willing to participate in V2X. However, using EV as a back-up power source for V2H is preferred.

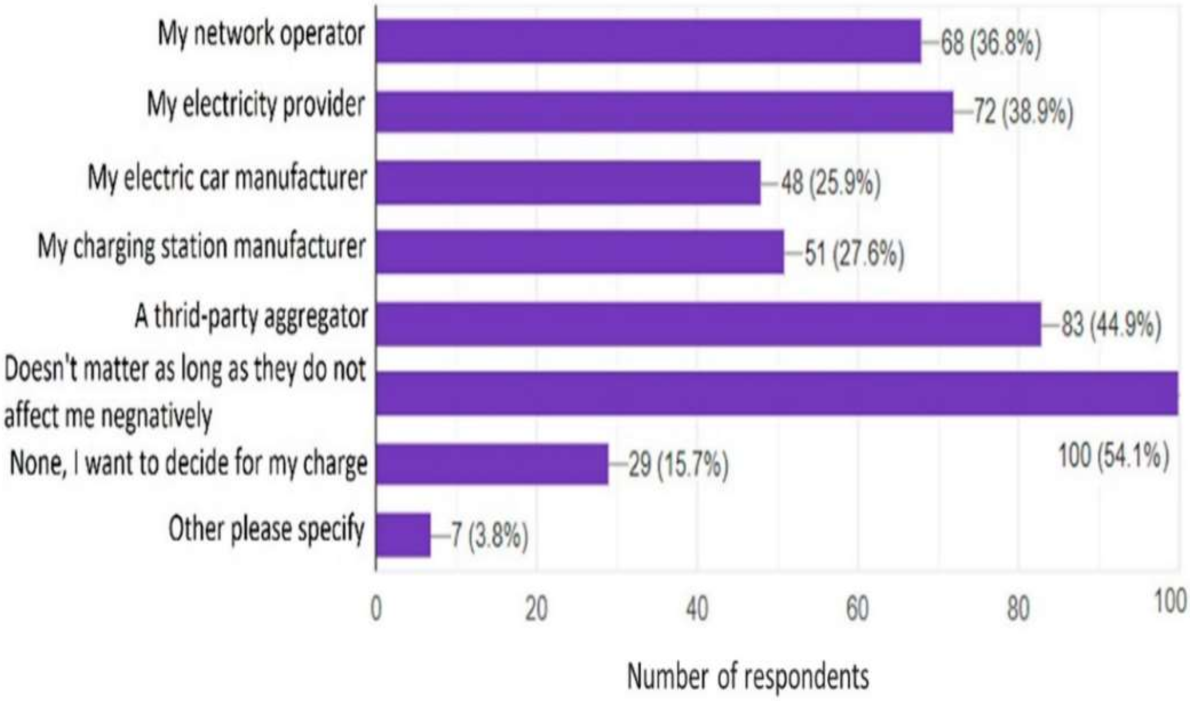


Figure 9: V2G participation survey in Sweden (Khezri et al., 2024)

Another important aspect of this study is to encourage a coordination between EV manufacturers, charging equipment manufacturers, network operators, insurance companies and owners to develop an understanding about the ownership in the event of damaging EV equipment using V2G.

There has been a debate on EVs owners' data that is essential for this solution to be used fairly with energy suppliers without impacting the privacy and security.

Network companies do have an obligation, as per EU regulations, to provide power to its users when needed however connecting large number of EVs pose a challenge to energy suppliers and network companies because it can overload the network during peak hours can violate thermal limits of grid infrastructure. This can consequently damage the equipment, disrupt power supply, and increase energy prices. This is because most of the EV owners tend to plug-in their EV right after coming back home (Yilmaz & Krein, 2013). V2G technology can handle this situation by utilizing stored power in grid services and charge the vehicle when surplus renewable energy is available. The benefit flow of V2G business scheme framework is shown in figure 10 (Mastoi et al., 2023).

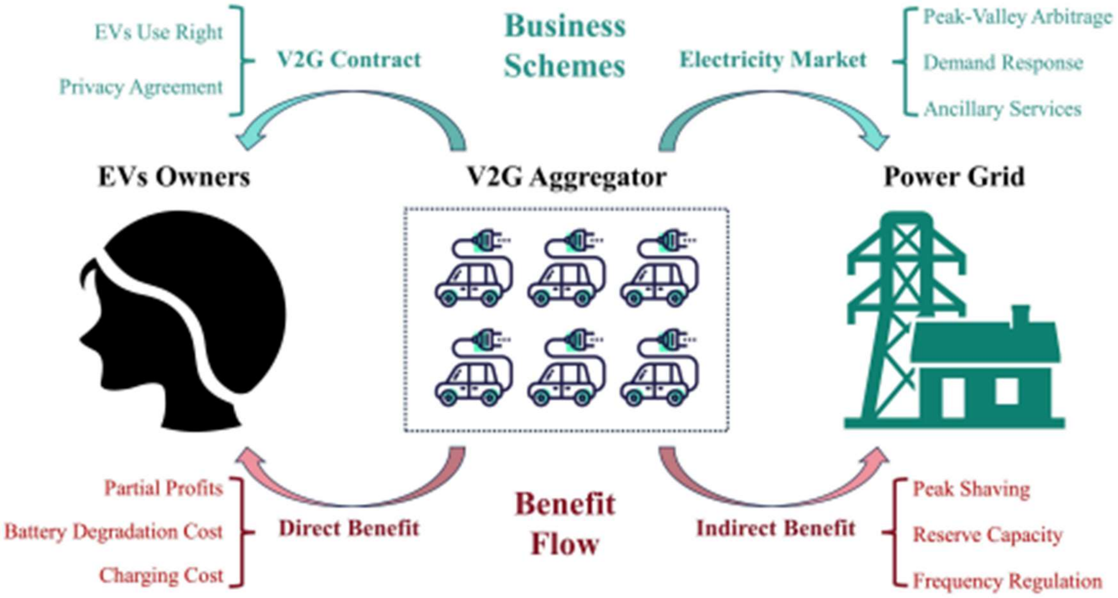


Figure 10: V2G business framework with aggregator (Mastoi et al., 2023)

Aggregated volume of EVs is a huge potential for system operators and driving behavior depicts the total available capacity and state of charge (SoC) of whole EV cluster. In this scheme an individual EV can leave or join at any time and has no restriction to be connected to grid. V2G technology contract between EV owners and aggregator can provide legal permission to control charging and discharging of EVs when idle. In return the aggregator provides energy trading profits, battery degradation cost and savings on charging. V2G is a promising technology and its success mainly depends on a business scheme designed to have market-based incentive is a critical issue. For many EV owners the benefit associated with compromising battery life is not sufficient. Clearly, there is a lack of understanding on how much it affects the battery life versus its economic and social benefits. Economic incentive can be the main driver to change this perception but other factors associated with its impact on reducing carbon footprint can also be convincing. Technical benefits such as peak shaving, reserve capacity, demand response, frequency regulation, voltage regulation notably during an island mode operation for TSOs and DSO are just more than financial benefits. Therefore, government incentive is crucial for the widespread implementation of this technology specially to EV owners. From an aggregator point of view the economic benefit in participating in energy market – ancillary services, frequency reserves, and balancing power – is huge as currently TSOs and DSOs are utilizing expensive sources for these services.

2.1 Peak-to-Valley arbitrage

Integrating high volume of RES notably solar and wind power is challenging because of the variable production, and surplus energy production during low demand can lead to negative price that is not encouraging for the investors. In such situation most of time the power is curtailed that is loss of clean power than could be utilized and could have impact in reducing CO_2 emissions. Germany is leading in solar power - Photovoltaic (PV) - installation with more than 7.9 GW installed in 2022 followed by Spain (7.5 GW), Poland (4.9 GW) and Netherlands (4 GW). (EU Market Outlook for Solar Power, 2022). As a part of European Green Deal and REPowerEU plan the European Commission adopted EU solar energy strategy in 2022 to install 320 GW solar PV by 2025 and 600 GW by 2030 (European Commission, Solar Energy, 2023). The increase in RES is changing the load profile of European countries. As shown in figure 11 the increase in solar generation decreases the load to zero and in some cases to negative forming a duck curve (GridX – Germany’s Electricity Duck Curve, n.d.).

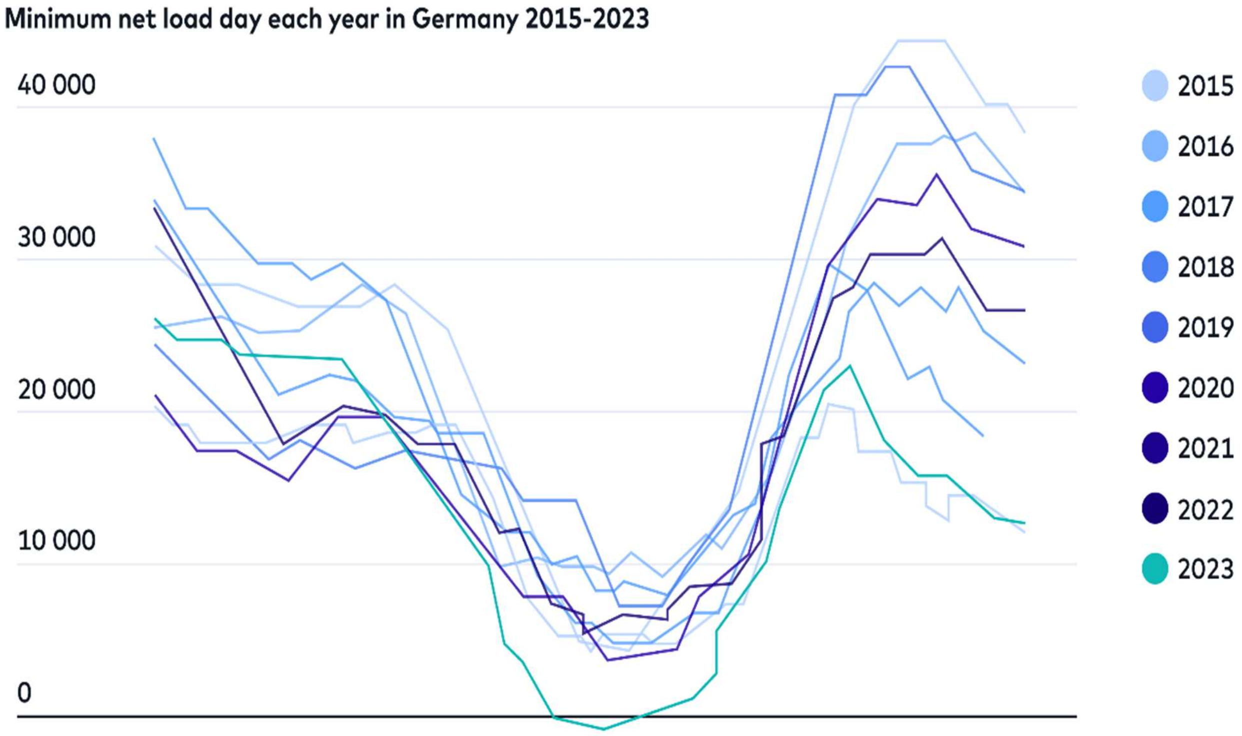


Figure 11: Germany's electricity curve (GridX – Germany’s Electricity Duck Curve, n.d.)

This is the time when surplus energy is available but not enough load. However, as the sun sets there is a need for flexible power that can ramp up quickly to support the transition to other generating sources. This increases the overall electricity prices because of utilising coal fired and gas plants during ramp-up, and overload the network. Demand side management using aggregated V2G is promising in dealing these scenarios by absorbing surplus energy from solar and discharging during ramp up time as a single source of dispatch that can decrease overall energy cost and emissions. Germany is one of leading EV manufacturer and millions of electric vehicles are registered in last five years with an approximately battery size of 50 - 75 KWh per vehicle. Adding these numbers with the EVs sold in 2024 approximately 10 GWh of dispersed storage capacity that is available and can be utilised to tap full potential of RES and to cater uncertainty in renewable energy.

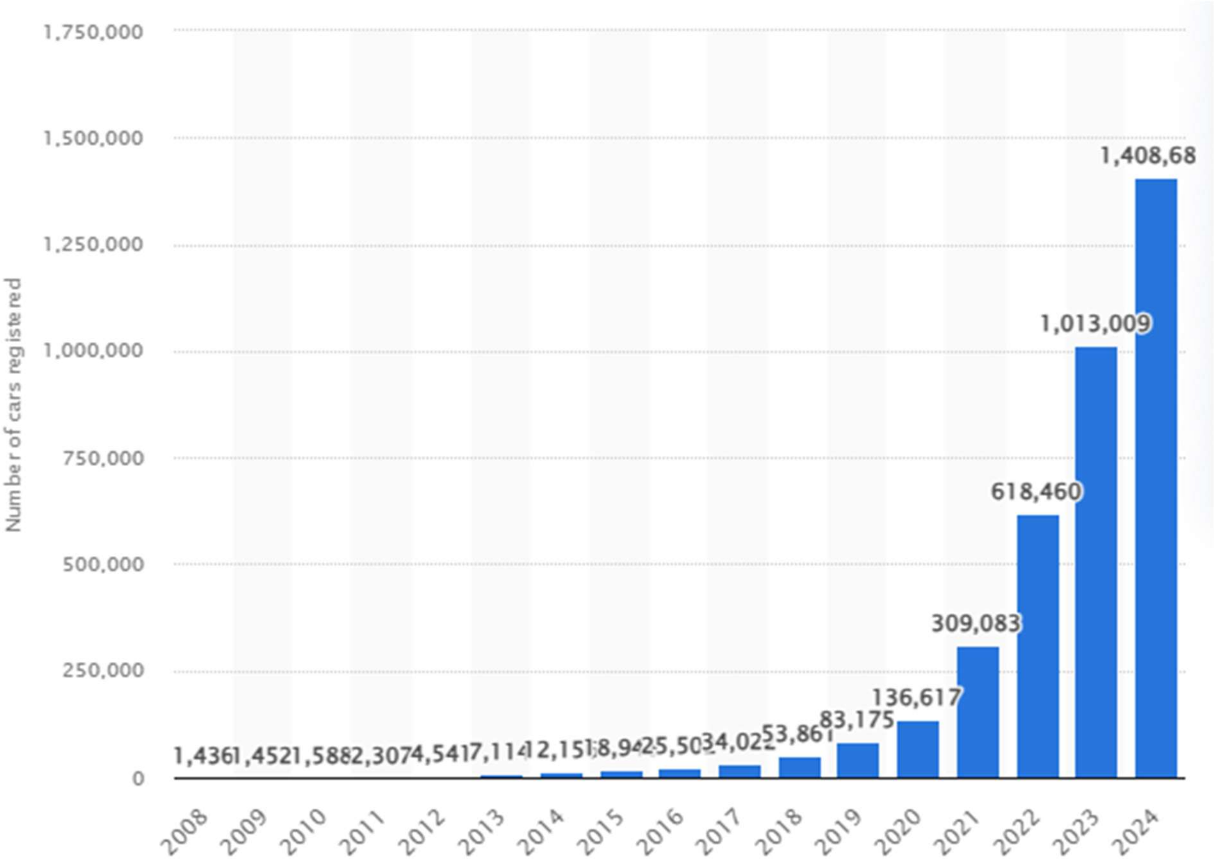


Figure 12: Number of EVs registered in Germany

With increasing electricity demand the load-to-valley differential is increasing that is affecting prices but also the stability of the grid. Variable tariffs also known as TOU (Time-of-use) are introduced to shift this load to valley and change user behavior in consuming electricity. For instance, in December 2023 in the Zhejiang, China a peak tariff is 1.203 CNY/KWh to 0.314 CNY/KWh valley tariff.

Deeming its potential benefits V2G field trial started in Germany in 2021 (Field Trial Begins to Integrate Electric Vehicles into the Electricity System, 2021) in a collective research work named ‘Bidirectional charging management’ and ‘Bidirectional load management’ to pursue climate goals under Climate Protection Act that is effective since August 2021 (FfE München, 2025) (Federal Law Gazette 2024, no. 235). In the first phase of the field trial equipment required for V2G such as bidirectional chargers and digital platform to monitor power consumption and user behavior is provided to the EV owners. Additionally, intelligent energy management system (EMS) is installed that works with the PV. Primary function of the EMS is to optimize energy consumption produced by PV and later V2G functionality is integrated that allows prosumers to participate in energy trading and grid services. In the final stage EV fleets will be added that can act as an aggregator or participate in energy market through an aggregator to provide ancillary services to the grid. This research work enabled private and public sector to gather requirements and to provide roadmap for the widespread implementation of V2G in German grids.

2.2 Provision of ancillary services

Ancillary services are the provision of energy for a reliable grid operation of transferring power to end user at required voltages and frequency while balancing supply and demand. V2G technology with bidirectional power flow can assist in redistributing load, can reduce energy consumption, can enable integration of RES at distribution level, and can improve power quality. Kempton & Letendre, (1997) first introduced the idea of EV aggregators that can connect to the grid and provide competitive charging and discharging strategies for EV owners by participating in energy market notably for the provision of ancillary services. System frequency is normally controlled by synchronous generators that react to power changes and voltage is controlled with reactive power either from conventional generators or reactive power compensators for instance Static Var Compensators (SVCs) and Static Synchronous Compensators (STATCOMs). The system frequency using V2G can be implemented with primary, secondary or tertiary control schemes for an EV-DSM operation is discussed in (Mohanty et al., 2022). System operators in Nordic countries follow conventional wholesale market model to secure necessary energy to provide frequency and voltage support for their day-to-day operation in a centralized generation scheduling. However, integration of DER sources in the network is challenging due to changing load and generation yet beneficial because of the flexibility these sources can provide. Frequencies are normally assigned based on the bids for secondary and tertiary frequencies for economic dispatch. However, primary control gives the best results for EV owners (Mastoi et al., 2023). An intelligent charging schedule based on market price can reduce peak load that can benefit both EV owners, grid operators and retailers. In a study for California power grid it is concluded that no additional power plants are required for almost 4 million EVs if smart charging strategies are implemented using variable price signals and intelligent charging mechanism through aggregators (Ferdowsi, 2007).

The author of (Yanikara et al., 2019) proposed a method of co-optimizing transmission network with central generation and distribution network with connected EVs in 24-h day ahead market in a decentralized market design. Algorithms used in centralized markets provide hourly marginal prices

(LMPs) and generation schedules however if large number of DERs are connected at distribution network can also be optimized in a decentralized market considering distribution locational marginal prices (DLMPs) – DLMP is an hourly price obtained from LMPs to include distribution line losses. The researchers compared two models (i) A single network operator that solves optimal power flow (OPF) for an economic dispatch by taking into consideration all network parameters and its limitations to schedule centralized generation and DER, and in (ii) approach TSO can coordinates with multiple DSOs for an economic dispatch. It is concluded that aggregated EV scheduling can benefit EV owners if network cost information is available to them and how their participation can affect price but lower cost can be achieved as aggregated scheduling. Should aggregators provide sufficient load at times of high energy production from RES and communicate information – energy consumption, available storage – to network operators, can provide regulation services at low cost and that is more responsive to load fluctuations.

2.3 Flexibility in power system

As discussed previously, according to Mario Draghi's report the energy prices in EU can go down if the fossil fuel plants in the energy mix are replaced by RES – wind, solar, nuclear – and investments in grid infrastructure, energy storage systems and flexibility are fulfilled and amortized. By 2030, RES share in EU energy mix is expected to reach 67% however price setting by fossil-fuels will largely remain the same despite RES replacing inefficient expensive gas-powered plants. Moreover, RES generation during low load will increase price volatility and price cannibalization for instance Germany's power duck curve as discussed previously can deter investments in renewable sector unless there is sufficient flexibility in the system to conserve energy and cater intermittency. It is therefore essential that addition of RES is accompanied by investment is flexibility, storage systems and grids (Draghi, 2023). In a study KOOLEN et al., (2023) the modeling assessment of high integration of RES is studied with 2030 and 2050 target. It is concluded that the flexibility requirement will significantly increase up to 30% compared to 11% in 2021 to ensure security of supply with affordable price.

V2G in this sense is vital as it adds flexibility in the system, reduces price volatility, reduce operational cost, reduce high investment in grid infrastructure, reduce capacity payments, reduces RES curtailment, improve network stability, power quality and decrease energy cost to prosumer (Nagel et al., 2024). There has been a lot of development in V2G technology recently covering different aspects for instance optimal economic dispatching deeming user behavior, user comfort, economic consideration for both operators and EV owners. Li et al., (2021) proposed a control scheme to improve grid efficiency and resilience using Deep-LSTM algorithms. Grid operating cost can be reduced using an intelligent charging management scheme that can minimize load variance in uncertainty based on multi-objective planning deeming priority based V2G scheduling. The optimization model in this paper also considers active and reactive power indices to ensure best power quality. In brief, probabilistic model is used to find unknown variables of EVs considering charging pattern is affected by grid load. These values, generated by normal distribution, are used in optimization problem consisting of two parts – valley filling and peak shaving. The method is effective and shows reduction in peak load and charging cost whilst improving power quality by providing additional reactive power to reduce voltage drop (Singh et al., 2023). However, this study made a lot of assumptions to simplify the problem for example limited and constant number of EVs with fixed probability density function, and does not include real life scenarios for instance its behavior in island mode, during a fault or with other RES in system.

A comprehensive review of various charging and discharging optimization methods, and challenges for aggregators are discussed in (Mastoi et al., 2023) from a performance point of view that includes overloading, power quality and its effects on distribution network. The interaction of grid and vehicle is shown in figure 13.

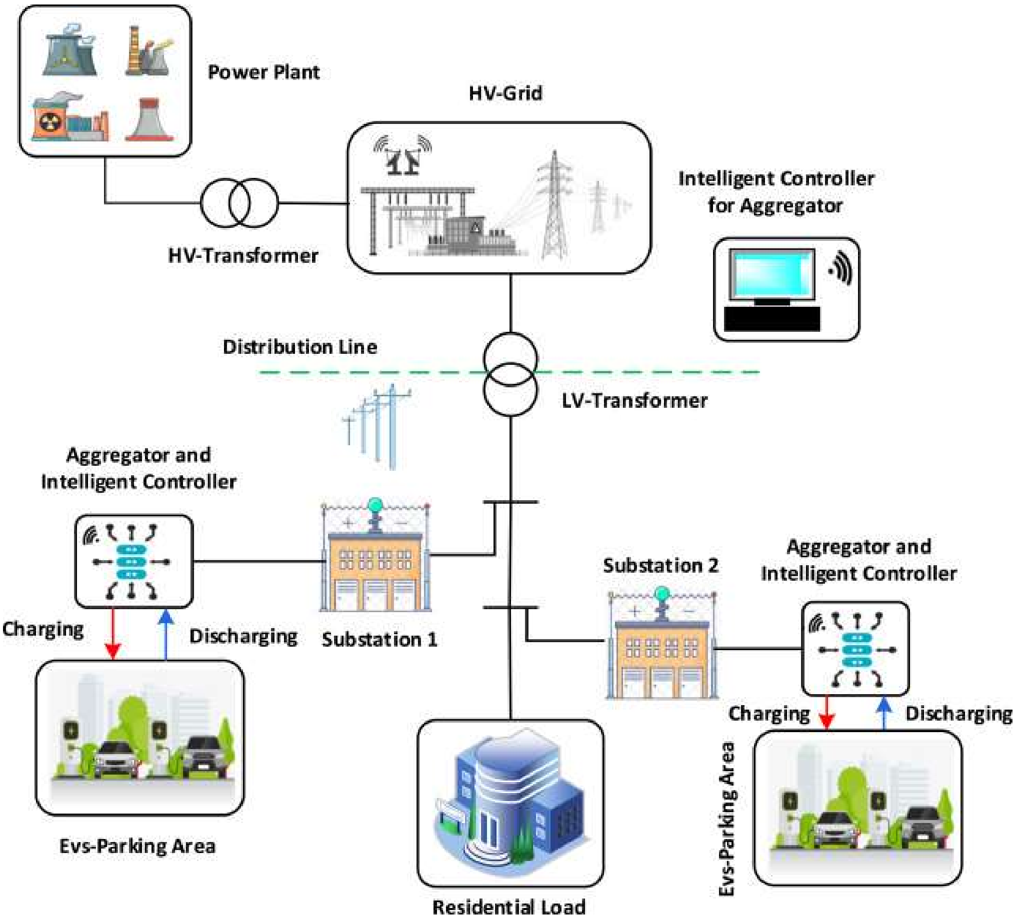


Figure 13: EV interaction with Grid (Mastoi et al., 2023)

V2G can improve electricity grid stability, reliability and performance with active power regulation, load balancing, RES monitoring, active and reactive power management and filtering of harmonics. Moreover, aggregators can act as spinning reserves and can provide synthetic inertia to support low inertia RES integration in power grids. V2G can also provide voltage and frequency support other than ancillary services. However, the charging process causes network instability due to power spikes than can cause power outages and must be taken into consideration. The grid connection should be resilient enough to withstand such spikes caused by charging and switching devices – power converters (Mastoi et al., 2023).

Because of higher charge density and low discharge rate Li-ion based energy storage system has the highest efficiency at about 85%-95% compared to other commercial storage systems – Flywheel at 70-95%, lead acid batteries at 80-90%, thermal energy storage at 80-90%, and pumped hydro at 70-85%. The per megawatt-hour cost for these storage technologies are Flywheel $560 / MWh, Pumped hydro $480/MWh, Li-ion $280/MWh, and V2G $158-$290 MWh (Rahman et al., 2023).

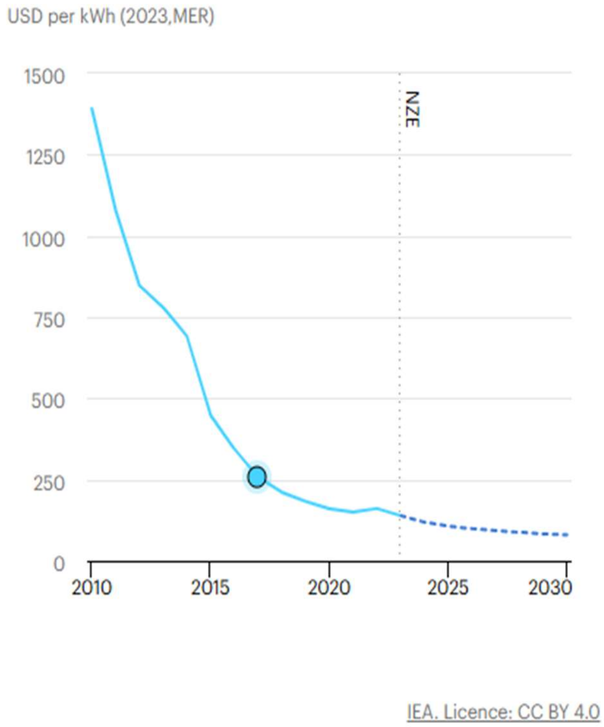


Figure 14: Average EV battery price (IEA (2024)

This is mainly because Li-ion batteries cost have reduced 90% since 2010 due to maturity in technology and high production in EU, US and China. There are however regional factors that affect the capital cost of energy storage due to high production cost mainly affected by high energy cost and high installation costs of projects. The Global EV market is valued around USD 4 trillion and is directly dependent on the production of high quality and low-cost batteries. Li-ion batteries also enable high penetration of intermittent PV and wind energy into grid by providing flexibility in power system for grid reliability, and is expected to have an additional USD 6 trillion investment in net-zero scenario from 2024 to 2030 (IEA (2024), Batteries and Secure Energy Transitions).

2.4 Fingrid Financial Report 2024

Fingrid – transmission system operator (TSO) – published its Annual Review and Financial Statement of 2024 in March 2025 that stated high turnover despite the grid fee was waived for three months. Moreover, it shows high growth in renewable sector, reduction in carbon emissions from electricity consumption, decline in electricity prices, and high investments in the grid. Additionally, new grid connection agreements are concluded for energy consumption and increased to new high – 82.7 terawatt hours. However, the price volatility was high due to the integration of intermittent renewable energy sources and Fingrid sold € million 636.8 imbalance power that accounts for more than 50% of the turnover, and congestion income is more than three hundred million euros. Similarly cost of reserves is more than two hundred million euros as shown in table 1

Table 1: Fingrid turnover 2024, financial statement

(Turnover and other operating income, € million)

	JanDec/24	JanDec/23	JulyDec/24	JulyDec/23
Grid service revenue	275.4	164.5	191.8	80.9
Sales of imbalance power	636.8	682.6	237.4	339.2
Congestion income	301.0	284.7	66.8	190.1
ITC income	10.8	20.8	5.0	6.7
Datahub income	20.9	20.6	10.5	10.4
Other turnover	24.2	19.9	11.2	11.2
Other operating income	133.4	119.7	91.1	74.3
Turnover and other income total	**1,402.8**	**1,312.9**	**613.8**	**712.8**
Purchase of imbalance power	457.4	491.1	150.3	254.6
Loss power costs	81.1	75.2	38.3	41.2
Depreciation and amortisation	128.7	123.3	65.0	64.3
Cost of reserves	217.6	185.6	108.4	114.1
Personnel costs	47.6	42.8	23.5	21.5
Grid maintenance costs	39.8	22.5	29.4	13.9
Costs from transmission rights	85.5	96.2	59.2	61.2
ITC charges	18.7	20.7	4.8	7.0
Other costs	87.2	69.4	46.9	36.1
Change in the value of derivatives	38.5	185.1	12.0	18.5
Costs total	**1,202.2**	**1,311.9**	**537.9**	**632.3**
Operating profit excluding the change in the fair value of commodity derivatives	238.9	186.1	87.9	99.0
Operating profit of Group, IFRS	200.6	1.0	75.9	80.5

Furthermore, limited flexibility in the system and addition of intermittent weather dependent energy sources, congestion due to limited capacity in cross-border links with Sweden and Estonia are main reasons of price volatility. Fingrid calls for more investment in flexibility services – energy storage, flexible power plants etc. – to increase the share of RES and to tap its full potential. Fingrid signed new reserve contracts with 24 operators to further enhance grid reliability and power security. Also, Fingrid introduced Automatic Frequency Restoration Reserve (aFRR) in 2024 that will decide the price for balancing power in 15-min time frame together with Manual Frequency Restoration Reserve mFRR. This is the market potential for V2G with high returns and short duration of supplying balancing power for frequency restoration and to tackle load fluctuations together with ancillary services. The prospect of 15-min time frame is to have access of European mFRR energy market that will further increase the return on such services sufficient for the aggregators and EV owners to participate. Large scale BESS have already reached a commercially viable point notably due to lower price of batteries in last ten years, and return on utilization in providing flexibility, in most cases, twice a day. However, current regulations tax BESS twice during charging and discharging of energy which is not favorable for investors and of course increase the total electricity price. Regulatory bodies are reviewing these tax codes to make it more favorable for concerned parties whilst maintaining the mandate of security of supply for an affordable price. One important aspect of calculating the impact of flexibility in the power system notably with energy storage is the amount of money saved in upgrading grid infrastructure, installation of new plants, capacity payment, price variation, and potential damage to grid and its impact on businesses. It is recommended that a part of these savings can be used as an incentive for EV owners to encourage participation in V2G schemes.

The ultimate goal of security of supply often expressed in the literal term “keeping the lights on”, is to continuously provide affordable electricity of good quality. Security of supply can be defined as:

“Electricity security is the electricity system’s capability to ensure uninterrupted availability of electricity by withstanding and recovering from disturbances and contingencies”

According to EU legislation and regulations - responsible authorities in member states cooperate in such a manner that electric power flows where it is required in the time of crisis (Regulation - 2019/941 - EN - EUR-LEX, n.d.-b). European energy market is transforming into more decentralized with new distribution energy resources integrated in the system with higher share of RES that would require better interconnected systems capable of supporting member states in the time of crisis. According EU legislations European Network of Transmission System Operators for Electricity (‘ENTSO for Electricity’) and concerned stakeholders – energy producers, TSO, DSO, aggregators – must assess risk by simulating system failure scenarios considering grid topology, energy mix, supply and demand, and impact on businesses and to EU citizens and prepare an action plan that can be implemented to ensure fast recovery in the event of a crisis. Benefit of decentralized energy system with more integrated DER has its benefits as in the time of crisis for instance tripping of major plant can cause blackout unless sufficient power is available to restore system frequency in desired time. Decentralized grid in this sense is very important as it can operate without the input from main grid and can be disconnected if required without interrupting the power to customers. A large size aggregator thus can play a vital role for a successful microgrid operation in the time of crisis or at the time when disconnecting from the main grid is economical provided security of supply is ensured. A conventional electrical system acts as a single machine in which all elements - generators, transmission & distribution lines and load - work simultaneously in a synchronized manner to achieve stability. Therefore, if one or more elements trip (disconnects from the system) it causes other power sources to trip and consequently not only damages equipment but also loss of power can have dire consequences on economic activities and daily life.

Power system stability can be achieved in several ways for instance if we connect more power sources through a grid, it will create a contingency in the system to withstand disturbance in the power supply or a failure of a power source. Britain for example is connected to France, Netherlands and Ireland through four subsea cables which improve the supply of electricity in the event of low power from wind farms or as a result of a fault in a local power plant. Finland is connected with Nordic countries (Norway, Sweden and Denmark) through high voltage DC (direct current) lines through which electric power is imported and exported and hence improves power system stability. Furthermore, flexible sources in for instance DER, BESS, and RES with better forecasting methods and communication with TSO and DSO can improve power supply, power quality by reducing system harmonics, and reliability of system with appropriate control and protection schemes, and contingencies to recover from disturbances. In SMART grids faults can be isolated and disconnected areas can still operate on island mode with DER. Therefore, V2G is a promising technology which will increase system reliability, security of supply with affordable prices.

Figure 15 shows Finland’s electricity consumption of last ten years versus wind generation and its impact on electricity price. Price volatility is observed in last few years with increase share of wind energy despite a predictable load profile. With increased share of RES particularly wind energy more flexibility in power system is necessary to keep prices low and to ensure security of supply without compromising the grid reliability and power system stability.

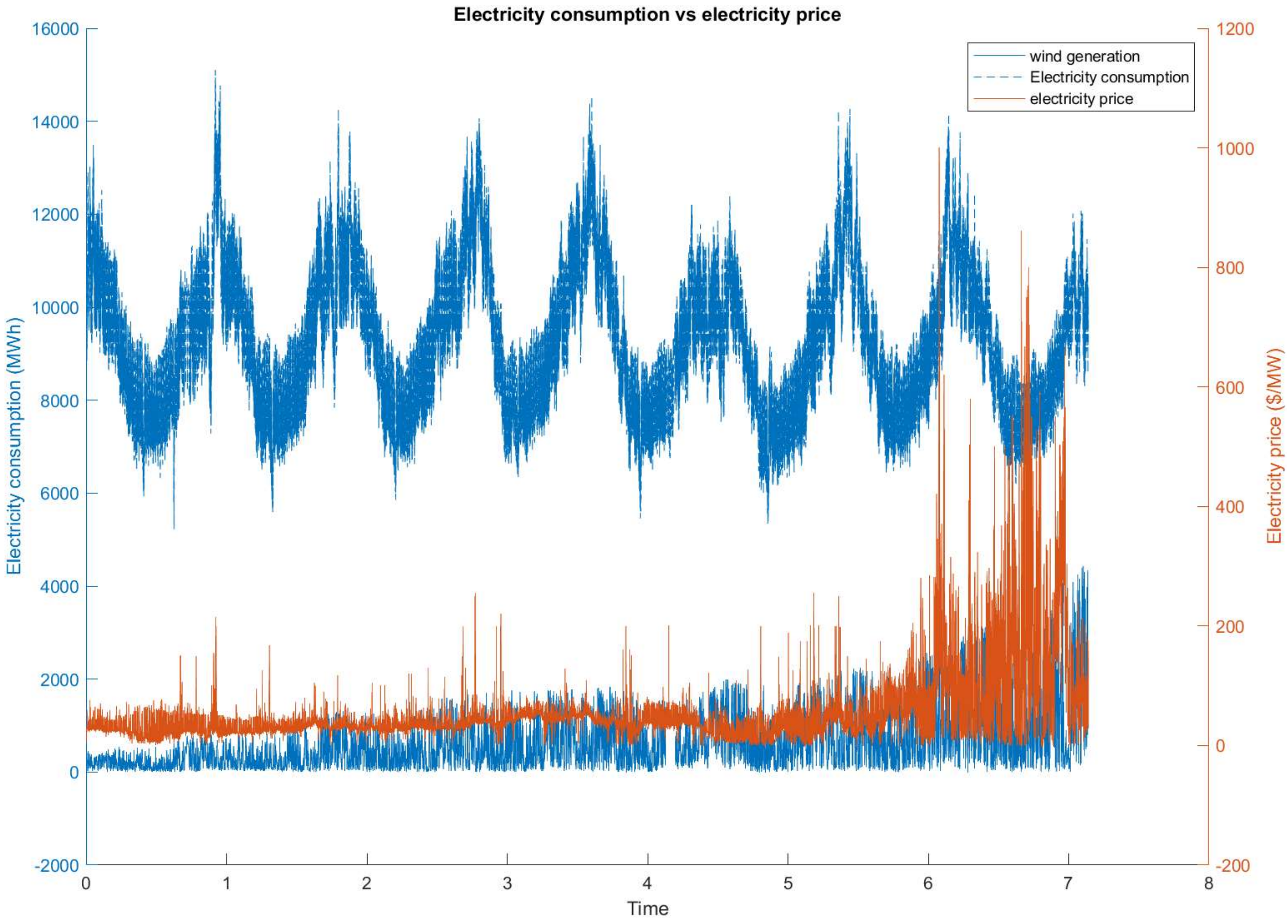


Figure 15: Finland electricity consumption versus wind generation and electricity price

2 Nordpool - Baltic-Nordic electricity market

Norpool is an energy market between Nordic and Baltic countries for power exchange to the extent the grid bottlenecks allow. Compared to larger EU energy market Norpool is more homogeneous and therefore tend to reach common solutions despite stringent regulations. Recent developments of introducing 15 min balancing market is a move to get access to a larger EU energy market and is favourable for aggregators. Nordic countries are energy intensive due to cold climate, energy intensive industries and higher standard of living. Moreover, Nordic countries have set ambitious net-zero targets. Finland, for instance, has an ambitious sustainability goals of becoming first carbon neutral country in the world by 2035. This is due to favourable policies that led the development of innovative energy efficient technologies and helped market to adapt accordingly. The new climate change act that is affective since 2022 introduced new emission reduction targets to accelerate the decarbonisation process. According to Annual Climate Report (2023), the greenhouse gas emissions reduced by 10% and ETS emissions decreased by 19% due to large share of RES – nuclear, wind and hydro in the energy mix (Central Government Debt Management – Carbon Neutral Finland 2035, 2025).

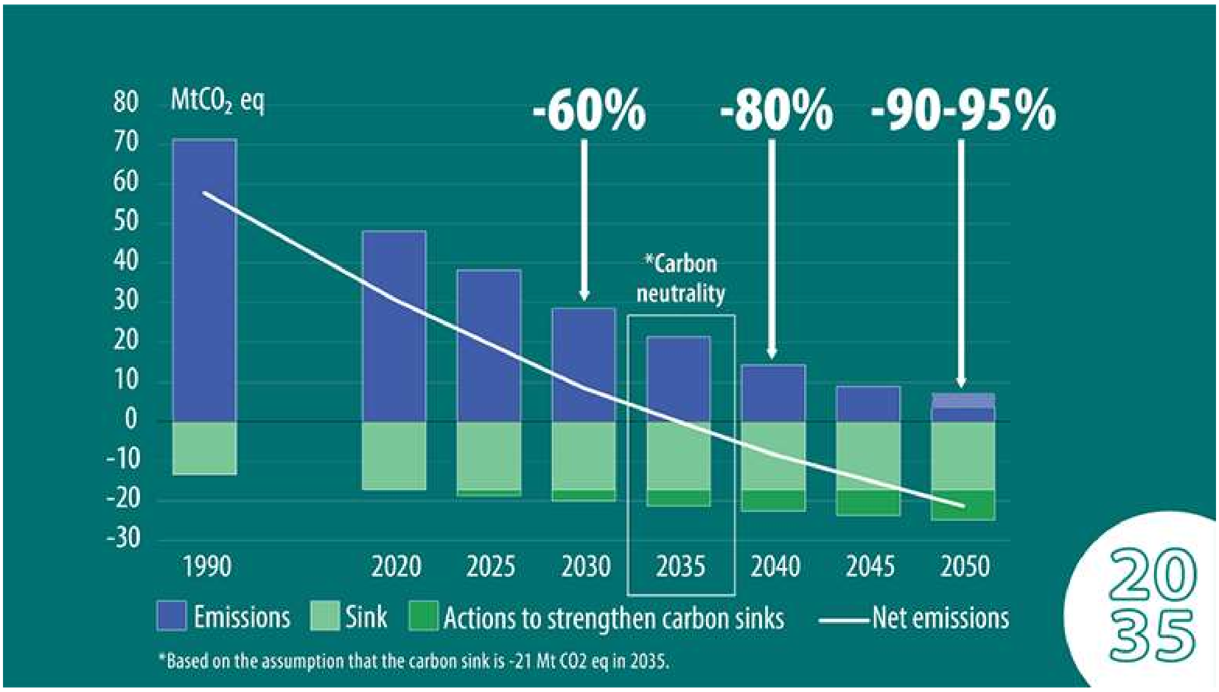


Figure 16: Finlandäs Net-zero goals (Source: Ministry of the Environment)

To further strengthen Finland's commitment towards clean energy and to attract investment in this sector, the government has set a target of doubling its RES production and phasing out fossil-fuel production by 2030 (Government Programme - Finnish Government, n.d.).

Finland's Electric vehicles Fleet

In 2025, 291,000 electric cars are registered with 124,000 are fully electric and 167,000 are plug-in hybrids. The share of electric cars has increased 31% compared to 2024. (Number of Electric Vehicles - Autoalan Tiedotuskeskus, n.d.).

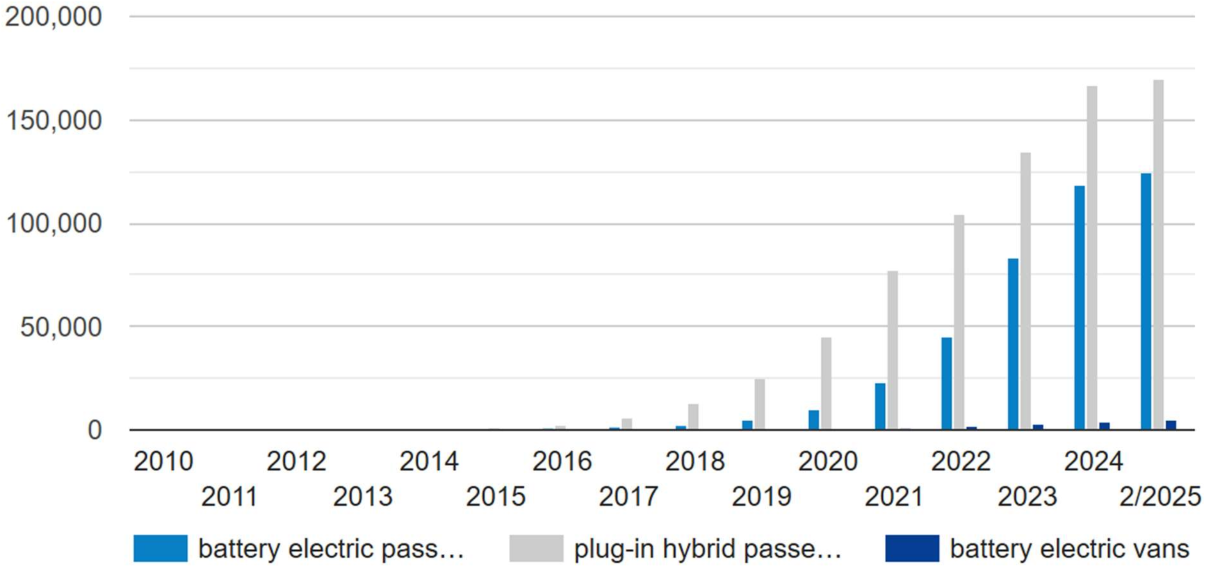


Figure 17: Finland EV fleet (Number of Electric Vehicles - Autoalan Tiedotuskeskus, n.d.)

Finland – Charging station Statistics (ChargeFinder - Charging Stations for Electric Cars (EV), n.d.)

Total station count	**3,428**	Chargers (CHAdeMO)	414
Realtime stations	3,005	Chargers (Type 2)	12,393
Chargers (150+ kW)	3,495	Chargers (Type 1)	3
Chargers (100-149 kW)	467	(Tesla Supercharger)	338
Chargers (50-99 kW)	933	Chargers (Tesla Other)	72
Chargers (CCS)	4,482	**Total charger count**	**17,400**

Finland is ranked fifth with respect to fast chargers in Europe and third for ultra-fast chargers. Also, Finland has highest number of DC chargers, currently ranked fourth in Europe. In 2023, 171% increase in DC chargers is reported. Yet Finland has lowest charging price – €4.6 / 100 km – for a public charging point in Europe. Figure 18 shows the charging infrastructure and its distribution. Helsinki, capital of Finland, is ranked in top five cities in Europe that has highest number of charging points per capita. North of Finland – Lapland known for Northern lights – also has a higher number of charging points per capita.

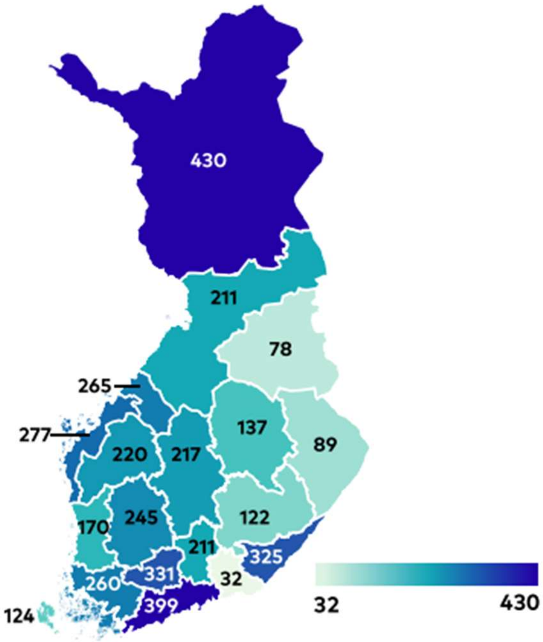
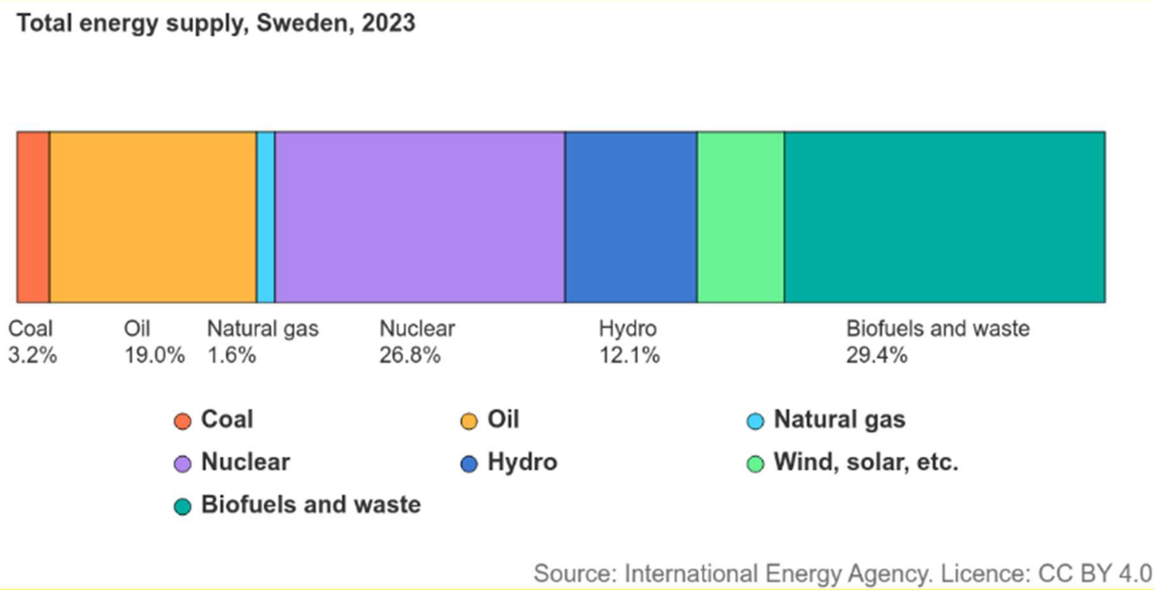


Figure 18: Distribution of charging points in Finland (gridX Charging Report 2024)

The high influx of EV require sufficient grid capacity to support charging load during high load times as worst-case scenario. As per Norwegian charging strategy grid companies are obliged to set up a grid connection to EV owners and private sector who intends to install fast chargers in a non-discriminatory manner. High volume of EVs is thus not an energy problem but a capacity problem notably for distribution grids. According to a survey conducted by The Norwegian EV Association almost 50% of EV users charge their vehicle at home with a 10A while 43% have a charging station that can support 16A or 32A. Moreover, the charging peaks are during afternoon and at night (Hanne Sæle, 2019). In response to high EV demand, the Electricity Grid commission proposed further development of grids in their report in June 2022 highlighting the need of investment in electricity grid to increase capacity, reducing processing time of new connections, allocate locations for charging stations based on load analysis, and incentives for demand side management including variable tariffs and subsidy in energy cost for charging EVs (Transport, 2023).

Energy system of Sweden

Sweden has an ambitious long-term plan to become carbon neutral economy by 2045 and in medium to short term reduce its greenhouse emissions by 59% by the end of 2030. One of the affective policies was to introduce carbon tax that is highest in the world, stringent regulations on emissions supported by incentives supporting the renewable technology, deployment of EVs in transport sector and programmes like Industrial Leap that enables innovative solutions for decarbonising industry, for instance, hydrogen-based steel production. Moreover, Sweden's electricity mix that is largely renewable – nuclear, hydro, biofuels and wind energy – and liberalised electricity market (Nordpool) laid a strong foundation to achieve its goal of becoming carbon free economy.



Source: International Energy Agency. Licence: CC BY 4.0

Figure 19: Total energy supply of Sweden in 2023

Sweden is net energy import country nonetheless domestic electricity production is largely from renewable sources – nuclear (29.1%), hydro (40.0%) and an increasing share of wind (20.5%). However, as per IEA's policy review Sweden has agreed on aggressive plans to increase its energy production mainly with nuclear and wind energy to cater the increasing demand because of EVs, energy intensive manufacturing industries and investment in artificial intelligence (AI). This would require more flexibility in power system (IEA (2024), Sweden 2024, IEA, Paris).

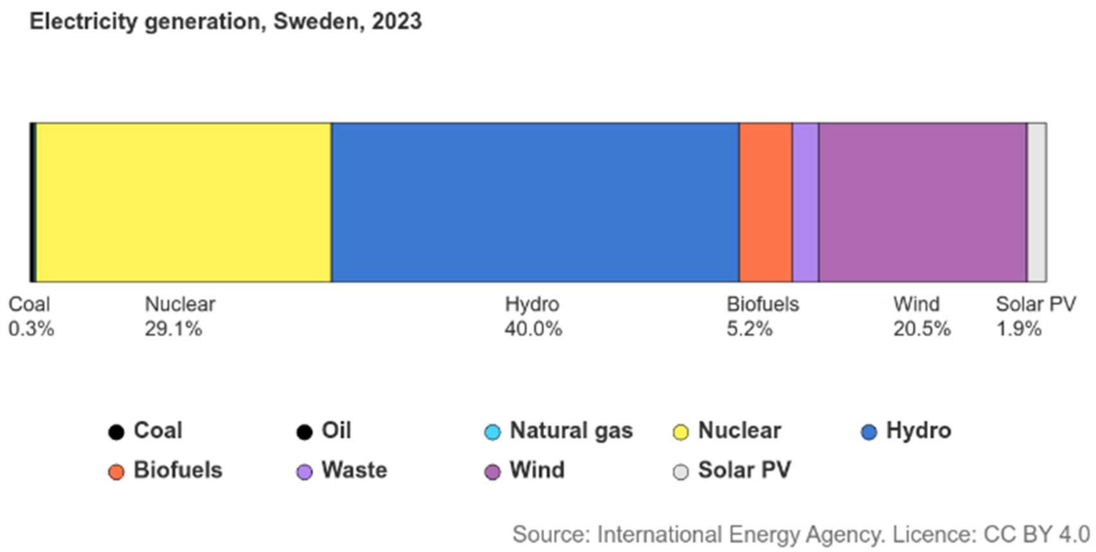


Figure 20: Electricity production in Sweden 2023

Transport sector in Sweden is the highest contributor of greenhouse gas emissions approximately 43% of the total emissions are due to high internal combustion engine vehicles. Sweden set a target of reducing 70% of transport emissions by 2030 and Swedish government supported the transition by introducing programmes like bonus-malus system (started in 2018) and by producing biofuels.

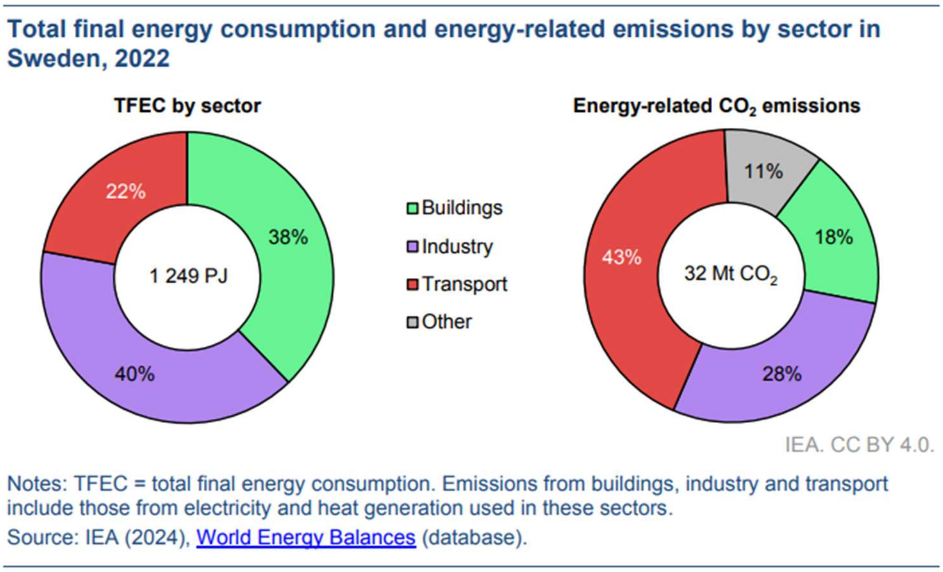
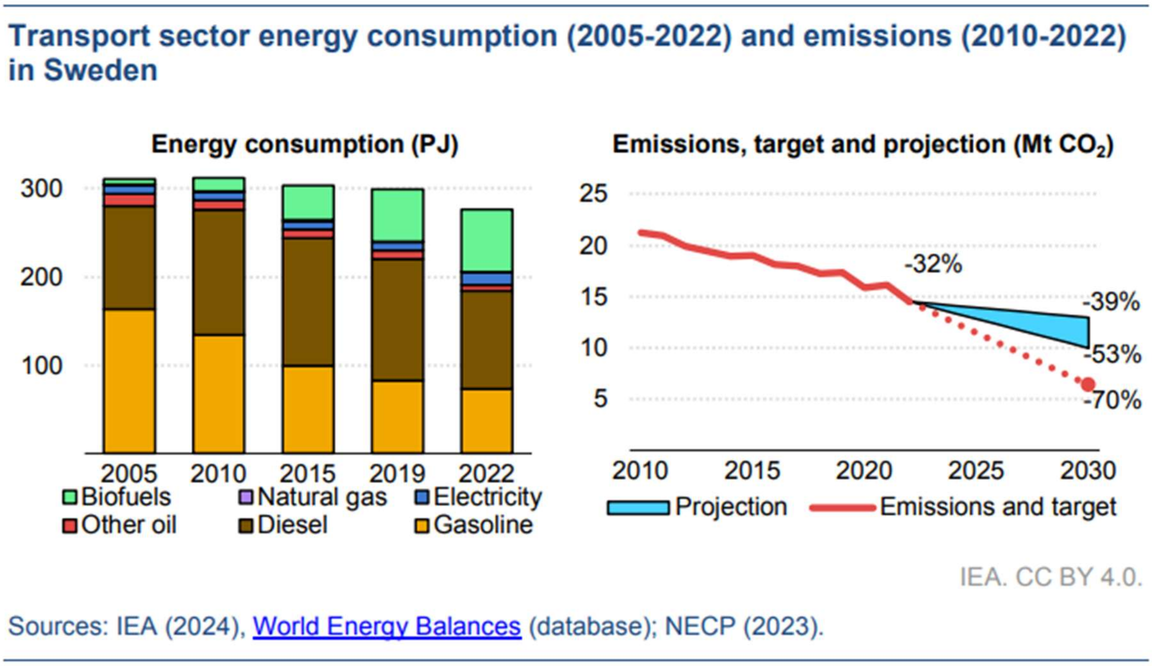


Figure 21: Carbon emissions in Sweden by sector (IEA, 2024)

Bonus-malus system phased out in 2023 because according to Swedish government it served the purpose of making EVs competitive compared to its counter internal combustion engine (ICT) vehicles. EVs are still cheaper considering high carbon tax on ICT vehicles and other incentives on EVs. However, to meet 70% emission reduction target compared to 2010 Swedish government should take additional policy actions to incentivize EVs by reducing taxes and charging cost. As per policy review on energy transition of Sweden by IEA this reversal in policy can discourage EV adoption and can in fact increase the emissions in transport sector rather than reducing it (IEA, 2024).


Transport sector energy consumption (2005-2022) and emissions (2010-2022) in Sweden

Energy consumption (PJ)

Emissions, target and projection (Mt CO_2)

Sources: IEA (2024), World Energy Balances (database); NECP (2023).

Figure 22: Transport energy consumption and emission reduction targets by 2030

As per current economic indicators Sweden’s economy will grow at a stable rate whilst transforming its energy needs to clean energy and to achieve energy independence. The electricity demand in Sweden is anticipated to double by 2045 that would require approximately 300TWh of energy (Economic Forecast for Sweden, n.d.). As per Svensk Vindenergi (2024), a total of 106 GW offshore wind farm is under construction with anticipated operational time before 2029. Out of which 48GW is awaiting approval from regional and national authorities, and another 56GW is at an early stage as shown in figure 23. The delay is due to long permit times, lack of grid infrastructure and storage capacity (Statistik och prognos – Q1 2024) (IEA, 2024).

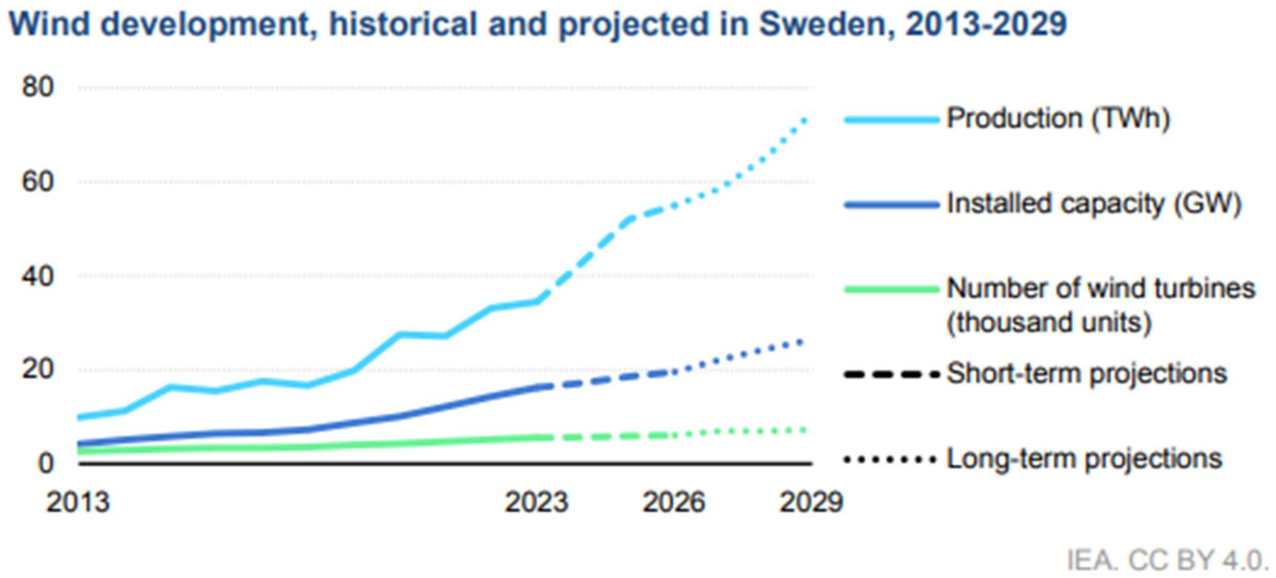


Figure 23: Wind power projection in Sweden based on announced projects

As discussed previously, increase in electricity production notably with high share of RES would require flexibility in the power system. Sweden has pumped hydro to store surplus energy to utilise at hour of high demand however development of new hydro plants are very unlikely because of high capital cost and construction time. Meanwhile, advancement in battery technology and significant reduction in battery price has made Li-ion energy storage more cost effective and profitable deeming Swedish energy market structure. Hence, V2G in Sweden has high prospects notably in balancing market and ancillary services, and is definitely a business case for EV owners and aggregators/operators. With 15-minutes resolution for balancing power and ancillary services battery storage is more cost-effective option compared to other storage systems. Many research projects for V2G for instance Stockholm Flex that is aimed to provide ancillary services to grid using aggregated capacity of EVs and secondary batteries for discounted price for EV charging. This report is part of Best4Grid project aimed for the widespread implementation of V2G in Nordic countries.

Nordic countries have the highest EV adoption and are well known for their scientific contribution in energy sector for instance development and adoption of SMART power systems, introduction of SMART cities and communities, energy storage and conservation technologies, decarbonisation of Marine with future fuels and carbon capture systems, development of advance battery technologies, renewable energy resources notably wind energy, use of AI in additive manufacturing, recycling and production of organic fuels, RES powered energy efficient datacentres, and robotics. This is largely due to favourable policies, pragmatic approach to market-based economy, higher spending on research and development, and a strong social structure. Moreover, Nordpool electricity market is still a level playing field for producers' distributors and unlike UK energy market that is dominated by few energy giants that dictate the energy prices. In the wake of energy crisis, according or Mario Draghi's report, it is however recommended to adopt more long-term bilateral energy contracts to ensure security of supply and affordability, and to attract investment from companies in innovative solutions to increase the capacity and flexibility of the power system. Furthermore, collective EU bargain for gas contracts is far stronger than individual states that can be leveraged to ensure affordable gas supply however to decrease electricity price it is imperative to decrease reliance on fossil fuels and electricity produced by old and expensive power plants. During the energy crisis after Russia-Ukraine conflict Nordic countries were least affected by the price hike compared to other EU countries mainly because of diverse energy mix with less reliance on fossil fuels and robust market structure. Nevertheless, according to Houmøller, (2017) the Nordic energy market is free of political influence however if electricity prices keep increasing and market gets out of control due to a number of factors it is likely to see a strong political reaction. The Nordic countries have set a roadmap for other nations to transition to sustainable energy by prioritizing the electrification of transportation that has a big impact on air quality and hence health of people but also unlocked new and innovative solutions like of V2G that enables high penetration of RES by utilising renewable energy efficiently whilst improving grid capacity and reliability.

Sweden’s Electric Fleet

In 2024, 62.8% of total vehicle sales was EVs with 40.8% full electric and 22.0% plug-in hybrids. A slight decrease in sale which is approximately 7% compared to 2022-23 can be linked with 2022 EV purchase incentive cut. Yet Sweden is ranked fourth in EVs per capita and seventh for highest charging point per capita. Nordic countries are ahead in EV adoption compared to other EU countries due to the policy incentives and availability of charging infrastructure. Sweden under EU guidelines introduced climate leap program to finance local and regional carbon emission reduction projects. In Sweden new public charging infrastructure is installed and Swedish government embarked SEK 1.4 billion till 2025 to expand and upgrade charging infrastructure. More than 180 000 charging points are already installed with bi-directional power flow capabilities that can support V2G. Moreover, there is a tax credit for charging infrastructure at home and at work (Local and Regional Climate Investments (Climate Leap), 2023).

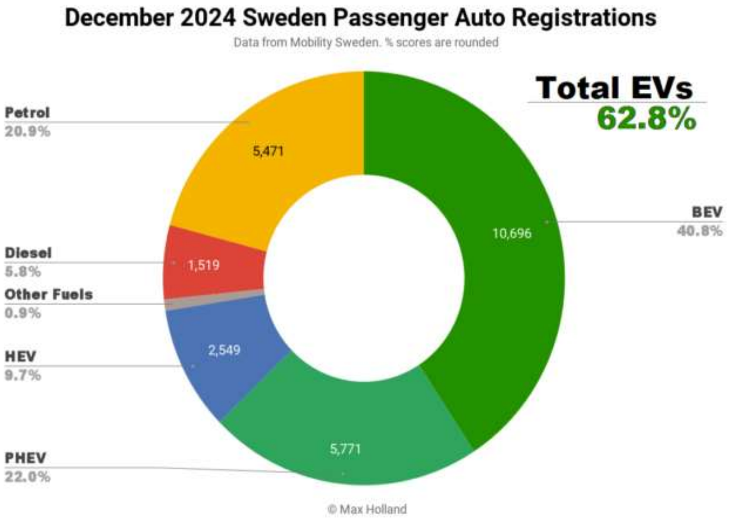


Figure 25: *Sweden's EV Fleet (Holland, 2025)*

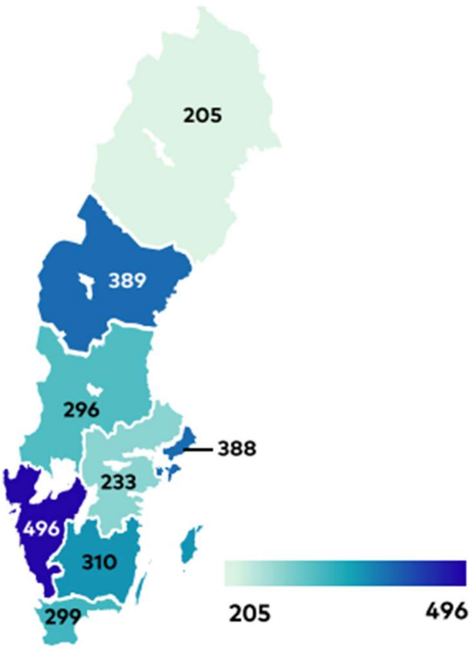
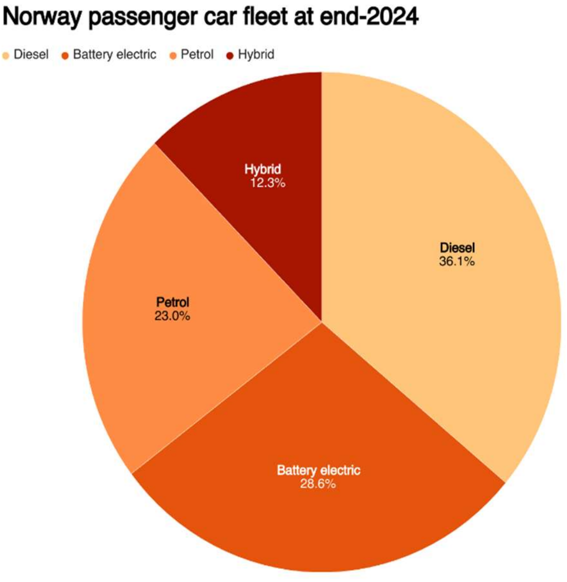


Figure 24: Charging points in Sweden (gridX Charging Report 2024)

Charging infrastructure however lacks in number of fast chargers. This is mainly because the technology is improving rapidly but deployment of new chargers is slow. Despite eleventh is ultra-fast charging points, average charging power (32KW) is still lower than EU average charging power of EU countries – 38KW. The charging network of Sweden is shown in figure 24 (gridX Charging Report 2024).

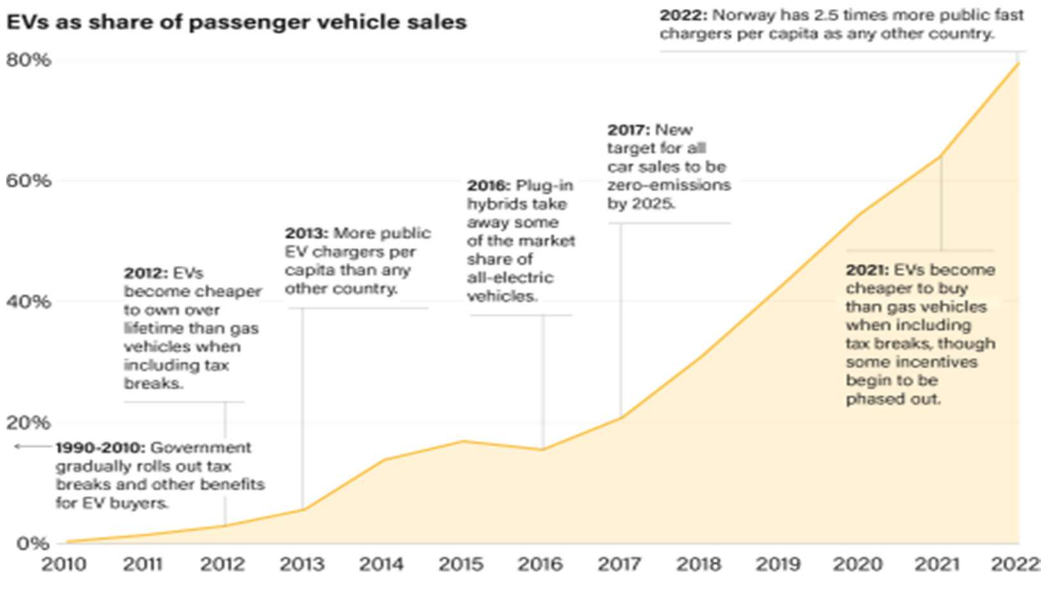
Norway’s Electric Vehicle Fleet

In 2024, almost 90% of the new cars sold in Norway were electric as per registration data published by Norwegian Road Federation (OFV) compared to 82.4% in 2023. By the end of 2024 28% of total car fleet is battery electric and 12.3% hybrid. The road of adopting EVs was not easy but government policies and incentives made is more cost effective for buyers to own an EV rather than its counter combustion engine car (OECD, 2022). Despite one of the largest oil & gas exporter Norway adopted all electric policies deeming environmental benefits and to be among first sustainable countries in the world. The government policy of incentivizing EVs, investment in charging infrastructure in collaboration with private sector enabled long distance travel that helped adoption of EVs (Jaeger, 2023).



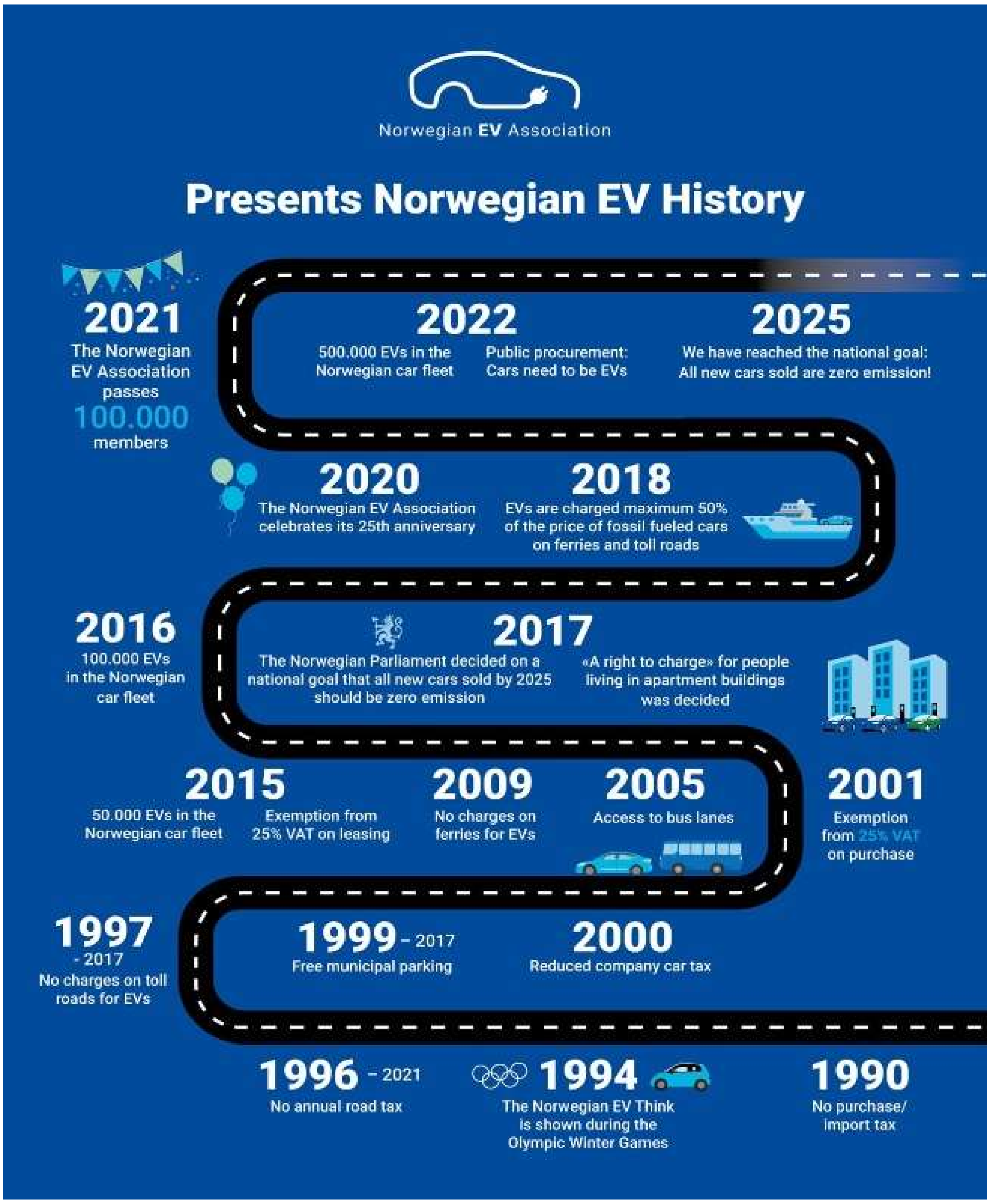
Note: Hybrid cars include both plug-in and non plug-in hybrids; most hybrids have petrol engines.
• Source: Norwegian Public Roads Administration

Figure 27: Norway’s car fleet (Jaeger, 2023)



Notes: EVs include all-electric vehicles, not plug-in hybrid electric vehicles.
Source: Author analysis of IEA data; FIER Automotive and Mobility 2021; Figenbaum 2022; Ewing 2023; Elbil Forening n.d.

Figure 26: Norway's EV adoption (Jaeger, 2023).



Norwegian **EV** Association

Presents Norwegian EV History

2021 The Norwegian EV Association passes 100.000 members

2022 500.000 EVs in the Norwegian car fleet

Public procurement: Cars need to be EVs

2025 We have reached the national goal: All new cars sold are zero emission!

2020 The Norwegian EV Association celebrates its 25th anniversary

2018 EVs are charged maximum 50% of the price of fossil fueled cars on ferries and toll roads

2016 100.000 EVs in the Norwegian car fleet

2017 The Norwegian Parliament decided on a national goal that all new cars sold by 2025 should be zero emission

«A right to charge» for people living in apartment buildings was decided

2015 50.000 EVs in the Norwegian car fleet

Exemption from 25% VAT on leasing

2009 No charges on ferries for EVs

2005 Access to bus lanes

2001 Exemption from 25% VAT on purchase

1997 - 2017 No charges on toll roads for EVs

1999 - 2017 Free municipal parking

2000 Reduced company car tax

1996 - 2021 No annual road tax

1994 The Norwegian EV Think is shown during the Olympic Winter Games

1990 No purchase/ import tax

Figure 28: Norwegian history of EV incentives (Norsk elbilforening, 2024)

Pilot projects for V2G since 2018 in Europe are shown in table 2 aimed to study grid services – Load shifting, load levelling, spinning reserves, frequency regulation, backup power and arbitrage.

Table 2: Pilot projects of V2G for grid services

Project Name	**Country**	**Year**	**Number of EVs/ Charging stations**	Load shifting	Load levelling	**Spinning reserve**	**Frequency regulation**	Backup power	Arbitrage
Powerloop	UK	2018	135	✓	✓			✓	✓
Deelzedon Project	Netherlands	2019	80	✓	✓		✓		
BloRin	Italy	2019	1	✓			✓		
Peak Drive	Canada	2019	21	✓	✓				
Piha V2H trial	New Zealand	2019	2	✓					
Smart micro grid EMS	China	2019	5	✓			✓	✓	
UNDP Windhoek V2G	Namibia	2019	2	✓					
V2G EVSE Living Lab	UK	2019	2	✓				✓	
Realizing EV to Grid Services	Australia	2020	51			✓	✓		
Electric Nation V2G	UK	2020	100	✓	✓	✓			
Milton Keynes Council	UK	2020	4	✓					
V2G at Lelystad	Netherlands	2020	14	✓	✓		✓	✓	
V2G Zelzate	Belgium	2020	22	✓		✓	✓		
VIGIL	UK	2020	4	✓	✓	✓			
V2G@home	Netherlands	2021	1	✓				✓	
Bidirektionales Lademanagement	Germany	2021	50	✓			✓		✓

3 Challenges in Implementing V2G

Despite V2G benefits there are technical, commercial and social challenges that needs to be addressed for the widespread implementation of V2G. Battery ageing, high power bi-directional charging infrastructure, high speed and secure communication, impact on distribution networks for instance protection schemes for smart grid operation capable of operating in island mode – Microgrid – are some of the key challenges in implementing V2G. Moreover, not all EVs support bidirectional power flow however almost all EV manufacturers have updated their design to include charging equipment and EMS to support V2G. Also, the charging ports should support these services to enable active participation from the prosumers. Another issue is the lack of clarity to end user considering too many stakeholders are involved for instance energy retailers, grid operators, EV manufacturers, insurance companies and of course legislative bodies. As shown previously most of the EV owners are comfortable using V2G with their energy suppliers however clear regulatory guidelines, for insurance, coverage and compensation on battery degradation is crucial in developing confidence in V2G and for the widespread implementation (Vehicle-to-grid (V2G) and Vehicle-to-home (V2H) – gridX, n.d.).

3.1 Battery Degradation

Most of the EV owners are concerned with battery life when utilizing the V2G. Battery life reduces on number of charging and discharging cycles. Also, how much and how quickly battery is discharged in response to demand. Battery life decreases with faster, deeper cycles of charging and discharging therefore it is essential to consider ageing in objective function of system modeling and percentage of battery that can be used for one charging and discharging cycle. These parameters can be read from BMS as State of Charge (SoC) and State of Health (SoH) of the vehicle. SoH is defined in terms of total capacity and internal impedance (Z) also known as capacity fade and power fade respectively. Internal impedance affects the power delivery and is generally caused by kinetic resistance within storage whereas the loss of capacity is due to loss of active material (Sagaria et al., 2024). Battery life also referred as EoL (End of Life) as per EU regulations is 80% of the total capacity (EUR-Lex - 32023R1542 - EN - EUR-Lex, n.d.). Thus, in modelling battery ageing 80% lower limit is used to calculate economic benefit to end user. In recent years however, the battery technology has improved significantly with high energy density and deeper charging discharging cycles that might influence regulations. Nevertheless, batteries with second life – less than 80% SoH – can also be used as a stationary storage system and participate in energy trading with aggregators.

There are two types of ageing mechanism in batteries namely calendar ageing and cyclic ageing. Calendar ageing only depends on temperature and SoC during charging and discharging cycles when stationary. Cyclic ageing depends on number of factors – operating temperature, Charging current, depth of discharge (DoD) and State of Charge SoC. For an accurate modeling of cyclic ageing the amount of energy extracted from the battery in each cycle should be included in the objective function in optimization problem. This can be estimated from the load profiles from network operators. Temperature rise is another important parameter that should be considered in the equation monitored by BMS/EMS that can trigger tripping of the respective storage unit if temperature increases above a specific threshold. For optimal performance low C-rate, low DoD at moderate temperature prescribed by the manufacturer is desired and should be modelled accordingly. As per experimental results 50% SoC is considered an optimal cycling point (Uddin et al., 2017). Type of ageing and respective factors are shown in the figure 29.

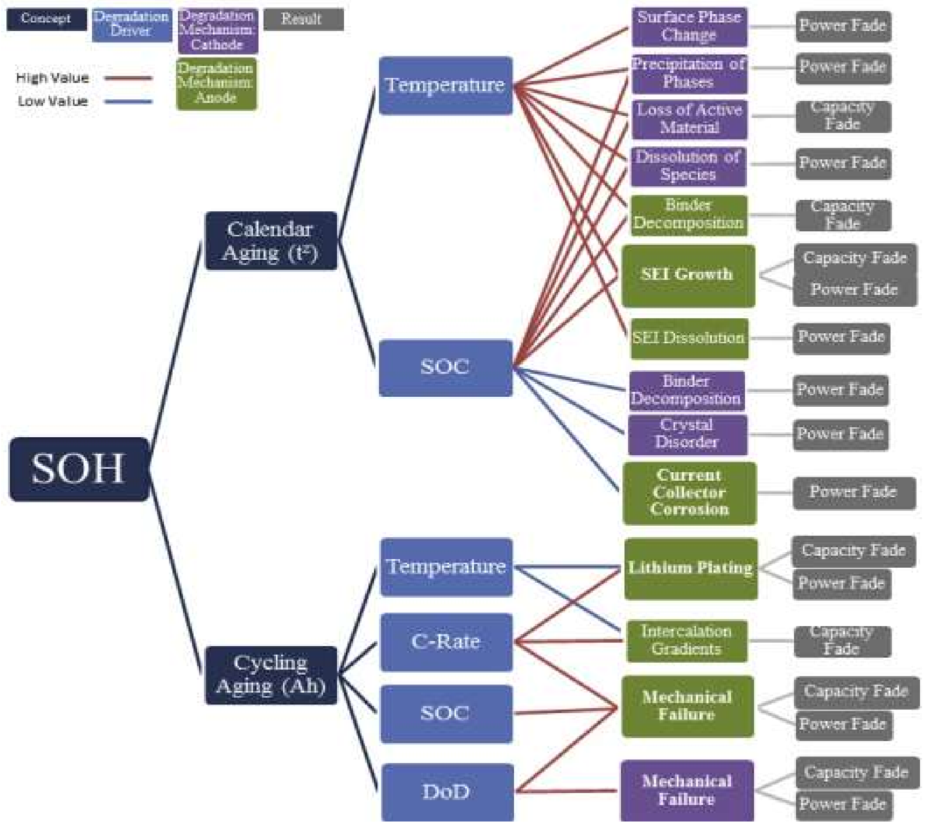


Figure 29: Battery degradation types and factors affecting (Sagaria et al., 2024)

A thermal management system is critical in prolonging battery life as high temperature causes chemical degradation also known as calendar ageing whereas high charging and discharging rate causes more cyclic ageing which a mechanical degradation mainly caused by graphite loss and not because of lithium loss (Smith et al., 2014). As discussed earlier, most of the EVs are parked for almost 90% of the time with batteries charged with a certain capacity, calendar ageing is the main cause of degradation and how battery is managed while EV is immobile can improve its life expectancy. Cyclic ageing is also critical and must be modelled in calculating battery ageing for V2G applications. As a rule of thumb both deep discharging and prolonged charging capacity adversely affect its life and an optimal solution under the guidelines of manufacturer are necessary to ensure best economic output for EV owners and network operators. As this technology is picking up incentives from government are essential for its success for instance in Norway each EV owner is subsidized almost a thousand Euro per year in energy cost (How Norway Built an EV Utopia While the U.S. Is Struggling to Go Electric | CNBC Documentary, n.d.). Below figure 30 shows simulation results of calendar ageing in green; cyclic ageing in black and total ageing in blue at 10, 20, 34, and 46 degree Celsius (Wang et al., 2014).

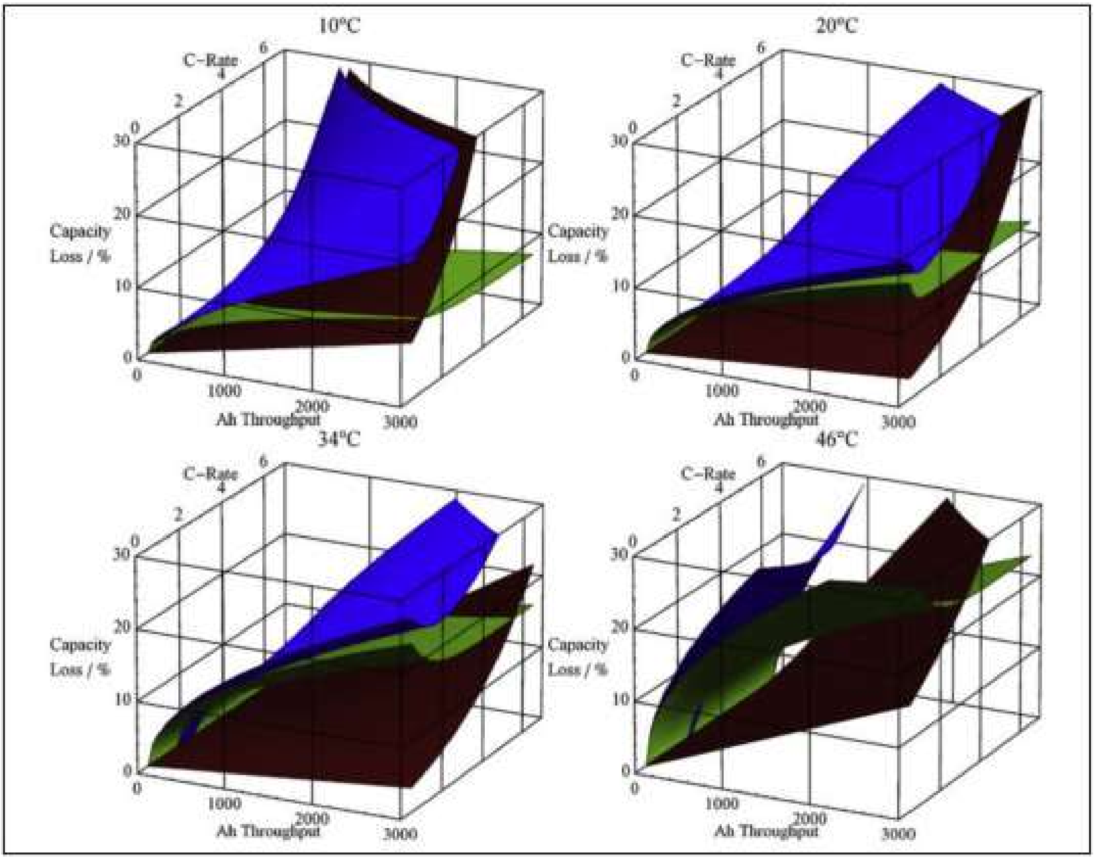


Figure 30: Calendar and cyclic ageing in terms of discharge rate and Ah at given temperatures (Wang et al., 2014)

3.2 Battery Degradation modelling

The benefit for EV owners in participating in V2G is to derive additional value out of their asset that can reduce energy cost and recover asset cost by providing energy to grid. As discussed previously V2G is more attractive for services that require fast response in a small timeframe. Peak shaving, spinning reserves, demand side response, and frequency restoration services such as aFRR and mFRR are available services in energy market. As per Fingrid's financial report discussed in previous section aFRR and mFRR services are most lucrative for aggregators and subsequently for EV owners. SMART home owners and EV fleet owners with solar power and a secondary storage can benefit from V2G to a degree that they can reduce electricity bills with ToU (time-of-use) tariffs, SMART charging and can make it a profitable business case using a smart EMS (Energy Management System) that can communicate with grid and other devices to optimize savings and maximize efficiency without compromising user comfort. A high frequency charging and discharging load profile with a net low energy exchange for short duration is less detrimental to EV's battery thus makes EV's an ideal solution for energy storage and to provide above mentioned services to grid. In all models the degradation effect from Calendar Aging and Cycling Aging is assumed to be additive.

3.2.1 NREL model

NREL model is primarily rely on NCA chemistry datasets that later included LFP chemistry and is true for all lithium ion technologies with degradation coefficients that can be tuned based on specific battery chemistry

$$\mathrm{R} = a_0 + a_1 t^{1/2} + a_2 N$$

where

a_1 is time effect on resistance

a_2 is effect of number of charging/discharging cycles on resistance

Cell capacity loss can be equated using loss of active material (lithium – Li) and loss of active sites.

$$\mathrm{Q} = \min\left(\mathrm{Q}_{\mathrm{Li}}, \mathrm{Q}_{\mathrm{sites}}\right)$$

where

$$\mathrm{Q}_{\mathrm{Li}} = \mathrm{b}_0 + \mathrm{b}_1 \mathrm{t}^{\mathrm{z}} + \dots$$

$$Q_{\mathrm{sites}} = c_0 + c_1 t$$

b_1 is time loss of material (Li) and c_1 site loss because of charging/discharging cycles. The upside of this model is that it can include further degradation terms based on ageing data. Moreover, the coefficients are derived from rate constant equations which assumes an Arrhenius dependence on temperature, open circuit voltage (V_{oc}), and a Wöhler dependence on changes in DOD as shown below:

$$\theta_T = \exp\left[-\frac{E}{R_{ug}}\left(\frac{1}{T(t)} - \frac{1}{T_{ref}}\right)\right]$$

$$\theta_{Voc} = \exp\left[\frac{\alpha F}{R_{ug}}\left(\frac{Voc(t)}{T(t)} - \frac{V_{ref}}{T_{ref}}\right)\right]$$

$$\theta_{\Delta DoD} = \left(\frac{\Delta DoD}{\Delta DoD_{ref}}\right)^{\beta}$$

$$\theta = \theta_{ref} \pi \theta_k$$

The parameters E, α, β and θ_{ref} are tuning parameters to model battery chemistry, R_{ug} is the universal gas constant, and F is Faraday's constant.

3.2.2 Knee region modeling

For more accurate modelling the knee region is to be included as a mechanical loss of graphite site loss rather than Li loss which is a chemical process. If knee region under high charging and discharging rate is not modelled accurately it can over predict batter life loss by 25%. The mechanical stress is due to following

- Thermal strain
- polymer failure at high temperature
- intercalation strain
- intercalation due to low temperature

Below equation can be used of c1 rate constant for more accuracy

$$\begin{aligned} c1 = c1,\mathrm{ref}\,\{&\exp(-\mathrm{Eabinder}\,/R(1/T - 1/Tref))[m1DoD + m2\Delta T] \\ &+ m3\,exp((-Eabinder\,/R(1/T - 1/Tref))\,(Crate/Crate,ref)(tpulse/\,tpulse,ref\} \end{aligned}$$

A generalized equation for the overall lifetime of a battery can be described below (Wang et al., 2014)

$$Q_{\mathrm{loss}},\ \% = (a.\mathrm{T}^2 + \mathrm{b.T} + \mathrm{c})\exp[(\mathrm{d.T} + \mathrm{e}).\mathrm{I}_{\mathrm{rate}}]\,.Ah_{throughput}(\mathrm{t}) + \mathrm{f.t}^{1/2}.\exp\left(-\frac{E_a}{R.T}\right)$$

Coefficient values from table 3 can be used

Table 3: Coefficient values used in Wang model

Coefficient values			
a	8.61E-6, 1/Ah-k^2	I_{rate}	C-rate
b	-5.13E-3, 1/Ah-k	t	Days
c	7.63E-1, 1/Ah	E_a	24.5, Kjmol^{-1}
d	-6.7E-3, 1/K-(C-rate)	R	8.314, J mol^{-1}
e	2.35, 1/(C-rate)	T	K
f	14,876, 1/day$^{1/2}$		

It is observed from the model that at lower temperature degradation process is linear due to cyclic ageing however at higher temperatures (above 45^{0}C) the relationship is more exponential due to the dominance of calendar ageing as shown previously in figure 30.

3.2.3 MOBICUS Model

Modeling of Batteries Including the coupling between Calendar and Usage ageing (MOBICUS) model is a simplified model of NREL that, according to the writer, can predict knee region with more accuracy and considers time dependency of both calendar and cyclic ageing. Following technologies were studied to develop the ageing models of batteries as a part of SIMSTOCK for cyclic ageing (Gyan et al., 2013b) and SIMCAL project for calendar ageing (Grolleau et al., 2013).

	NCA	LMO-NMC	NMC	LFP
SIMSTOCK	Salt 7 Ah	LG Chem 5.3 Ah	-	LiFeBatt 8Ah
SIMCAL	Salt 7 Ah	LG Chem 5.3 Ah	Kokam 12 Ah	LiFeBatt 8 Ah LiFeBatt 15 Ah A123 2.3 Ah

SIMSTOCK study finds out that NREL model has a limitation of static ageing parameters during battery lifecycle which is not accurate description because degradation parameters change as battery ages at a different rate. Therefore, following expression was derived to accurately model battery ageing

$$\left(\frac{\mathrm{dQ_{Li}}}{\mathrm{d}\left(\sqrt{\mathrm{t}}\right)}\right) = \mathrm{aj}$$

where,

$$\mathrm{aj} \;=\; \mathrm{a_{00}} \;+\; \mathrm{a_{01}.X_1} + \mathrm{a_{02}.X_2} + \mathrm{a_{03}.X_3} + \mathrm{a_{04}.X_4}$$

where X_1 is current in amperes, X_2 is temperature in ^{0}C and X_3 is throughput in Ah, X_4 is percentage of change in state of charge ΔSOC (%). This research work on LMO-NMC calendar ageing model concluded that Ah throughput is larger than the effect of charging/discharging current and without stress the coefficients (a_0) are positive that implies that battery would restore to its full capacity that can prolong battery life and can reduce cyclic ageing effect.

For SIMCAL calendar ageing model following the test conditions were applied to extract data to formulate the expression

- SOC: 30, 65 and 100
- Temperature 30^{0}C, 45 ^{0}C and 60 ^{0}C
- An additional thermal cyclic test (30 to 45 ^{0}C)

$$dQ_{\frac{loss}{dt}} = \; k(T, SOC).(1 + \frac{Q_{loss}(t)}{C_{nom}})^{-\alpha(T)}$$

k (T, SOC) is capacity fade evolution with temperature (T) and SOC during storage

$\frac{\mathrm{Q_{loss}(t)}}{\mathrm{C_{nom}}}$ is the fractional capacity loss at time t.

$\left(1+\frac{\mathrm{Q_{loss}(t)}}{\mathrm{C_{nom}}}\right)^{-\alpha(\mathrm{T})}$ diffusion limitation of solvent molecules inside SEI layer that tends to decrease the capacity fade rate at given temperature.

The differential term is integrated to present it as a function of time with assumptions α = 1 at t=0 for initial Q_{loss} = 0 to obtain the following expression

$$\mathrm{Q_{loss}}\,(\mathrm{t})\ +\frac{1}{2}.\frac{\mathrm{Q_{loss}(t)}}{\mathrm{C_{nom}}} = \mathrm{k(T,\ SOC).(t)}$$

The above expression is further generalized to fit the ageing dataset by further integrating with an assumption the T and SOC remains constant to achieve following

$$\mathrm{t} = \frac{C_{nom}}{(\alpha+1).k(T,\ SOC)}\ .\ \left(1+\frac{Q_{loss}(t)}{C_{nom}}\right)^{\alpha+1} - 1$$

Moreover, kinetic dependence capacity fade can be expressed as

$$\mathrm{k}(T,\ SOC) = \mathrm{A}(T).\ \mathrm{SOC} + \mathrm{B(T)}$$

$$\mathrm{A}(T) = k_a.\exp-\frac{E_{aA}}{R}.\ \left(\frac{1}{T}-\frac{1}{T_{ref}}\right)$$

$$\mathrm{B}(T) = k_b.\exp-\frac{E_{aB}}{R}.\ \left(\frac{1}{T}-\frac{1}{T_{ref}}\right)$$

where

- R is gas constant (8.314 $JmolK^{-1}$)
- T in temperature in kelvin
- α and k are tuned parameter using non-linear regression method to fit base line model

This research studied the effect of temperature proportional to state of charge (SOC) and concluded that higher temperature and SOC at higher storage values reduces the battery life more than lower storage values. Moreover, battery temperature during storage, charging and discharging is main factor reducing battery life however if controlled can increase battery life significantly. Nevertheless, faster discharging for frequency reserves is more suitable for V2G economically provided the dispatch abide the optimal temperature and lower bounds of battery advised by the OEM to improve life of prosumer asset. Having said that fast discharging increases the temperature rapidly (Surya & Mn, 2020) therefore a tradeoff ensuring longer life of asset, economical for owners – lower charging cost, battery degradation cost and profit in participating in V2G – without compromising their comfort can be the objective function for the optimization problem. Optimal case was observed at 65^0C at $t^{1/2}$ however at lower temperature the battery life fade shows linear degradation.

If $t^{1/2}$ is considered then the equation can be further simplified. The main idea for this simplification is battery degradation is dominated by calendar ageing and the effect of cyclic degradation is minimal however both factors are time dependent therefore the internal resistance caused by degradation can be written as

$$\mathrm{R} = a_0 + a_1 t^{1/2} + a_2 \mathrm{N}$$

$$\mathrm{Q} = \min(Q_{Li}, Q_{sites}))$$

Where

$$Q_{Li} = b_0 + b_1 t^{1/2}$$

$$Q_{sites} = c_0 + c_1 \mathrm{t}$$

3.3 Battery models – limitations

Semi-empirical models are data dependent to formulate rate of degradation are time/cost effective compared to empirical models however these models have limitation that can be describe as below:

Time resolution

Training data, for instance temperature and SOC, for semi-empirical models is generally in hourly or minutes frequency that does not capture high resolution changes in battery degradation caused by temperature rise thus it is not accurate in predicting battery degradation in high discharging grid services for instance Frequency Regulations that has a time resolution in seconds.

Data Limitation

Data is limited in predicting accelerating degradation mechanism because such data is very costly due to experimental setup for very longer period. Cyclic data if not defined properly can over predict battery life. Moreover, data for a single cell cannot describe degradation at a pack level however approximation in parameters can be tuned to improve accuracy using optimization techniques and AI models.

Battery Chemistry

Battery chemistry is very critical in training a semi-empirical model as each type of battery has different ageing rate and SOC at different operating points. Therefore, chemistry specific models should be trained and used in optimization problems calculating the cost.

Constant C Rate

Most of the battery degradation models assume constant C-Rate for simplicity however real-world scenarios are different and require variable C-Rate for different load requirements and response time. Sagaria et al. (2024) provides an in-depth analysis of battery degradation based on variable C-rate energy flow, multiple drive cycles utilizing V2G.

3.4 Battery models – Approximations

Cost Estimation

Cost estimation is based on many factors such as CAPEX, energy cost, and labour cost that are well defined however the battery degradation cost is solely based on its charging/discharging lifecycle at a certain level of DoD and assumes that battery capacity – extractable energy – does not decorates over time as shown in the following equation.

$$c_d = \frac{c_{bat}}{L_{ET}}$$

$$L_{ET} = L_c E_s \, \mathrm{DoD}$$

Where

- c_d is battery degradation cost,
- c_{bat} is the battery capital cost including labor for replacement of the battery,
- L_{ET} is the lifetime energy throughput of the battery.
- L_C is the cycle lifetime number,
- E_S the total energy storage of the battery,
- and DoD is the depth-of-discharge at which L_C was determined.

Present Value of Throughput (PVT) (Neubauer et al.)

Calendar ageing is the dominant reason of battery degradation and thus it should also be modelled as a time dependent equation

$$\mathrm{PVT} = \sum_{i=1}^{n} \frac{(1+0.025)^{i-0.5}}{(1+0.10)^{i-0.5}} x_i$$

Where

- i = years,
- n = battery life in years,
- xi = annual battery energy throughput in kWh.
- PVT accounts for the present value of both the capacity and cycle life of the battery assuming a discount rate associated with the time value of money of 10% per year and that the value of a kWh of energy storage increases at a rate of 2.5% per year

3.5 Battery degradation with V2G

For comparison battery degradation without V2G is simulated that is then compared with battery degradation with V2G. Below figure 31 shows the calendar and cyclic ageing. It is noted that major factor for battery degradation with calendar ageing and cyclic ageing is less than 0.25% on average to maximum of 0.5% under high usage.

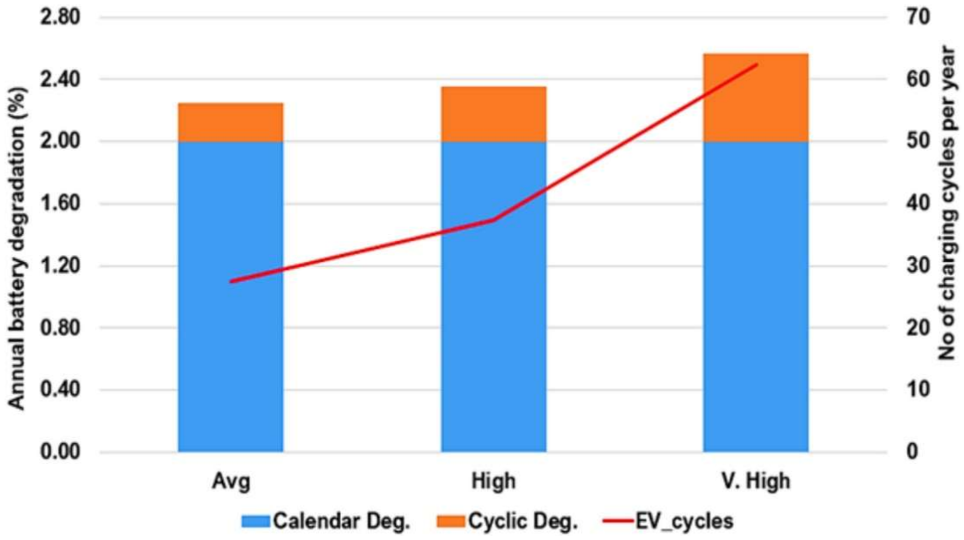


Figure 31: Battery degradation without V2G

In the second simulation study three scenario with very favourable (V.F), moderately favourable (M.F), and least favourable (L.F) V2G is included. This study depicts the effect of driving pattern, charging frequency and participation in V2G on battery life. It is observed that the calendar ageing remains same regardless of driving pattern, discharging cycles and participation in V2G however with SoC set at minimum 40-45% a very small increased is noted. It can also be concluded that reducing SoC to lower levels will increase battery degradation.

V2G participation with allocated number of cycles, the battery degradation under V.F scenario increased to 0.57%. In M.F scenario with increased number of discharging cycles it is increased to 0.63% and in least favourable scenario it can go up to 0.68% per year. It is also noted that with high discharge applications the number of cycles reduce and thus reduces degradation however SoC should be set to limit full discharge because that reduces battery life faster.

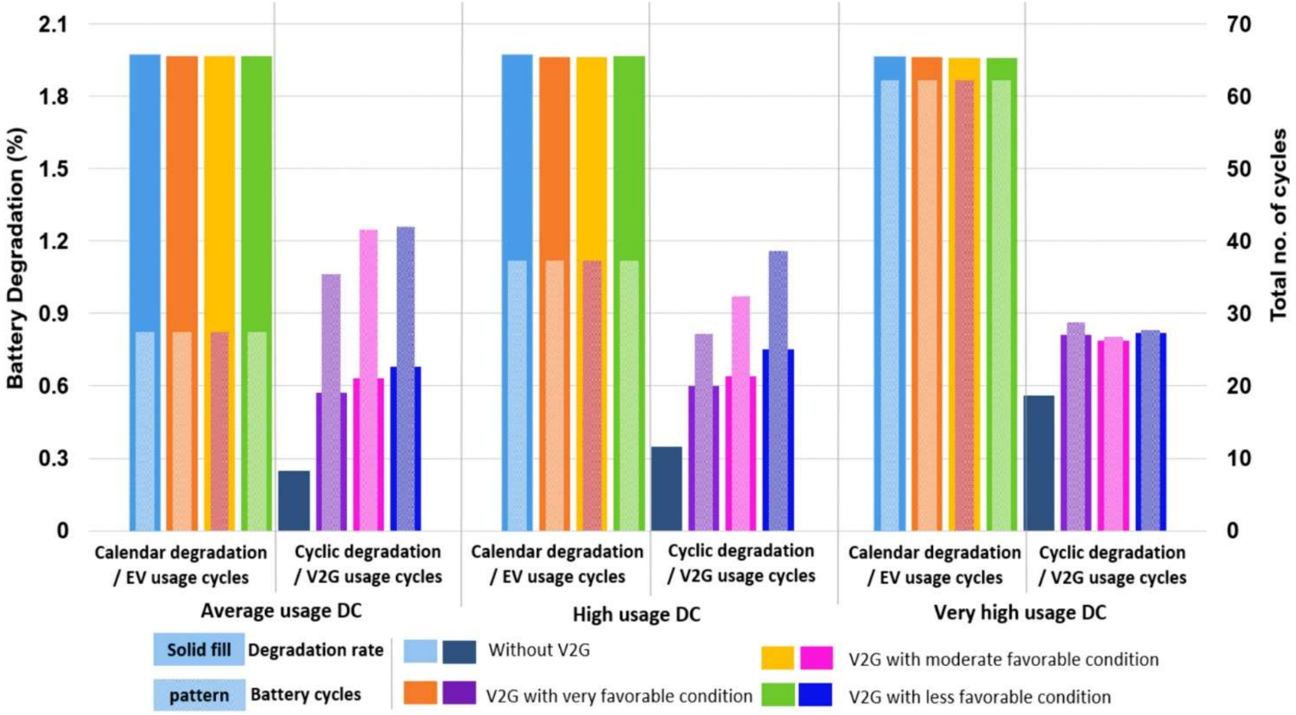


Figure 32: Battery degradation with V2G (Sagaria et al., 2024)

Drive cycles relation with battery degradation is shown in figure 32. In all three scenarios it is noted that battery degradation based on driving cycles is non-linear and shows higher degradation than simulation results or actual degradation of the battery. This is because the battery models are mostly linear and do not calculate the adaptive nature of battery and its ability to restore to its original state. Also, it does not account for the non-linear effects of temperature and charging pattern on battery health. Recently, BYD has launched a 5-minute supercharger called BYD Super E-platform that can charge up to 1MWh (Bloomberg Television, 2025). However, it is too early to find out its effect on EV battery life as fast charging do increase the temperature and thus reduces the life of the battery. This is a new area of research is recommended for further study. Overall with V2G reduces the battery life to 3-4% in 10years and with different scenarios – V.F, M.F & L.F – the variation is less than 1%.

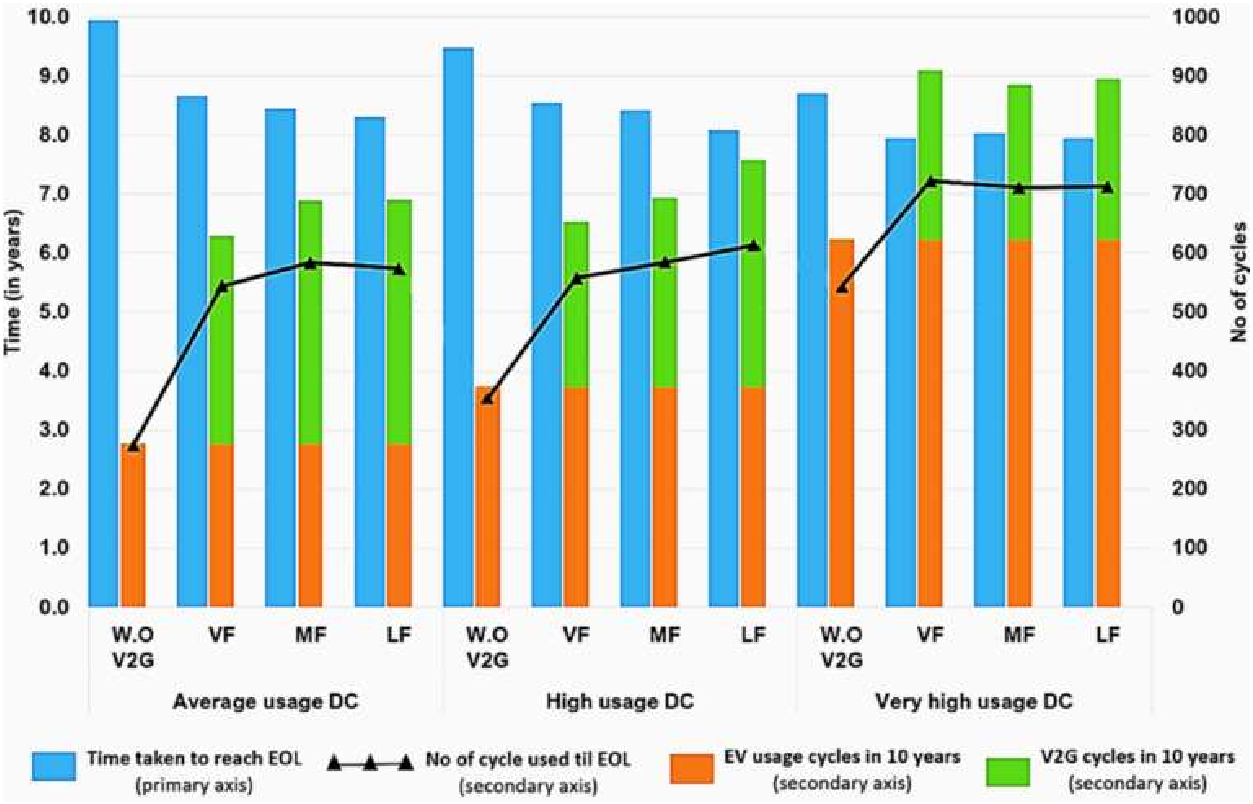


Figure 33: Number of cycles versus battery life (Sagaria et al., 2024)

It is further studied that battery degradation with high Dcycles and V2G increases on average 1.7% and is less than 10% in 10yeaers. Varying charging/discharging rate has a minimal effect on battery life compared to constant charging/discharging rate. Larger EV fleet can further reduce the negative effect of participating in V2G as it distributes the load evenly with less cycles on each EV. The option of allocating fixed number of battery cycles for V2G and SoC threshold is recommended in our study which reduces battery degradation significantly. Nevertheless, a high compensation for battery degradation is critical in promoting V2G and to offset its negative effect.

3.6 Battery degradation compensation for V2G

Favourable and attractive V2G compensation can improve the V2G acceptance and participation rate. To estimate compensation cost for the battery degradation only it is assumed that the cost of energy provided to grid and received from grid is same. This will exclude any profits/loss from energy trade and thus provides cost associated with battery life. It can be expressed mathematically as

$$Cost_{Bat}(\text{EUR}) = C_B * \frac{cost}{kWh} * 1.5$$

$$Cost_{Opp}(\text{EUR/cycle}) = \frac{Cost_{Bat}}{cycles_{EV}}$$

$$Comp_{exp}(\text{EUR}) = Cost_{Bat} \; - \left(Cost_{Opp} * cycles_{ev(V2G)}\right)$$

where

battery degradation cost ($Cost_{BD}$)

infrastructure cost ($Cost_{INF}$).

C_B is the battery cost with 50% labour cost.

Cost of battery degradation can thus be calculated as

$$Cost_{BD}(\text{EUR/cycle}) = \frac{Comp_{exp}}{cycles_{v2g}}$$

$$Cost_{inf}(\text{EUR/cycle}) = \frac{Cost\ of\ \ charger}{cycles_{v2g}}$$

$$V2G_{comp}(\text{EUR/MWh}) = \frac{\left(Cost_{BD} + Cost_{inf}\right)}{C_B} * 1000$$

A kilowatt-hour battery replacement cost is used in the NREL model to calculate battery degradation cost factor and is included in the objective function of optimization problem.

3.7 Battery degradation simulations (NREL)

We use NREL model for our analysis because updated data and Li-ion battery chemistry. NREL model development is already discussed previously. LFP-Gr battery model is based on the calendar and cyclic aging data, and model identification is based on Naumann et al. (2018), Naumann et al. (2020) and Gasper et al. (2022) respectively.

As discussed previously battery degradation model used is a function of temperature, SoC, DOD and charging/discharging rates with a thermal management option. Calendar and cyclic battery degradation over a period of 20 years is simulated to verify validity of the model and algorithm. The battery chemistry is LFP/Gr with average ambient temperature of Finland 10 degrees Celsius with a thermal management system that keeps temperature between 10 and 40 degrees Celsius and applications FCR, EV and peak shaving (PV) for one cycle per day.

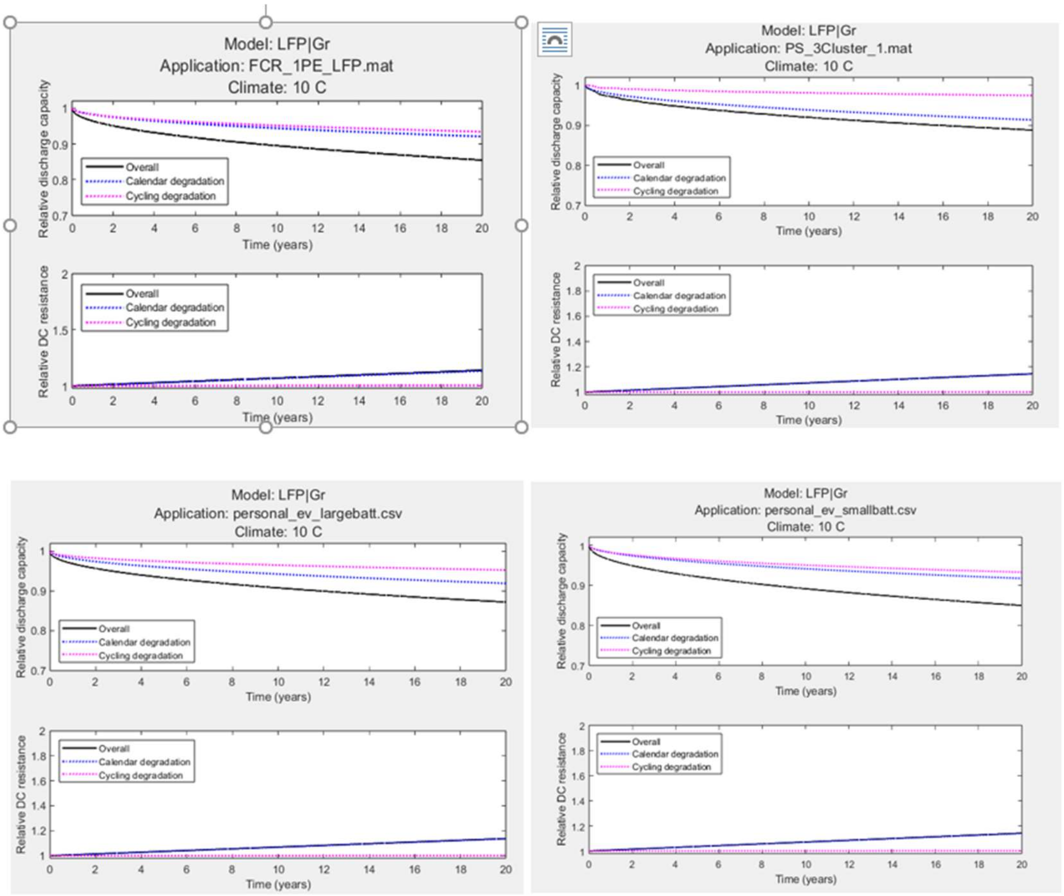


Figure 34: Simulation results of battery degradation model over a period of 20 years for various applications.

NREL battery degradation model is built with experimental data and non-linear equations. It is integrated in our V2G SMART charging model by running it in parallel to calculate battery degradation cost factor per cycle by simulating a charging / discharging profile over a 1-year period which is then fed in the V2G optimizer. This is further explained later in section 7.3 Model integration.

4 Vehicle-to-Grid (V2G) Modelling Process

Process flowchart for V2G modelling is shown in the figure 35. The inputs for the model are annual energy consumption, load profile, RES production, energy storage capacity and energy market participation potential. EV is considered as a primary source of energy with pumped hydro as a secondary storage source. Moreover, energy consumption and energy import/export are included in the model to calculate V2G impact on the grid.

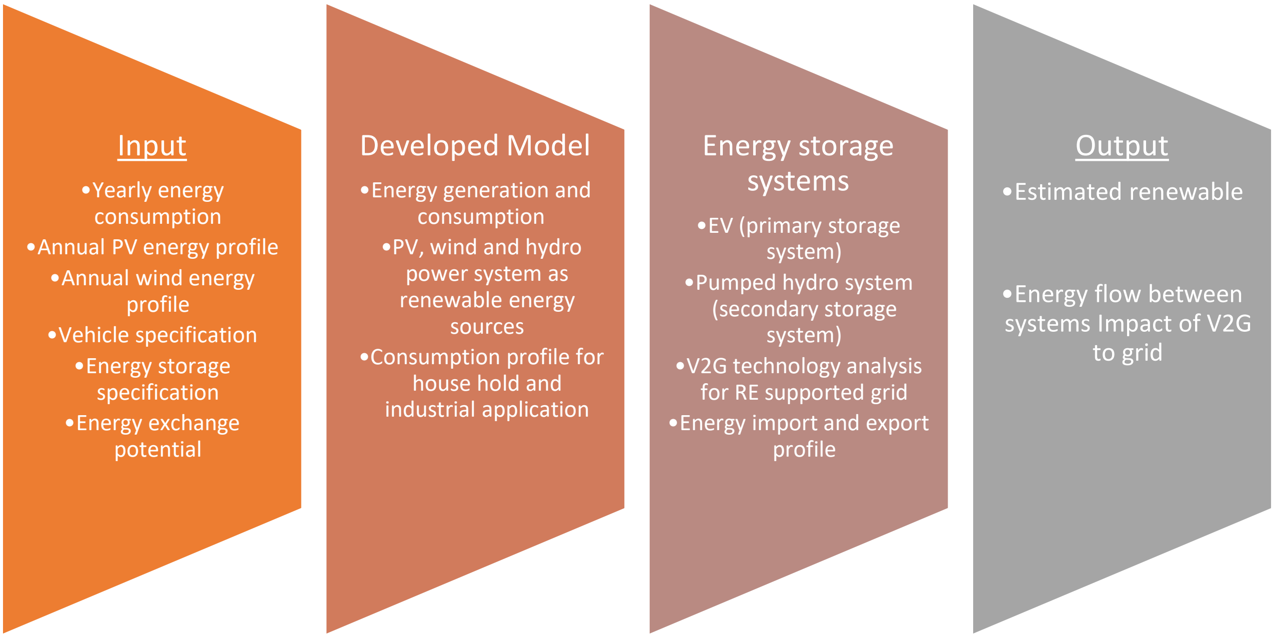


Figure 35: V2G modelling process flow chart

To estimate EV charging impact of grid, a load flow analysis is to be performed on the EV charging demand data of at least one year to calculate its impact on overall system including transformers, lines, line losses and impact on system voltages prior dispatch.

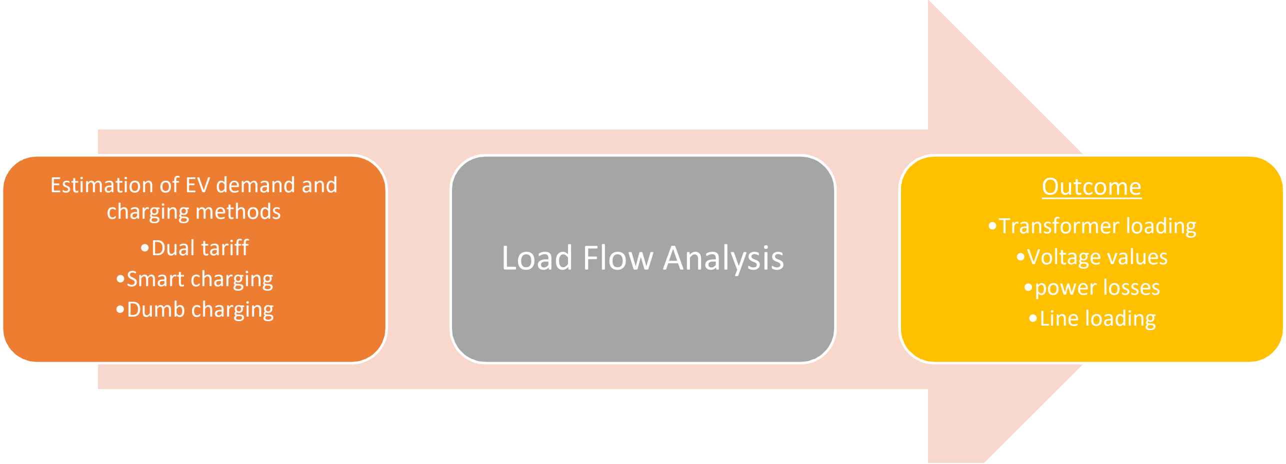


Figure 36: Process for calculating V2G impact on grid

Steady state analysis process flow is shown in the figure 37. Hourly EV charging demand along with area load, RES production and/or other energy storage systems (ESS) is added as an input. Load flow analysis is performed on the data using MATPOWER in MATLAB. This process is repeated for the whole year and the results are collected, and plotted for analysis.

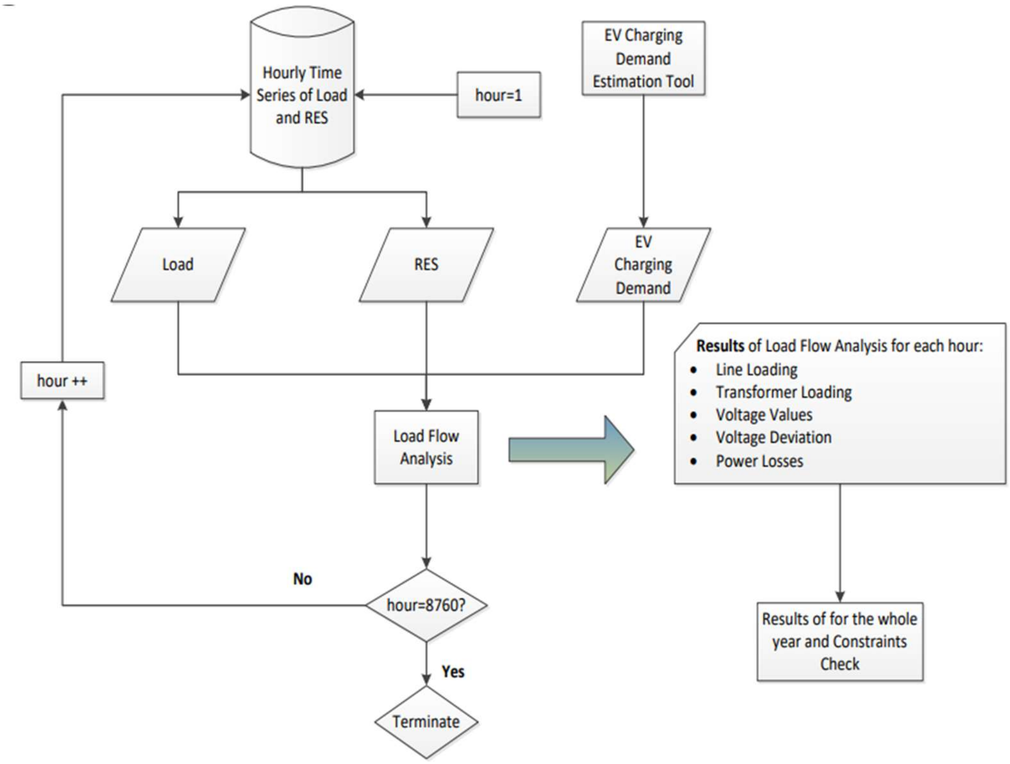


Figure 37: Steady state process flow for Load flow analysis

With uncontrolled charging, normally referred as dumb charging can increase system peak demand at times of high demand. This can be adjusted with variable tariff scheme but as discussed previously it can cause load spike at the start of low tariff because of connected EVs charge at the same time. Therefore, for both system operators and EV owners SMART charging that can enable valley filling is more attractive option. However, as smart charging is more beneficial for system operators or aggregators to utilise RES and/or low-price energy an additional incentive for EV owners can be a carrot to participate in V2G.

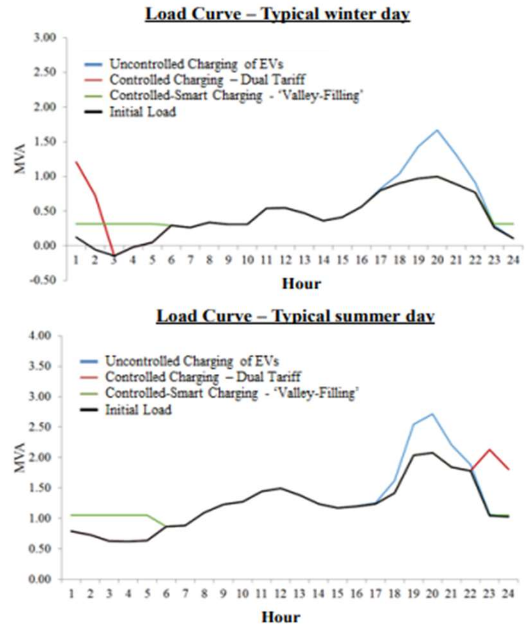


Figure 38: Load curve of charging schemes

A study on the voltage deviation of a distribution grid on a Greek island Ikaria with 300 EVs concluded that with uncontrolled charging and dual tariff schemes increases the voltages by 3% from regulatory limit and in winter it decreases to 0.93 p.u that is lower than the regulatory limit of 0.95. Penetration of RES with uncontrolled charging causes more uncertainty that increases the risk of network damage and price fluctuation. Variable tariff is an effective scheme with lower EV penetration in the network however with high number of EVs SMART charging can increases RES penetration without violating network constraints with stable price. It is also observed that with V2G participation more RES production can be utilised without upgrading distribution infrastructure or installing large scale energy storage systems (ESS) and hence reduces the CO_2 footprint by tapping maximum potential of RES in the power system.

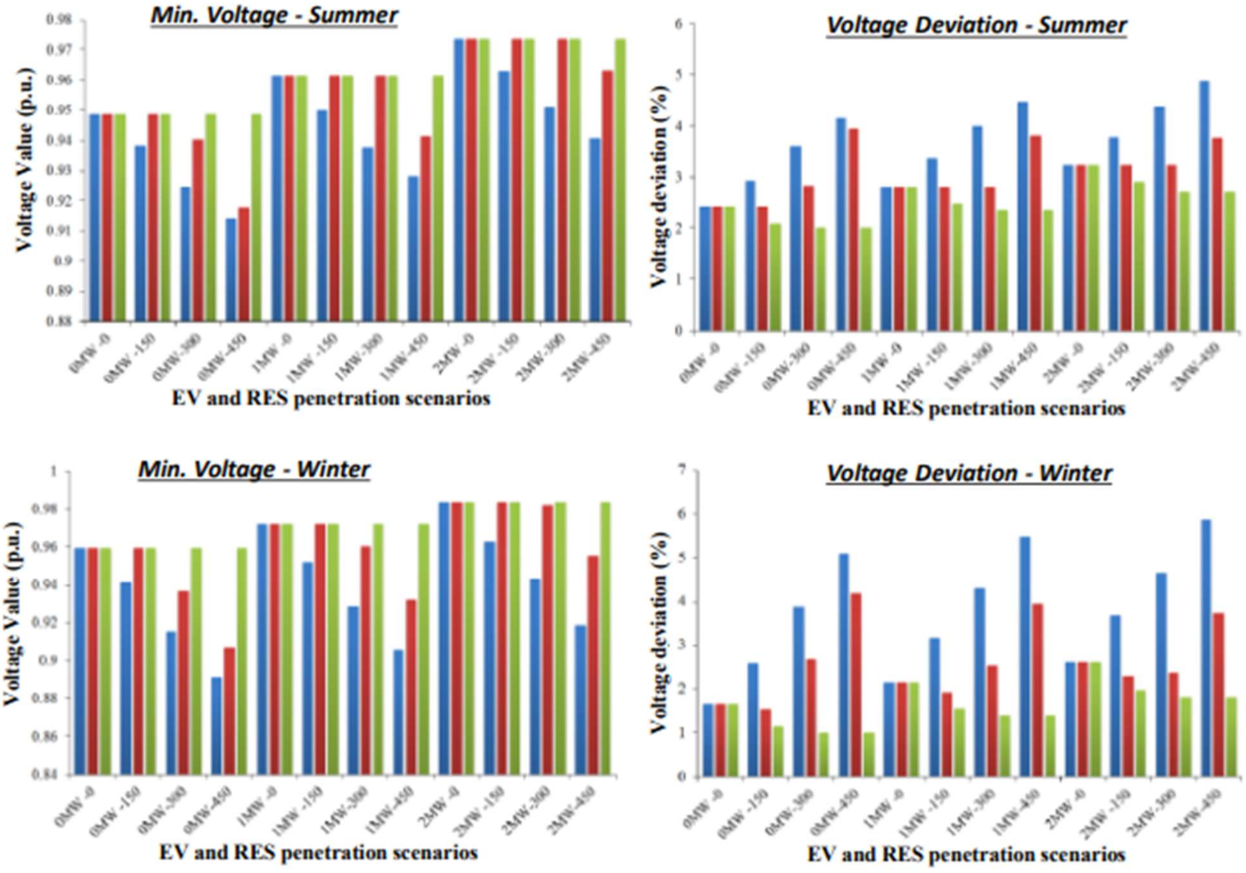


Figure 39: Voltage deviation with high RES penetration with V2G (Distribution grid in the Greek Island Ikaria - 300 EVs)

In addition, the EV aggregators can offer services such as Frequency Containment Reserves (FCR) by adjusting charging of EV fleet to support system frequency. In the event of underfrequency the charging can be reduced or completely stopped and charging power can be increased if system frequency increases (over-frequency). Moreover, the aggregated capacity of EV fleet can be discharged to support system frequency as a response to recover from power drop using droop control (Ota et al., 2010).

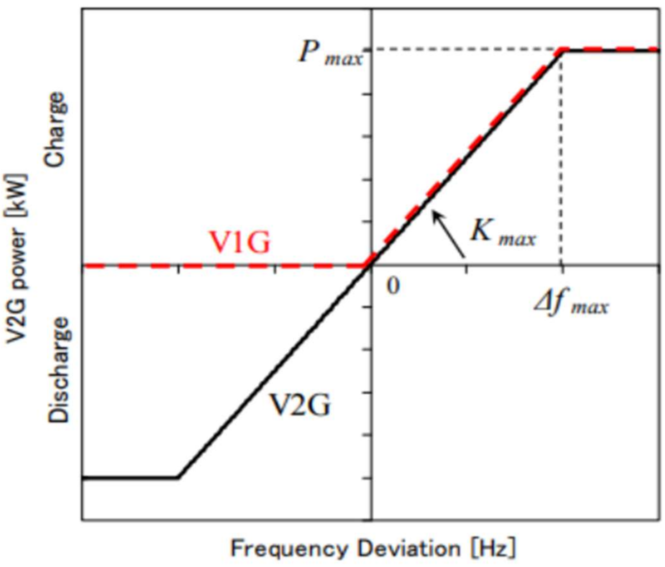


Figure 40: Power droop control (F-f)

5 Management of EV Charging

Types of EVs

According to EU directives – DIRECTIVE 2002/24/EC and DIRECTIVE 2007/46/EC with repealed regulations: Regulation (EU) No 168/2013 and Regulation (EU) 2018/858 respectively – EVs are classified as per their wheels, passenger seating and load carrying capacity.

Table 4: Vehicle categorization as per EU directive and regulations

EV Categories	Description
L3e	vehicle (two-wheel motorcycle)
L6e	vehicle (light quadricycle)
L7e	vehicle (heavy quadricycles)
M1	motor vehicles with not more than eight seating positions
M2, M3	motor vehicles with more than eight seating positions in addition to the driver's seating position and having a maximum mass not exceeding 5 tonnes
N1	carriage mass not exceeding 3,5 tonnes
N2	carriage mass exceeding 3,5 but not 12 tonnes
N3	carriage mass more than 12 tonnes

Estimation of the EV demand

To avoid overloading of lines/transformers and to abide voltage regulation EV charging load can be managed smartly by signing into a charging management schemes with an aggregator. There are constant and variable parameters associated with an EV charging. A single EV can be estimated with probabilistic parameters whereas demand of an EV fleet can be calculated using stochastic models. Possible charging scenarios are

- Modelling of home charging
- Modelling work-place charging
- Modelling of public charging stations

Constant Parameters

- **EV penetration level:** Anticipated number of EVs to be connected with the grid
- **Classification of EVs:** The type of the vehicles (e.g. small or larger commercial vehicles, two-wheelers, etc.)

- **Energy Consumption (kWh/km):** per kilometre energy consumption of the EV
- **Charging Level of the station:** The power (kW) of the charger
- **Charging losses:** The efficiency (Pout/Pin) for the charging station will indicate the charging losses.

Probabilistic Parameters:

- **Travel Distance:** Battery capacity (kWh) – Total distance travelled in terms of energy consumed.
- **Time of arrival** at the charging station

EV customer modelling parameters are shown in figure 41.

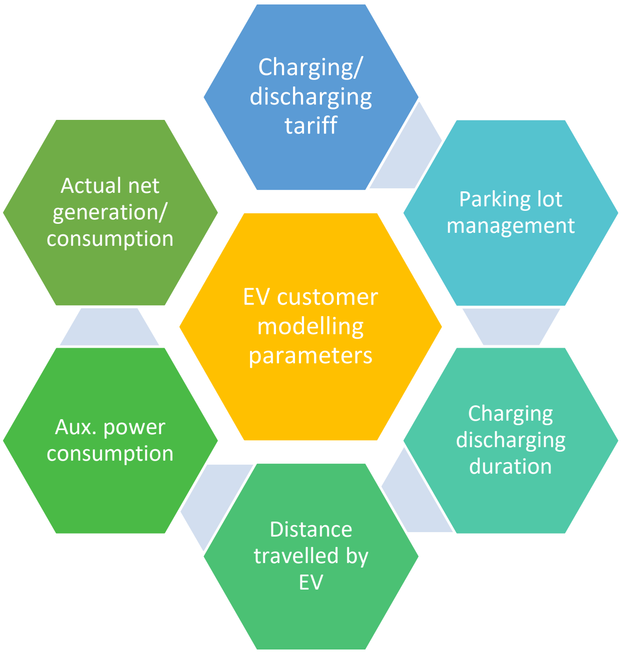


Figure 41: EV customer modelling parameters (Mohammad et al., 2020)

Actual net generation and consumption is calculated based on number of EVs, state of charge (SoC) of battery energy storage system (BESS) of EV, and owner's consent of participation (Mohammad et al., 2020).

This information is essential for EV demand forecasting for the EV aggregator to make decisions regarding bidding for ancillary services or balancing market. For instance, surplus wind energy can be consumed in charging these vehicles instead of curtailing the wind energy and then this power can be provided to grid in if wind power decreases instead of starting a new generator or utilising a spin reserve. Also, demand can be reduced to smoothen power fluctuations. Each type of EV, its battery capacity, average daily travel distance. It is further assumed that some EVs will be partially charged at workplace Level-3 (22KW), Level-2 (7.2kW) and rest at home the rest at Level-1 (3.2kW).

5.1 Home Charging EV

The procedure to estimate the energy demand for EV charging at home within a specific area covered by the grid is defined as per the flowchart (figure 42).

- EVs of a specific city or grid area are categorised to reflect charging level (SoC) and type of EV.
- Travel distance and arrival time is randomly defined for each EV however it is assumed that daily travel distance is approximately 40 km with a 15 km deviation N(40,15).
- It is assumed that the charging power options
    - 22KW, 11 KW, 7.4 KW or 2.4 KW
- with respective probability for each charging type is assumed to be
    - 10%, 25%, 50% and 15%
- Arrival time is assumed 6pm with a deviation of 2.5 hours and departure time is set 7 am with a 1.5 hours deviation N(18.0,2.5).
- Vehicle efficiency is 18% (KW/h) with a sigma of 2% (KW/h)
- Monte-Carlo method is applied to calculate the total EV demand and thus total home charging energy requirement. The process generates a random sample from the defined distribution – normal distribution in this case – for each parameter of N vehicles.
- The process is repeated for all EVs until a predefined convergence point is reached. Through these parameters the total charging time need to fully charge the EV is calculated.
- Small energy demand – less than 10% – is filtered out.

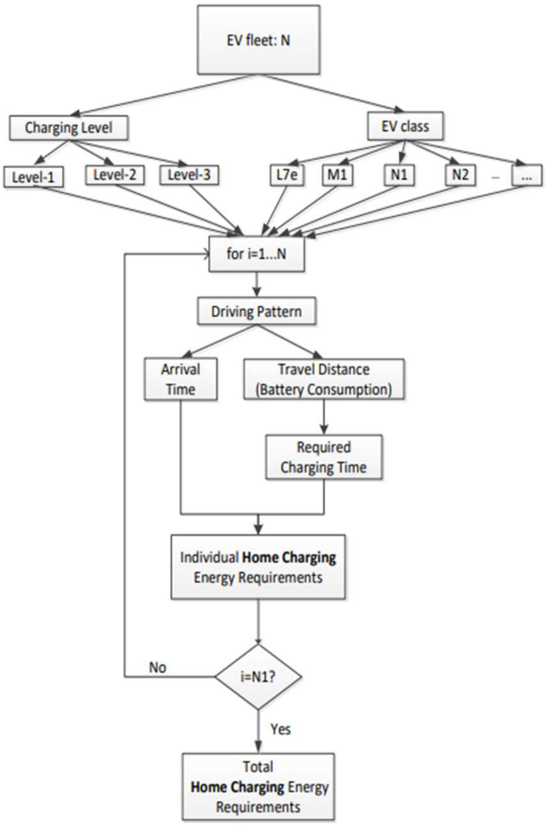


Figure 42: Flowchart for home charging

- Aggregated home charging demand created using Normal distribution is shown in figure 43.

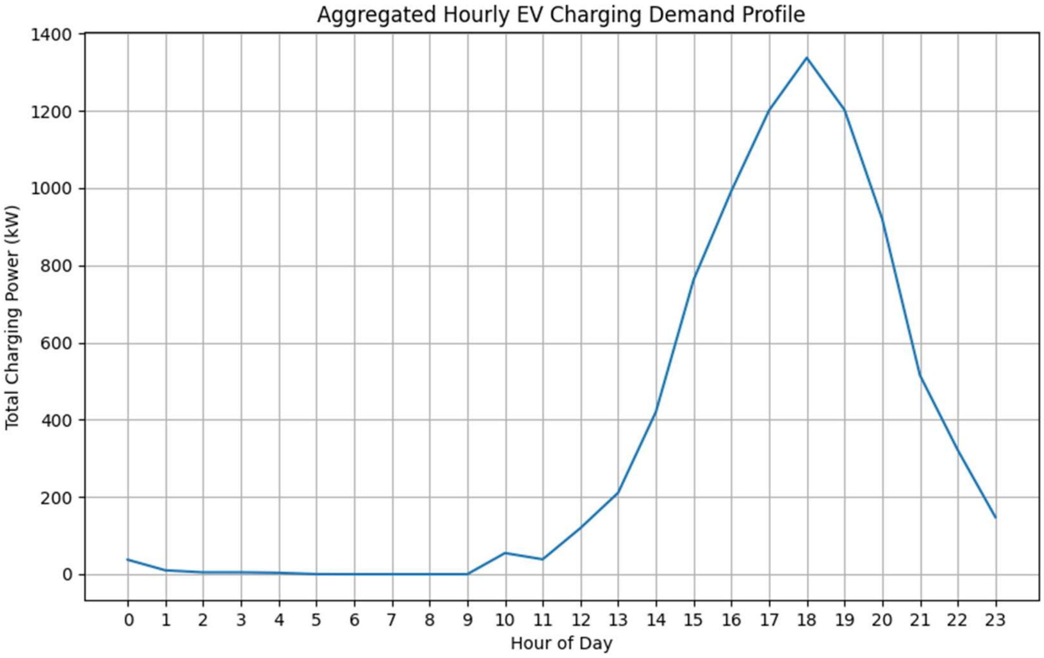


Figure 43: Aggregated EV charging demand of 1000 EVs

Recommendation to further enhance model

Home charging demand model can further be enhanced by including following

- Seasonal energy requirements for instance for heating in winter and air conditioning in summers.
- Various driving patterns of Taxi drivers, delivery vans or commuters can be included as 'clusters' of EVs
- More complex distribution for travel distance correlated with arrival time and SoC can be included.

5.2 Public Charging Stations

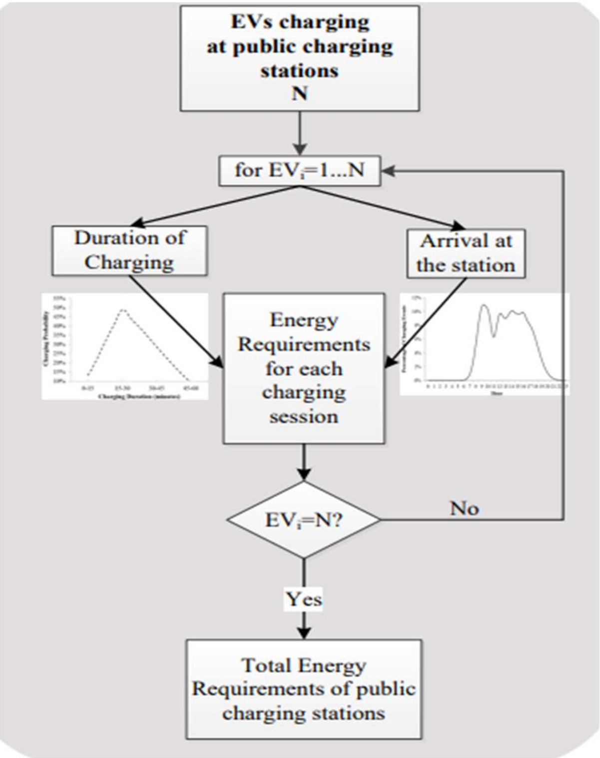


Figure 44: Flowchart for public charging

Smart charging or using ToU tariffs EV can be fully charged as it is plugged-in for hours however for public charging station it is parked for the duration of charging and thus required instant charging. Therefore, slightly different approach is required for the public chargers for calculating energy demand. Following probabilistic parameters are used in the analysis

- Arrival time – The hour each vehicle arrives
- Charging duration
- Historical data of charging stations can be used to accurately determine the energy demand.
- Monte Carlo method is applied iteratively until a convergence point is achieved.

The daily charging frequency is recorded from various conductive charging stations connected to a grid feeder is processed and plotted in figure 45 and is defined as a Gaussian Distribution with n-components. The mathematical expression with eight components is used in our analysis that give the information about the time and number of vehicles.

$$\mathrm{f}(x) = \sum_{i=1}^{n} \rho_i * \frac{1}{\sigma\sqrt{2\pi}} * e^{\left(-\frac{(x-\mu)^2}{2\sigma^2}\right)}$$

$$\mathrm{f}(x) = \sum_{i=1}^{n} \rho_i * \frac{1}{\sigma\sqrt{2\pi}} * e^{\left(-\frac{(x-\mu)^2}{2\sigma^2}\right)}$$

where

μ and σ are the mean and standard deviation of each of the k components respectively. the variance would be σ^2 and p specifies the mixing proportions of each component.

Table 5: Gaussian distribution of 8 components

Component	p	μ	σ
1	0.27	9.2	0.99
2	0.03	10.30	0.44
3	0.00	14.05	0.18
4	0.33	16.73	1.64
5	0.14	11.93	0.70
6	0.02	15.95	0.43
7	0.04	15.05	0.64
8	0.18	13.66	0.91

where μ and σ are the mean and standard deviation of each of the k components (the variance is, therefore, σ^2) and p specifies the mixing proportions of each component. The public charging demand of EVs is simulated using Gaussian Mixture Model (GMM) or a sum of Gaussian (Normal) distributions is shown in figure 45.

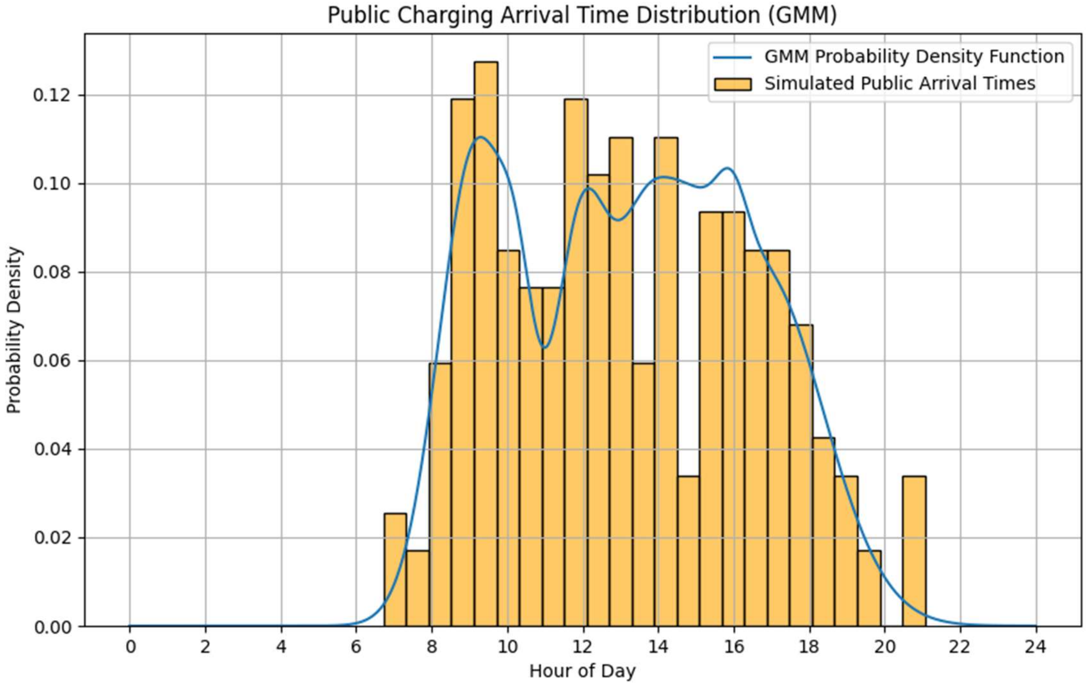


Figure 45: Public charging demand during a day using GMM

5.3 EV fleet demand analysis

EV owners can also charge their vehicle at public charging stations that reduces home charging requirement. This is often occurring at different time with fast chargers (Level-2 or DC fast chargers. The overall flowchart of smart charging with public and home charging demand profiles is shown

```
graph TD
    A[EV Fleet: N] --> B{For each EV_i = 1...N}

    B -- Loop --> C(Initial Conditions for EV_i)
    C --> C1(Current SoC)
    C --> C2(Desired SoC for Departure)
    C --> C3(User Departure Time)
    C --> C4(Home Charger Level or Max Power)
    C --> C5(Home Grid Connection Limit or Available Power)

    B --> D(Driving Pattern)
    D --> D1(Daily Travel Distance)
    D --> D2(Arrival Time Home)

    B --> E{Public Charging Event?}
    E -- Yes --> F[Public Charging Flow]
    F --> F1(Arrival at Public Station)
    F --> F2(Duration of Public Charging)
    F --> F3(Energy Gained from Public Charging)
    F3 --> G(Update SoC after Public Charging)
    G --> H{Calculate Home Charging Energy Gap}
    E -- No --> H

    H --> I(Available Charging Window at Home)
    I --> I1(Arrival Time Home)
    I --> I2(User Departure Time)

    H --> J{Smart Charging Controller for EV_i}
    J --> J1(Objective: Minimize Cost or Peak Load)
    J --> J2(Inputs: Energy Gap, Available Window, Home Charger Power, Grid Limit, Dynamic Prices or Grid Forecast)
    J --> J3(Output: Optimized Home Charging Schedule for EV_i)
    J3 --> K(Actual Home Charging Profile for EV_i)

    K --> L{All EV_i processed?}
    L -- No --> B
    L -- Yes --> M(Aggregate All Individual Home Charging Profiles)
    M --> N[Total Home Charging Demand Profile kW over time]
    M --> O[Total Home Charging Energy Requirements kWh]

    F3 --> P[Total Public Charging Energy Requirements kWh]
    F --> P

    N & P --> Q[Overall EV Fleet Demand Analysis]
```

Initial Conditions for EV_i (Start of Loop):

- Current SoC (Before Travel/Public Charging): Initial SoC values are obtained when an EV is plugged in and can also be estimated from previous night’s home charging. In our analysis this value comes from the demand curve – distribution generated from home and public charging.

- Desired SoC for Departure: This is user input and can be preset. In our analysis we considered 80% SoC by the departure time with 1-5% adjustable tolerance.
- User Departure Time: This is also a preset time to include user comfort. In our analysis 6-7am is considered.
- Charging Level at Home / Max Home Charger Power: Home chargers 7.4 kW (single phase), 11 kW (three phase). This is the maximum charging power and is one of the constraints in optimization problem.
- Home Grid Connection Limit / Available Home Power: This is modelled as a fuse and is a limit on maximum power that can be delivered.

2. Driving Pattern:

- Daily Travel Distance: As per our previous discussion – N(40,15) km.
- Arrival Time Home: N(18.0,2.5) hours.

3. Public Charging Event? (Monte Carlo Decision Point):

- Probability of Public Charge: Public charging probability is P(Public Charge) = 0.2. This is also linked with daily travel and can be adjusted to a higher value for weekends and holidays.

If Yes, F[Public Charging Flow]:

  - Arrival at Public Station: If public charging event occurs a sample from the public charging distribution (figure 45) is taken as per arrival time and calculated departure time based on SoC and charger rating.
  - Duration of Public Charging: Public charging event is modelled for instant charging and it reduces the home charging requirement.
  - Public Charger Power: Fast DC chargers are modelled for public charging – Level 2, DC Fast Charging 50kW, 150kW, 350kW
  - Energy Gained from Public Charging: Public_Charging_Duration * Public_Charger_Power.

- G[Update SoC after Public Charging]: Subtract the energy consumed during travel and add the energy gained from public charging to get the *arrival SoC at home*.

4. H[Calculate Home Charging Energy Gap]:

- Energy_Gap = (Desired_SoC_Energy - SoC_at_Home_Arrival_Energy)
- Where Energy = Battery_Capacity * SoC.
- This is the total energy (kWh) that *needs* to be delivered by home charging.
- Consider battery degradation or desired charging limits (e.g., don't always charge to 100% daily).

5. I[Available Charging Window at Home]:

- The time between Arrival_Time_Home and User_Departure_Time. A fixed departure time is selected initially. Later on, EV data with different plug-in, departure time and different SoC values are tested to validate the algorithm.

6. J[Smart Charging Controller for EV_i]:

This is the core part and computes optimization problem of each EV.

J1: Objective Function:

- Cost Minimization**:** Minimize Sum(Power_i * Price_i) over all charging intervals i.
- Peak Load Minimization**:** Minimize Max(Aggregated_Power_at_Time_t). This would be done at a higher level (fleet-wide), but individual controllers can react to signals from a central controller.
- Minimize battery degradation**:** A cost factor calculated from NREL model is included in the model to minimize battery degradation.

J2: Inputs to the Controller:

- Energy_Gap (from H)
- Available_Charging_Window (from I)
- Max_Home_Charger_Power (from C4)
- Home_Grid_Connection_Limit (from C5)
- Dynamic_Electricity_Prices_Forecast (Hourly prices, Time-of-Use tariffs)

J3: Output: Optimized Home Charging Schedule:

  - Is the hourly demand of each EV and the algorithm will shift the Energy_Gap (divided by Max_Home_Charger_Power) to the most favorable times within the window, respecting all constraints.
  - Linear programming for linear equations and convex (CVX) for quadradic equations methods are used in our analysis.

7. K[Actual Home Charging Profile for EV_i]:

- Output of the smart charging controller: a series of power values (kW) for each hour (or finer resolution) within the charging window.

8. L[All EV_i Processed?]:

- In our initial analysis we have considered 1000 EVs. This loop iteerates until all N EVs are processed.

9. M[Aggregate All Individual Home Charging Profiles]:

- Sum of all individual EV profiles at each timeslot to get the fleet's total home charging demand.

10. N[Total Home Charging Demand Profile (kW over time)]:

- This is the fleet's aggregated smart-charged power demand over a 24-hour period.

11. O[Total Home Charging Energy Requirements (kWh)]:

- The sum of all energy gaps fulfilled by home charging.

12. P[Total Public Charging Energy Requirements (kWh)]:

- Sum of Energy Gained from Public Charging (from F3) for all EVs that publicly charged.

13. Q[Overall EV Fleet Demand Analysis]:

- Sum of home and public charging data to get total energy consumption and demand profiles for the entire fleet.

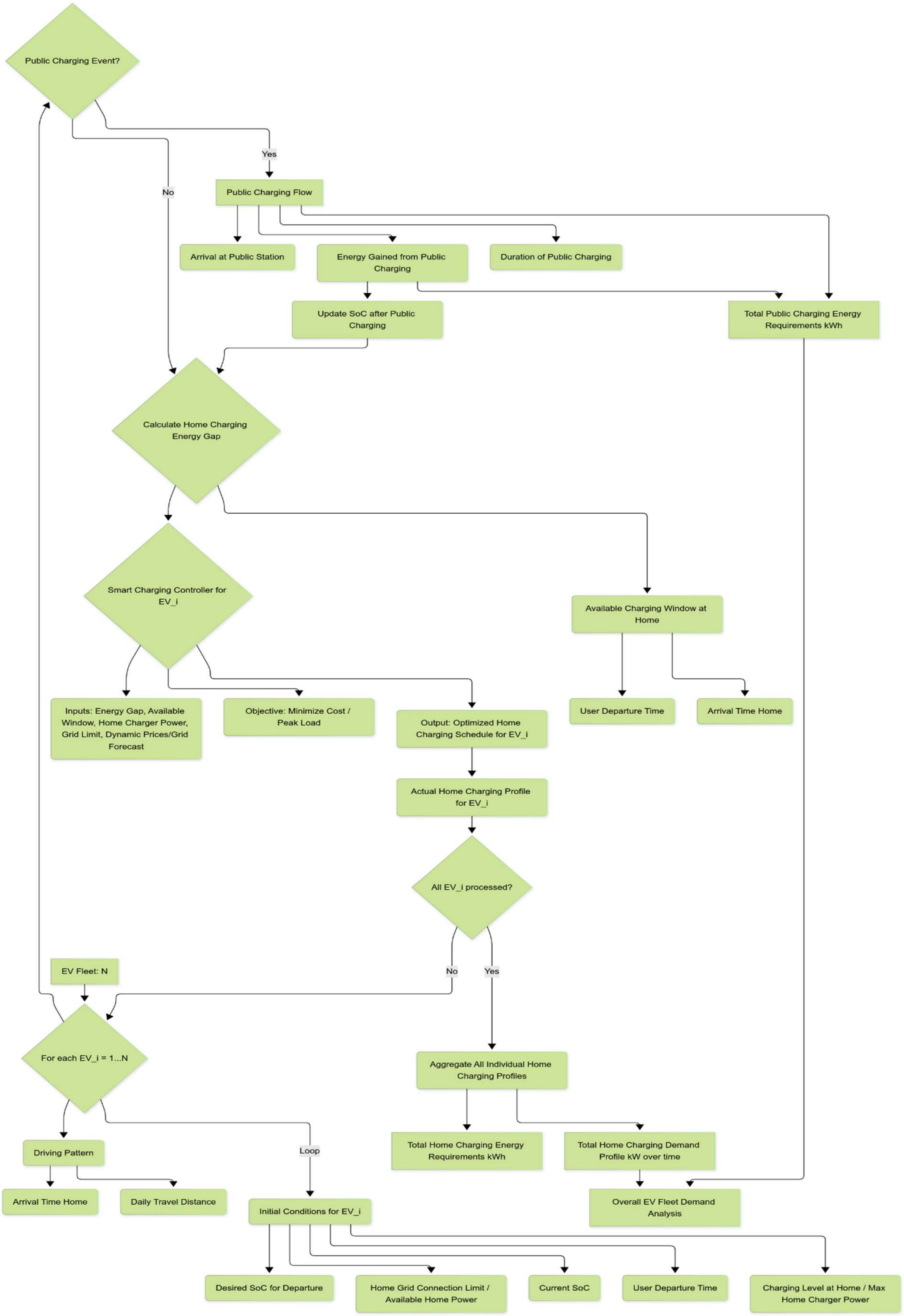


Figure 46: Flow chart for Home and Public SMART charging

6 Management of the EV Charging Demand

To avoid potential grid stability issues for instance overloading of feeders/transformers or voltage variation charging management schemes offered by the aggregators can be used.

Passive Measures: The EV owner respond to price signal of their energy supplier to charge their vehicle. This ToU tariff is a passive type of control as it does not provide a definitive idea of anticipated number of EVs and cause overloading if EV users charge their EV at the same time.

Active control scheme in which the E-mobility actor for instance the energy supplier or aggregator directly controls the charging and potential discharging for V2G. This scheme is beneficial for both EV owners and the system operators as energy can be utilised efficiently and effectively without any potential risk of network abnormalities. Different energy actors in these schemes are defined below

Core Principles for Smart Charging:

The objective function of Smart charging algorithms aims to minimize cost, minimize peak demand, minimize battery degradation cost, maximize renewable energy use (optional), or a combination thereof using pricing forecast and grid load information whilst respecting constraints and user comfort.

6.1 E-Mobility Roles:

- E-Mobility Service Providers (EMSPs)
- Charging Stations Operators
- Charging Stations Owners
- EV Supplier Aggregator (EVSA)

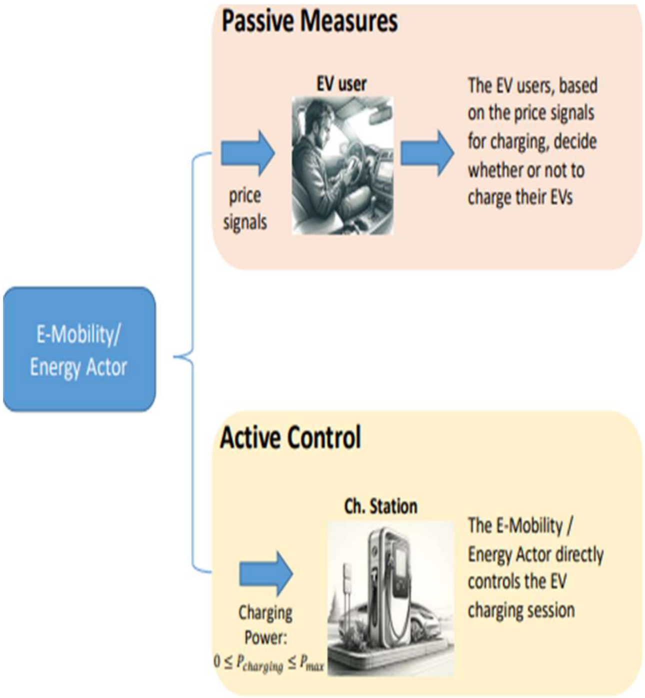


Figure 47: Active and passive charging control

In the E-mobility market, an EMSP can also be the owner and operator of charging station and a supplier can be an E-mobility service provider provided that the E-services are purchased are from a different entity. Effective communication between E-mobility actors and Energy market actors for instance system operators is essential for an effective operation. For instance, the DSO can communicate the increase or decrease in the power requirements for a given timeslot. This request is communicated to the aggregator by the supplier who accommodates the EV charging fleet accordingly. V2G is still in developing stages and participation from EV owners highly depends on the charging pattern data that can be basis of bidding in balancing or ancillary services market. Therefore, it is essential to have supplier between DSO and EV aggregator from a contingency point of view. In case the aggregated capacity changes there should be other sources of power to compensate without disrupting the power system.

6.2 Valley Filling Management Scheme

To address issue of high demand caused by Dual-tariff or ToU scheme an active control scheme known as Valley filling can be used. In this scheme the aggregator directly controls the charging of the EVs abiding the thermal limits of the network by distributing the charging of the EV fleet over the period of low tariff in the later hours, and without compromising the comfort of the EV owner. The EVSA procedure to collect and process data for smart charging is shown in the figure 48.

$$\min_{Pch,i} J_{cent} = \sum_{t=1}^{T} \left(\sum_{i=1}^{N} P_{ch,i,t}^{EV} + D^t - \mu \right)^2$$

The above objective function is subject to following Constraints

$$\mu = \frac{\mathbf{1}}{\boldsymbol{T}} \sum_{\boldsymbol{t=1}}^{\boldsymbol{T}} \left(\boldsymbol{D^t} + \sum_{\boldsymbol{i=1}}^{\boldsymbol{N}} \boldsymbol{P_{ch\,i,t}^{EV}} \right)$$

$$\sum_{t=1}^{T} P_{ch\,i,t}^{EV\Delta t} - \left(1 - SOC_{in,t}\right) \frac{C_{bat}}{C_{eff}} = 0$$

$$SOC_i(t+1) - SOC_i(t) = \frac{1}{C_{bat}} P_{ch\,i,t}^{EV} . C_{eff} \Delta t$$

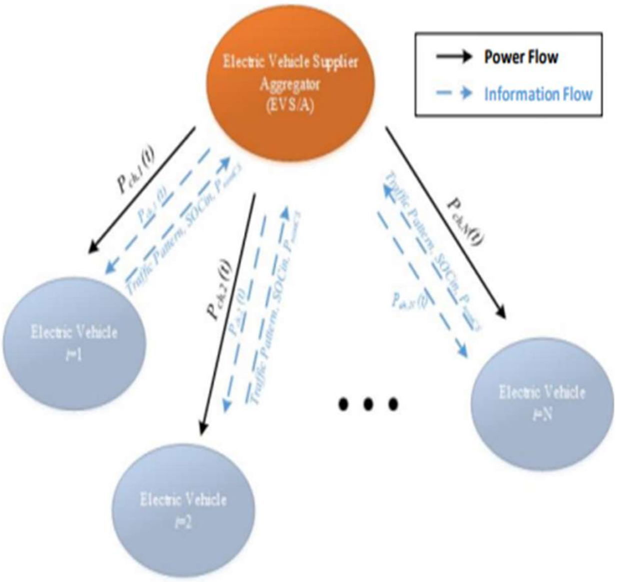


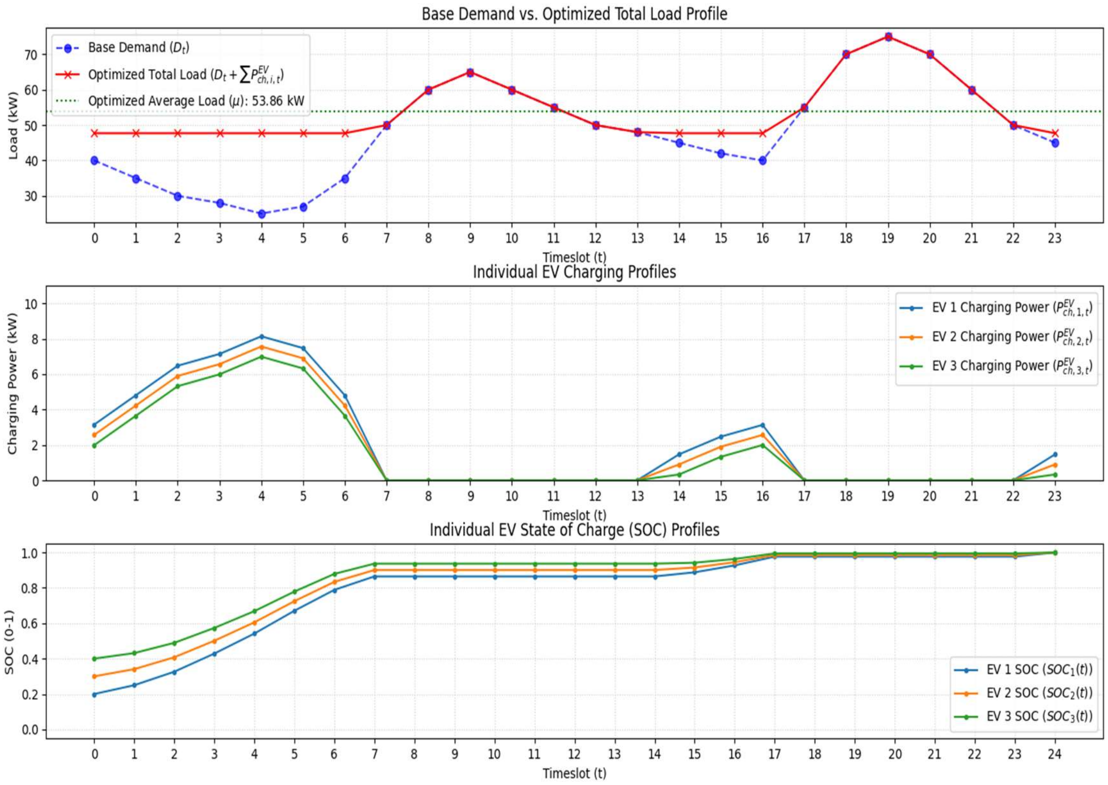
Figure 48: Data collection process for smart charging

$$P_{ch\,i,t}^{EV} - P_{nomCS} \leq 0$$

Where:

- $P^{EV}{}_{ch,i,t}$ is the charging level of the i-th EV during the timeslot t
- D^{t} is the Load Demand (without the EV demand) at timeslot t
- μ is the average value of the increased load for the examined timeslot
- $SOC_{in,\,i}$ is the initial battery SOC when the i-th EV plugs in,
- $SOC_{i}(t)$ is the SOC of the i-th EV at timeslot t
- C_{bat} is the energy capacity of the EV battery,
- C_{eff} is the charging efficiency and
- P_{nomCS} is the nominal power of the charging station

Quadprog in MATLAB or cvxpy in python is used to solve the objective function of the optimization problem. No load peaks are observed with valley filling scheme with operator responsible for the charging and potential participation in V2G. It is however important for the operator to keep the dispatch process open to customer to develop confidence and it should purely be based on calculations. Simulation results for first three EV's with valley filling is shown in figure 49. This is initial assessment of the model.


Base Demand vs. Optimized Total Load Profile

Individual EV Charging Profiles

Individual EV State of Charge (SOC) Profiles

Figure 49: *Valley filling for first three EVs*

For better comparison both optimized and unoptimized charging profiles are simulated for first five EVs and shown in figure 51. RED line in plot 1 is the total optimized load and yellow in plot 2 is the aggregated optimized EV charging compared to purple (unoptimized) in plot 1 and 2. The result shows that the algorithms significantly shifts the EV charging load to off-peak hours when total demand and prices are without compromising the user comfort. Plot 5 in the figure 51 is unoptimized charging profiles obtained from EV distribution. This is called dumb or naive charging and shows the behaviour of normal EV owners who plug-in their EVs after coming back home and end up charging their vehicle at high price and put extra load on grid. SMART charging controller using valley filing method shifts the charging of the EVs to later hours and thus significantly reducing the electricity cost for EV owner and reducing load on grid during peak hours.

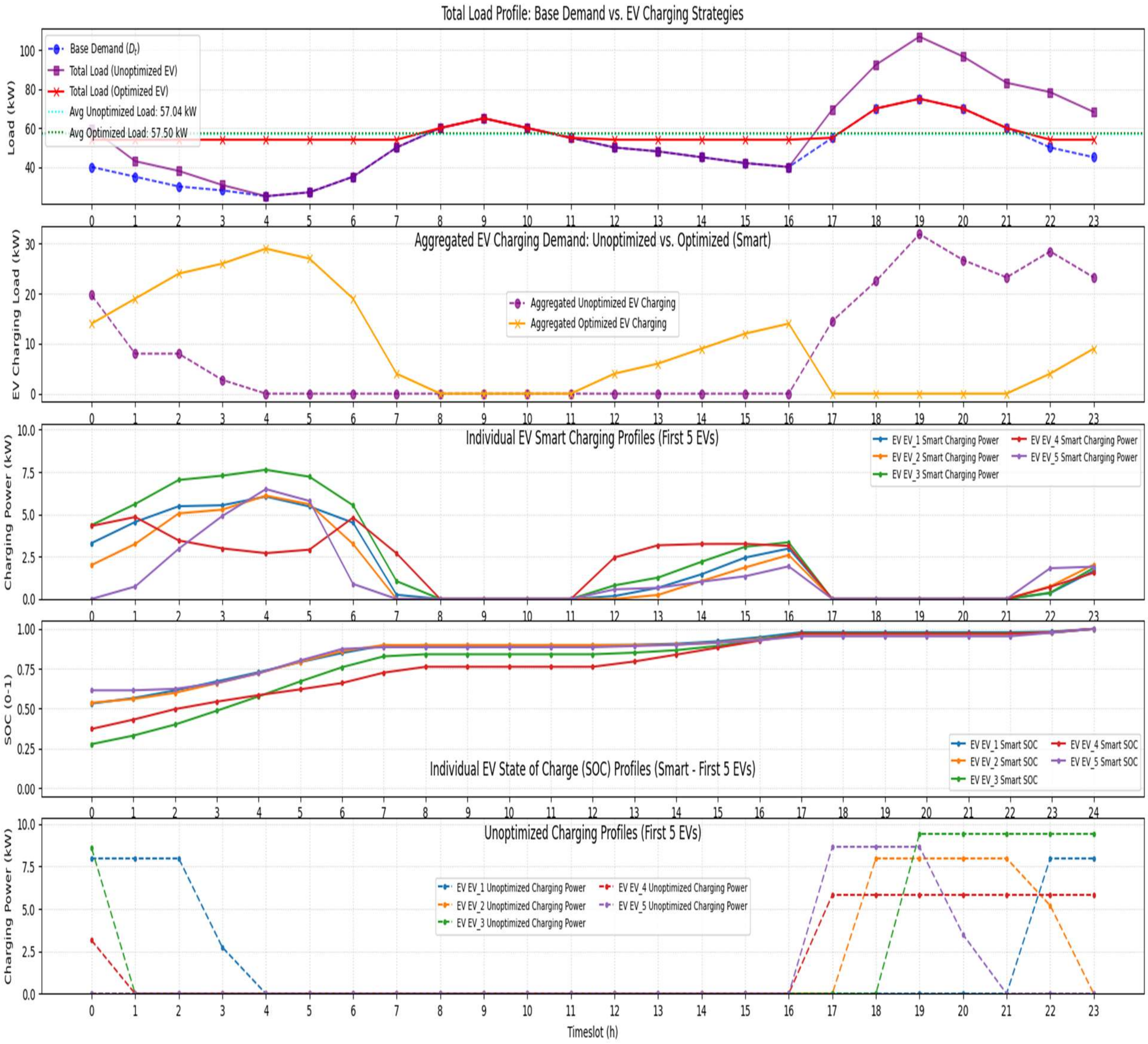


***Figure 50**: Optimized vs unoptimized valley filling of first 5 EVs*

It is noted that with increased number of EVs connected the computational time to solve optimization problem to calculate EV demand and apply charging schemes increases because the objective function is a quadradic equation, and it is essential to apply advance methods for instance Decision system problems or Game theory to make the control system more responsive (Karfopoulos & Hatziargyriou, 2012).

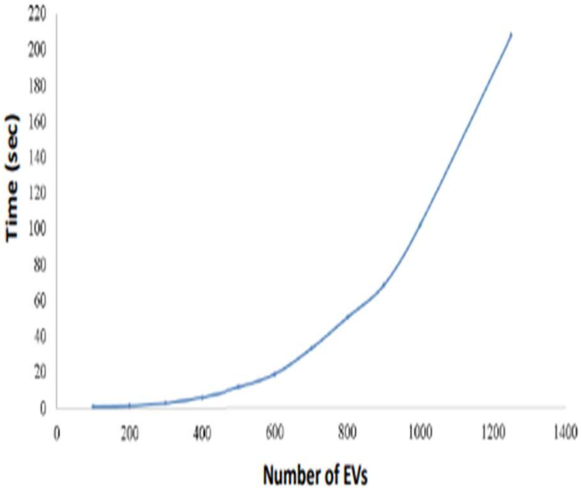


Figure 51: Number of EVs versus charging time (Karfopoulos & Hatziargyriou, 2012)

6.3 Minimize Charging Cost (V2G)

Valley filling optimization problem was from the grid point of view however if the customer wants to minimize charging cost following expression can be used. It should be noted that electricity price is normally high when demand is high therefore minimizing charging cost is linked with grid contingency though the user can choose their preference.

$$\min \sum_{i=1}^{N} \sum_{t_{0,t}}^{t_{0,t}+T_i} x_{i,t} . P_{nomCS} \cdot \rho_t \quad .\Delta t$$

Constraints:

$$\sum_{t_{0,t}}^{t_{0,t}+T_i} x_{i,t} . P_{nomCS} . \Delta\mathrm{t} - \left(1 - SOC_{in,i}\right) . \frac{C_{bat}}{C_{eff}} \geq 0$$

$$\forall\, \mathrm{i} = 1, \dots\dots, \mathrm{N}$$

The downside of this method is the high number of EVs will start charging at the beginning of low price that can violate the thermal limits of the lines or transformers. Also, to meet the demand more expensive generator can be utilized which will increase the price.

Minimize Charging Cost & Power limit

To avoid peak, load a maximum power limit constraint can be added in the objective function. This will shift additional EVs to a later timeslot to keep the load constant and hence the price. This can be achieved by increasing the price after a set number of EVs and by booking the charging slot for connected EVs for later hours.

$$\min \sum_{i=1}^{N} \sum_{t_{0,t}}^{t_{0,t}+T_i} x_{i,t} . P_{nomCS} \cdot \rho_t \quad .\Delta t$$

Constraints:

$$\sum_{t_{0,t}}^{t_{0,t}+T_i} x_{i,t} . P_{nomCS} .\Delta \mathrm{t} - \left(1 - SOC_{in,i}\right) . \frac{C_{bat}}{C_{eff}} \geq 0$$

$$\forall \mathrm{\ i} = 1, \dots\dots, \mathrm{N}$$

Additional constraint

$$\sum_{t_{0,t}}^{t_{0,t}+T_i} x_i(t) . P_{nomCS} \leq P\_k\_\mathrm{lim}(t)$$

$$\forall \mathrm{\ i} = 1, \dots\dots, \mathrm{N}$$

- p(t): energy price at timeslot t
- $t_{o,i}$: time interval for the i-th EV
- P_k_lim(t): maximum allowable peak demand at timeslot t
- P_{nomCS}: nominal charging power of the station to which the i-th EV is connected,
- $0 \leq SOC_{in,i} \leq 1$: initial battery charge level of the i-th EV at the time it connects to the station to charge,
- xi: binary vector that describes the intervals during which the i-th vehicle charges: if $x_{i,t}=0$ the vehicle remains idle, if $x_{i,t}=1$ the vehicle charges.

6.4 Energy balance

Energy balance is the equilibrium point of total power generation including variable RES and changing load profile. In EU countries the RES is given preference in the energy mix because of climate policies to reduce carbon foot print by utilizing maximum renewable energy. For optimization and economic dispatch, it is assumed that wind and solar do not have operational cost for instance fuel cost compare to conventional gas fired or coal plants.

Mathematically the energy balance (EB) can be defined as the load profile and energy required to EV charging versus RES production.

$$E_B(t) = \left(load\ cons.(t) + E_{EV}(t)\right) - \left(\text{wind energy}(t) + \text{PV}(t)\right)$$

Energy demand for the EV fleet can be calculated as

$$E_{EV}(t) = \frac{Average\ energy\ cons.}{km} * d\text{istance travelled} * T\text{otal EV} * E\text{V distribution}$$

Where – ‘t’ is the time step in hours of the simulation

The energy balance is positive when the demand is higher than the RES generation and negative when RES generation is surplus compared to load, and it is zero when generation meets the demand. Therefore, in the first case when EB is positive the additional energy is obtained from the primary ESS (EV) in the network and any additional energy is taken form pumped hydro to meet demand. In the second case when RES production is higher than the total demand – negative EB – the surplus energy is stored in the EVs first and then in pumped hydro. Any additional energy either be stored to some other storage devices if cannot be exported to other regions or countries. This model considers the surplus energy as wastage which in reality is curtailed by reducing the wind power using WT’s blade pitch, gears or by power converters by adjusting speed/torque to match the demand.

$$SOC_{EV-x}(t) = SOC_{EV-x+1}(\text{t} + 1)$$

$$E_{ava-}\quad(t) = \rho_s(t) * Cap_{T-EV}(SOC_{EV-x}(t) - SOC_{EV-mi}\ )$$

$$S_{ava-E}\ (\mathrm{t}) = \rho_s(t) * Cap_{T-EV}\left(SOC_{EV-m}\quad - SOC_{EV-x}(t)\right)$$

Where

$Cap_{T\text{-}EV}$ is the total battery capacity of the EV fleet. EVs provide energy ($E_{EV\text{-}X}$) to the grid during positive load balance $E_{ava-}\quad(t)$, and EV as primary ESS stores energy when $S_{ava-EV}(t)$ is positive – load balance is negative.

The updated SOC after energy transfer between grid and EVs can be expressed as

$$\mathrm{SOC}_{P_{EV(x+1)}(t)} = \begin{cases} if E_B < 0\text{:} \left(\left(\rho_s(t) * Cap_{T-EV} * SOC_{EV-x}(t)\right) + E_{ST}\right)/Cap_{T-EV} \\ if E_B > 0\text{:} \left(\left(\rho_s(t) * Cap_{T-EV} * SOC_{EV-x}(t)\right) - E_{Ex}\right)/Cap_{T-EV} \end{cases}$$

$$\mathrm{SOC}_{M_{EV(x+1)}(t)} = \left(\left(m_s(t) * Cap_{T-EV} * SOC_{EV-x}(t)\right) - E_{EV}(t)\right)/Cap_{T-EV}$$

$$SOC_{x+1}(t) = \rho_{share}(t) * SOC_{P_{EV(x+1)}(t)} + m_{share}(t) * SOC\_M_{EV(x+1)}(t))$$

6.5 Reliability and Resilience calculation

Next step is to calculate system reliability and resilience for a given timeslot. It is defined as system's ability to meet electricity demand for next hour. It is a key metrics to determine system stability and performance under different load conditions. It is however evaluated with historic load profiles including risk assessment of abnormal conditions such as faults or additional demand. If the generation is less than required to meet the demand external sources can be used. For system operators it is essential to analyze worst case scenario and engage other power sources during bidding process should an unforeseen event occur to avoid additional cost of using a new power source at spot market price. Rotating reserves, large scale BESS, or pumped hydro are more cost effective than gas fired plants. System should also consider contingency plan and evaluate the impact if a power plant disconnects from the grid. This is essential to restore system frequency from sources with high ramp-up rate as primary response and secondary response. The risk analysis should also consider the option of demand side management however it should be for a short time if new power sources are not readily available to synch with the system and inject power. In such scenarios extracting power from V2G can help stabilizing the system as batteries can inject power at a higher rate. Also, island option can be used to isolate a certain area from the main grid to reduce overall load while isolated area is fed by DER (distribution energy resources) like V2G in combination with wind, solar and balancing generators. It is however critical to evaluate the impact on system stability beforehand using simulations as in these scenarios whole power system dynamics change. For instance, in island mode the protection mechanism has to be adjusted to new values that can operate in small fault currents. This is an area of new research and is recommended.

The hourly reliability, expressed as hours, is zero when demand is met by the generation and can be expressed mathematically (Sagaria et al., 2024b)

$$\text{Hourly reliability} = \sum_{1}^{8760} \begin{cases} if(Ebal._{PHS} + E_{HP}) < 0; 0 \\ if\ (E\ bal._{PHS} + E_{HP}) \geq 0; 1 \end{cases} \}/8760$$

$$\text{System self} - \text{sufficiency} = \frac{Total\ energy\ produced}{Total\ energy\ required} * 100$$

The multivariable simulation model in enhancing grid stability, balancing energy supply-demand, reducing energy cost, carbon emissions provide more flexibility for V2G parameters in simulations. The key dependencies of the model such as effect of EV volume, V2G acceptance rate, collective storage capacity, effect of battery degradation, incentive for participating in energy market and integration of RES in power system can be determined using sensitivity analysis that can provide better insight for stakeholders to formulate policies favourable for V2G to accelerate energy transition.

7 Simulation Results

Monte Carlo method is used to calculate total home charging demand of one thousand EVs based on daily travel distance distribution, distribution of home assigned charging power, and distribution of arrival time.

Parameters and distribution for Monte Carlo method

1. Daily travel distance
    i. Approximately 40 km of daily travel distance is assumed with 15 km of deviation.
    ii. We have used normal distribution with lower bound restricting travel distance to be negative. Log normal distribution can also be used for better reflect real work driving patterns.
2. Vehicle efficiency
    i. Normal distribution (N(μ=0.18, σ=0.02) kWh/km) is used to model vehicle efficiency of various EVs that will also introduce variability in energy consumption.
3. Battery size
    i. We have assumed EV fleet with a uniform range of battery sizes from 40 to 80 KWh to model different battery sizes for our analysis. However, for more realistic calculation a list of commercial EV batteries can be used. As most of the commercial batteries start from 40 KWh to more than 100 KWh therefore a discrete distribution across this range can be used.
4. State of Charge
    i. Initial SoC at the start of day is assumed to be between (0.5, 1.0) which is then reduced based on the daily travel distance with a desired SoC of 80-100% at departure.
5. Chargers
    i. For home charging level 1 and level 2 chargers are used with 3.7 KW, 7.4 KW and 11 KW with probabilities 20%, 60% and 20% respectively.

6. Arrival and departure time
    i. Normal distribution is used for arrival and departure time (N(μ=18.0,σ=2.0)) and N(μ=7.0,σ=1.5) respectively.
7. Simulation – Monte Carlo
    i. EV fleet size (N) is 1000.
    ii. For each EV a random instance from the defined distribution for each parameter is generated.
    iii. The battery sizes once generated at the start remains unchanged for consistency. These battery sizes are passed to simulation function to define base parameters.

Integration of public charging

The aim of this study is to calculate EV demand and optimize the electricity cost, minimize peak load, minimize battery degradation and provide ancillary services to grid by SMART charging. SMART charging requires further information for instance SoC at arrival, departure time, available charging power, electricity price and grid load forecast.

As discussed previously public charging is modelled to charge the vehicle instantly so it is excluded from the objective function of optimization problem however public charging event reduces home charging requirement and hence total demand. In our analysis we have used 20% probability of public charging event is considered. As discussed previously the Gaussian mixture model (GMM) with 8 components is used for public or workplace charging event. The public charging function first selects one of the components based on its probability p and then create an instance from a normal distribution according to its mean and standard deviation. The integration of public charging with GMM makes the model more realistic in calculating total EV demand and energy requirements for home charging. This information is computed in SMART charging controller to allocate time slots required to charge all EVs before departure time as shown in figure 52.

It is recommended to add seasonal consumption and clusters of various driving pattern for instance taxi drivers, delivery vans and trucks in the model to further enhance its predictability to real world scenarios.

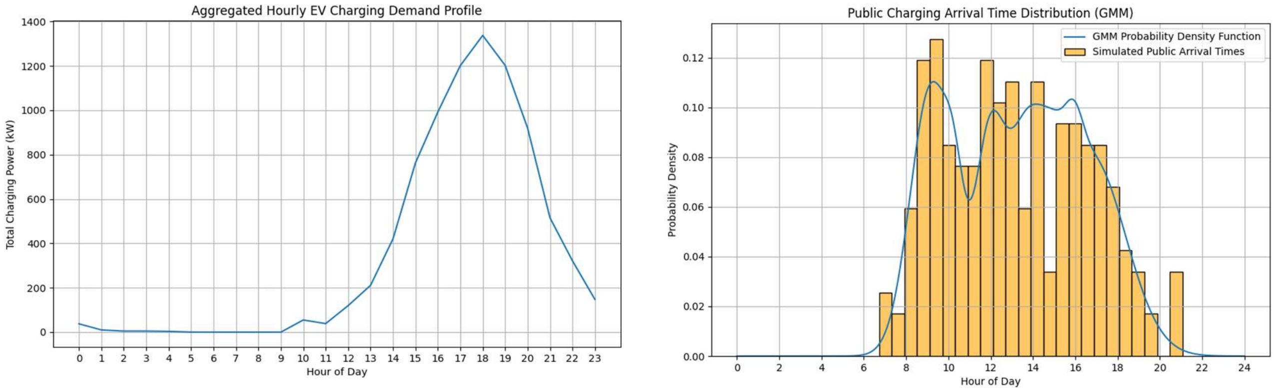


Figure 52: Home charging (left) and Public charging (right) distributions using Gaussian mixture model (GMM)

The distribution of daily travel distance, home charging energy gap, assigned charging power, arrival time and allocation of charging timeslots is calculated and shown in figure 54.

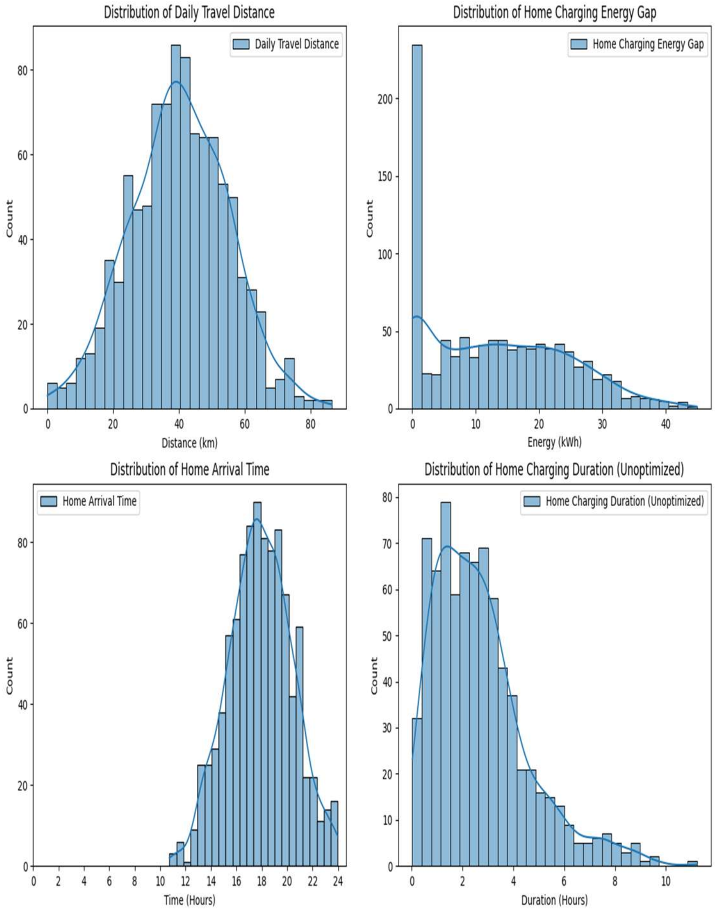


Figure 53: Distribution of home charging demand, allocation of chargers and time slots

The results from SMART charging of EV fleet is shown in figure 54. It can be noted that unoptimized home charging (orange) is shifted from the period of high price to low price later in night shown by blue/green line(s). All EVs are charged to required SoC before a pre-set time – 6 am when the price was lowest. The figure also illustrates unoptimized home and public charging scenario based on plug-in time shown in dotted purple line. It is noted that in the absence of SMART charging users end up charging when prices during peak hours as most of the EV owners plug-in their vehicle as soon as they return home.

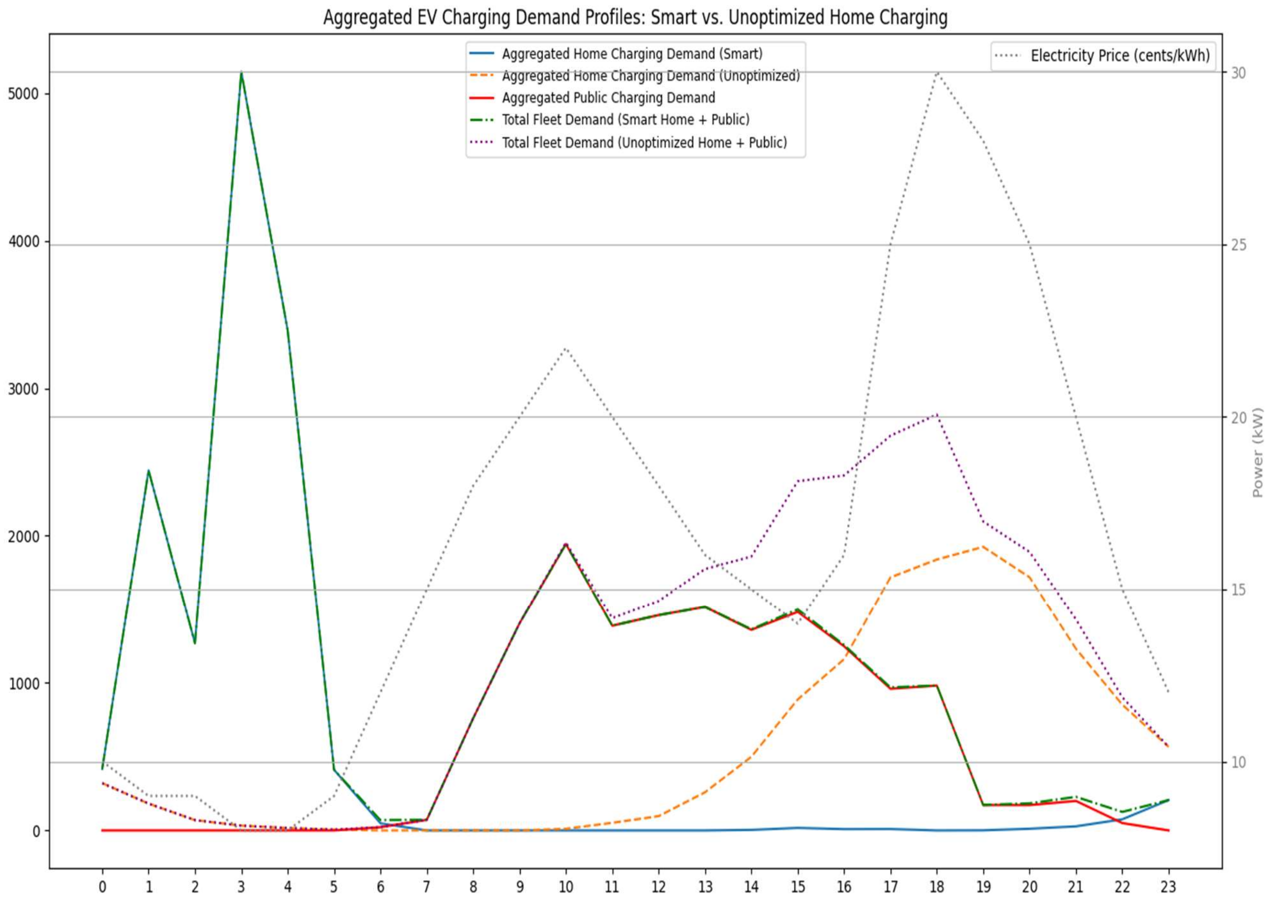


Figure 54: SMART vs Unoptimized charging

For comparison a cost summary is generated to illustrate the benefit of SMART charging for the entire fleet. With SMART charging a cost saving of 44% is noted however it is subject to electricity prices shown in grey dotted line in figure 55.

```
--- Cost Comparison (Daily for the entire fleet) ---

Total Home Charging Cost (Unoptimized): $2907.76

Total Home Charging Cost (Smart Optimized): $1152.86

Total Public Charging Cost (Fleet): $1021.78

------------------------------------------------

Total Fleet Charging Cost (Unoptimized Home + Public): $3929.54

Total Fleet Charging Cost (Smart Home + Public): $2174.64

Cost Savings from Smart Charging: $1754.91 (44.66%)
```

7.1 Vehicle-to-Grid (V2G) SMART charging

We further developed another model to integrate V2G energy trading, battery degradation model (NREL) with user comfort as a priority – user defines the plug-in and plug-out time.

Model approximation:

The model allows both charging and discharging at the same time however the objective function and constraints (SoC dynamics) assist the solver to choose either charging or discharging whichever is economical at a given timeslot. This keeps the model simple and linear. For strict mutual exclusivity that allows either charging or discharging and never both, a Mixed-Integer Linear Program (MILP) with binary variables is required and is out of the scope of this report however it is recommended for detailed analysis.

Simulation results

The simulation results for 3 EVs minimizing charging cost and battery degradation cost participating in V2G energy trade by considering plug-in and plug-out time (vertical dotted lines), target SoC (horizontal dotted lines) and abiding grid limits (horizontal dotted red line) is shown figure 56. The selection of plug-in and plug-out time is to test the algorithm with desired user comfort. For instance, EV3 (green) plot 4 presents overnight charging that should be complete before 6am so the EV owner can go to their work. EV 1(Blue) in plot 4 shows charging at workplace with plug-in time at around 8 and departure time is 5pm. Lastly, EV2 (orange) shows charging period after coming back home from work.

It is noted that EV1(blue) in plot 4 discharges the power back to grid when the price is high and recharge the battery when price is low and reaches the target SoC before plug-out time. EV2(orange) in plot 4 shows similar behavior and their respective charging and discharging power is shown in plot 3. The results show the benefits of SMART charging – net cost saving by charging the EV when electricity price is low and discharging the power back to grid when electricity price is high without compromising the EV owner comfort. By integrating battery degradation cost factor in the objective function of the optimization problem discharging of the battery is restricted to one cycle per day.

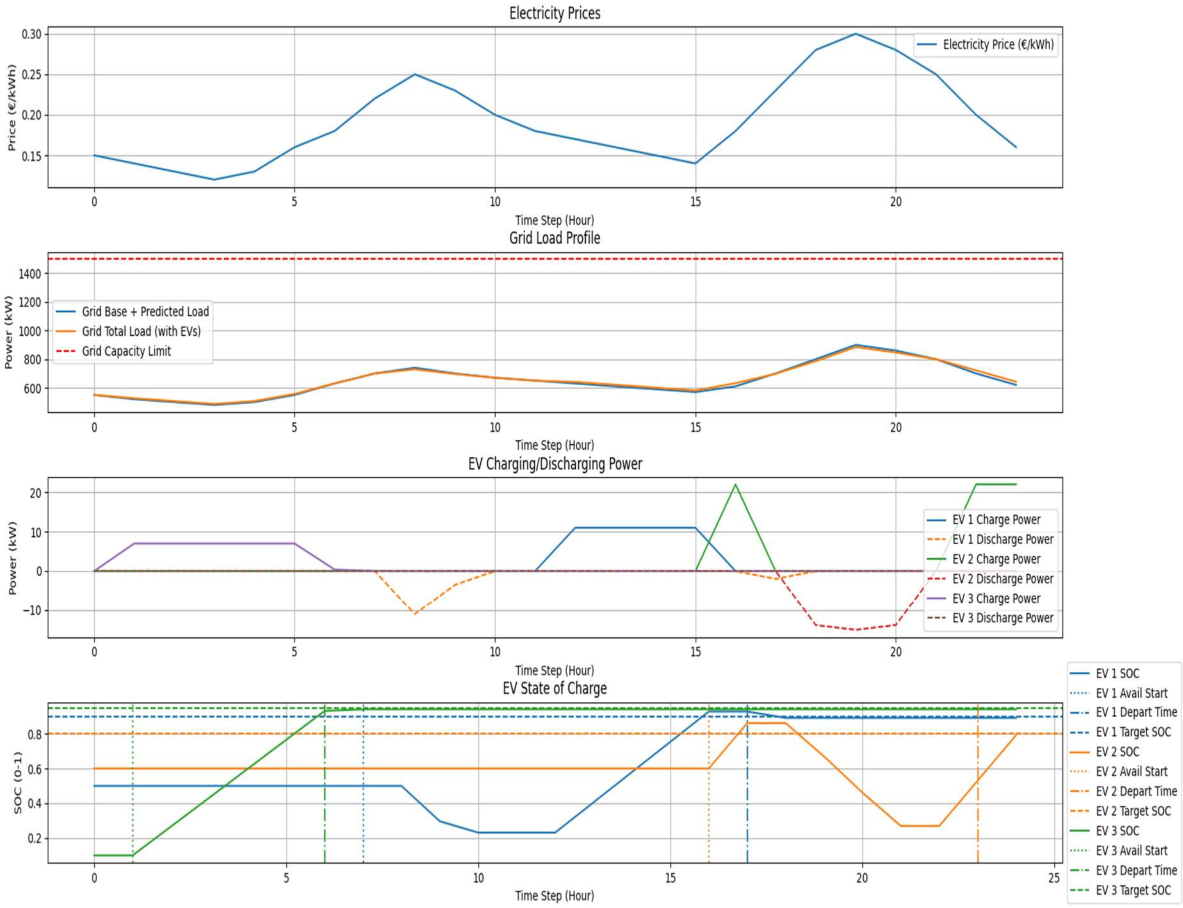


Figure 55: V2G optimized charging with SoC and plug-in/plug-out time

7.2 Vehicle-to-Grid (V2G) – Ancillary services

The model is further upgraded to include provision of ancillary services with a price to commit power (KWh) to grid. The new objective function is to minimize the summation of charging and battery degradation cost minus revenue from ancillary services subject to all constraints. 3 EVs are initially simulated to validate the model with different arrival and departure time inputs to reach target SoC while minimizing the charging cost, battery degradation cost and maximizing revenue.

With ancillary services included in the objective function it is noted committing power to ancillary services is more cost effective than discharging power back to grid considering price and charging / discharging efficiency of the chargers. For instance, when EV2 is plugged-in at 7am in plot4, the controller charges the battery enough to be in the threshold to commit power for ancillary services during high price and then it waits for later afternoon to charge the battery to required SoC when prices drop.

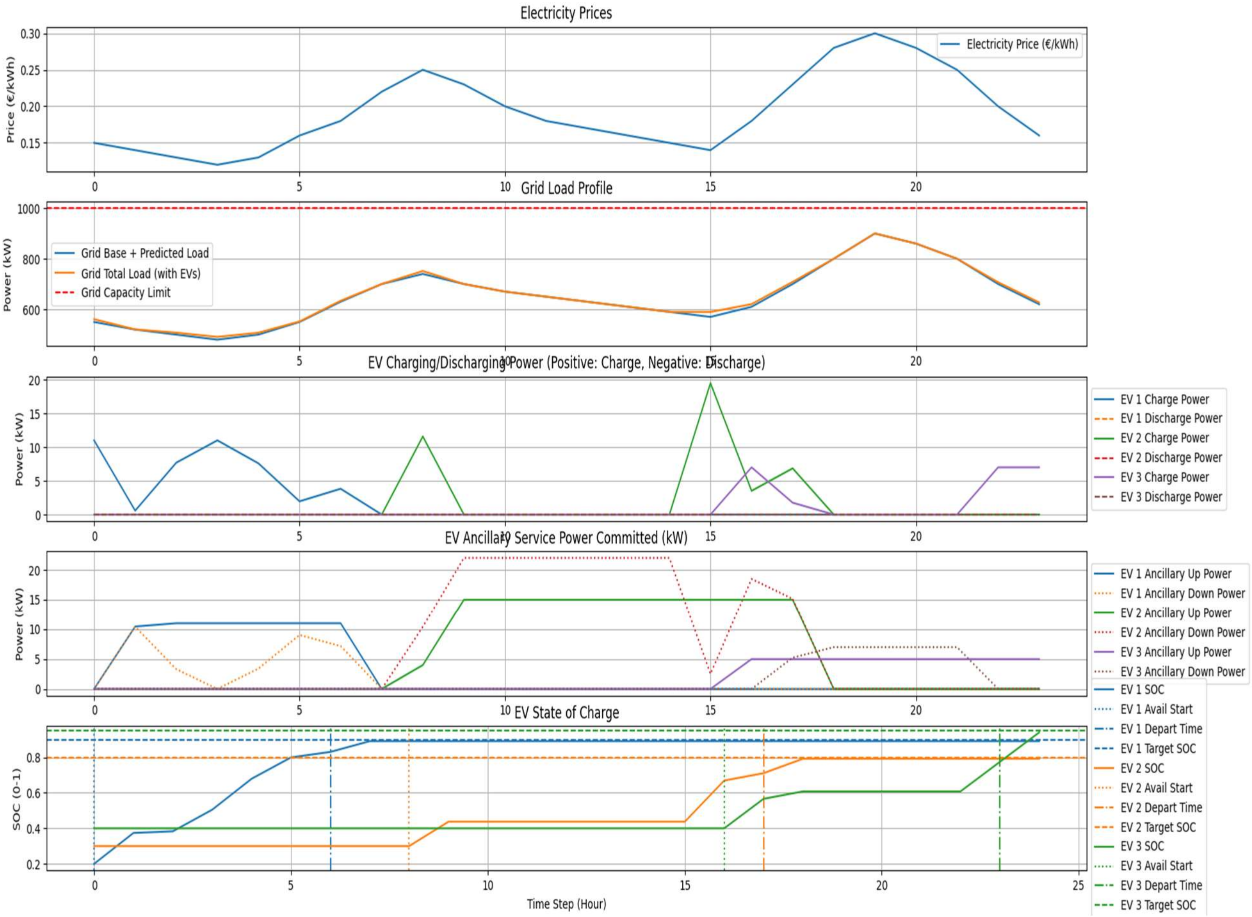


Figure 56: V2G SMART charging with ancillary services

7.3 Vehicle-to-Grid (V2G) – EV fleet Optimization with ancillary services

The optimization problem to minimize charging cost, minimize battery degradation and maximizing ancillary revenue is solved using MOSEK a CVX solver in python for 200 EVs with different arrival and departure requirements and random initial SoC levels.

Model integration

Integrating two non-linear models – convex optimization problem and non-linear battery degradation model (NREL) – is challenging and require advance problem formulation and advance solvers. It increases the computational time and makes the model less responsive with high number of EVs deeming non-linear equations, high number of variables and constraints. Non-linear degradation process curves can be used by approximating into multiple linear segments however it will make the problem into a Mixed-Integer Linear Program (MILP) with auxiliary variables that is not practical in this case because the focus is on optimizing the electricity cost associated with charging/discharging, battery degradation and maximizing ancillary services revenue.

To keep the overall model linear battery degradation model (NREL) is simulated first to calculate battery degradation of a single EV with a usage assumption of one cycle per day for a year, calculating total energy throughput and capacity loss. With an assumed cost of battery degradation compensation, per kWh cycled degradation cost is calculated. This cost factor is then fed into the optimization problem. Lastly, daily throughput – the amount of charging and discharging power – is converted into number of complete cycles and based on these cycles the capacity loss of each EV is calculated and cumulative degradation for all EVs is plotted for 30 days to show its impact on a monthly basis on the EV fleet.

```
--- Calibrating Battery Degradation Cost Factor ---
Calibration for 365 days for a 30.0 kWh EV at 1 equivalent full cycle/day:
Total throughput during calibration: 10950.00 kWh
Total capacity lost: 1.52 kWh (5.06%)
Estimated degradation cost in calibration: €303.80
Calibrated battery_degradation_cost_factor: €0.0277 per kWh cycled
```

Some additional checks are introduced in our algorithms to verify if requested departure time is valid by calculating required charging duration based on power rating of the charger and initial SoC. Figure 58 shows the optimized and unoptimized result of the EV fleet each with different SoC, arrival and departure time requirements whilst participating in V2G ancillary services (revenue), and minimizing charging and battery degradation cost.

Base parameters

To make model functional for different data base values are defined which are used in the absence of data but are mandatory for optimization. These parameters are as follows

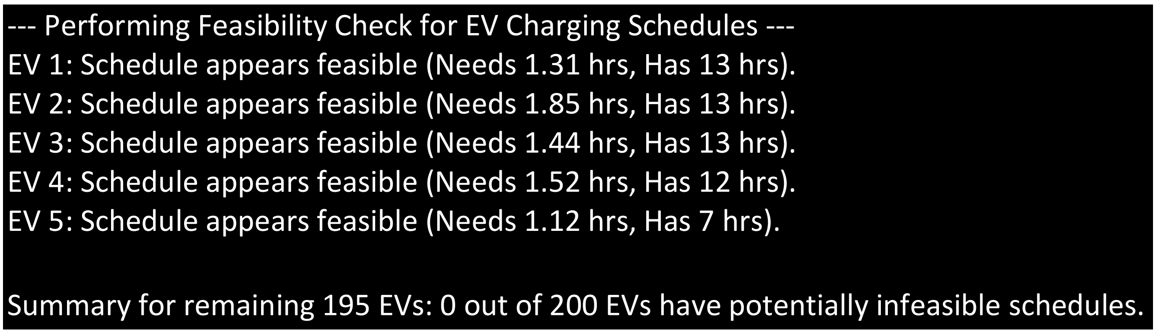
```
base_ev_capacity = 30.0 kWh
base_max_charge_rate = 11.0 kW
base_max_discharge_rate = 11.0 kW
base_target_soc = 0.8
base_min_soc_ancillary_discharge = 0.0
base_max_soc_ancillary_charge = 0.9
Min SOC for Discharge: 0.00, Max SOC for Charge: 0.90
cost_per_kwh_replacement = 200.0 €/kWh of lost capacity
```

- Test set includes arrival time, departure time set by the user and initial energy of the EV in first three columns respectively.
- Average hourly price of electricity for 2025 is extracted from electricity price of Finland dataset.

  ```
  Average price at 10:00 for 2025: 0.0671 EUR/KWh
  Cheapest hour in 2025: Hour 3.0 with price 0.0209 EUR/KWh
  Most expensive hour in 2025: Hour 9.0 with price 0.0781 EUR/KWh

  Price at hour 15: 0.0412 EUR/KWh
  ```

- The program first calculates if charging duration set by the user is valid by calculating time required to reach targeted SoC from initial power and available charger. The program then allocates a timeslot with lowest price, minimum battery degradation while maximising ancillary services revenue. A tolerance of 1 hour from departure time is added.



```
--- Performing Feasibility Check for EV Charging Schedules ---
EV 1: Schedule appears feasible (Needs 1.31 hrs, Has 13 hrs).
EV 2: Schedule appears feasible (Needs 1.85 hrs, Has 13 hrs).
EV 3: Schedule appears feasible (Needs 1.44 hrs, Has 13 hrs).
EV 4: Schedule appears feasible (Needs 1.52 hrs, Has 12 hrs).
EV 5: Schedule appears feasible (Needs 1.12 hrs, Has 7 hrs).

Summary for remaining 195 EVs: 0 out of 200 EVs have potentially infeasible schedules.
```

After verifying feasibility, the SMART controller optimizes and allocates the charging slot. The optimization of whole EV fleet charging is shown in figure 57.p

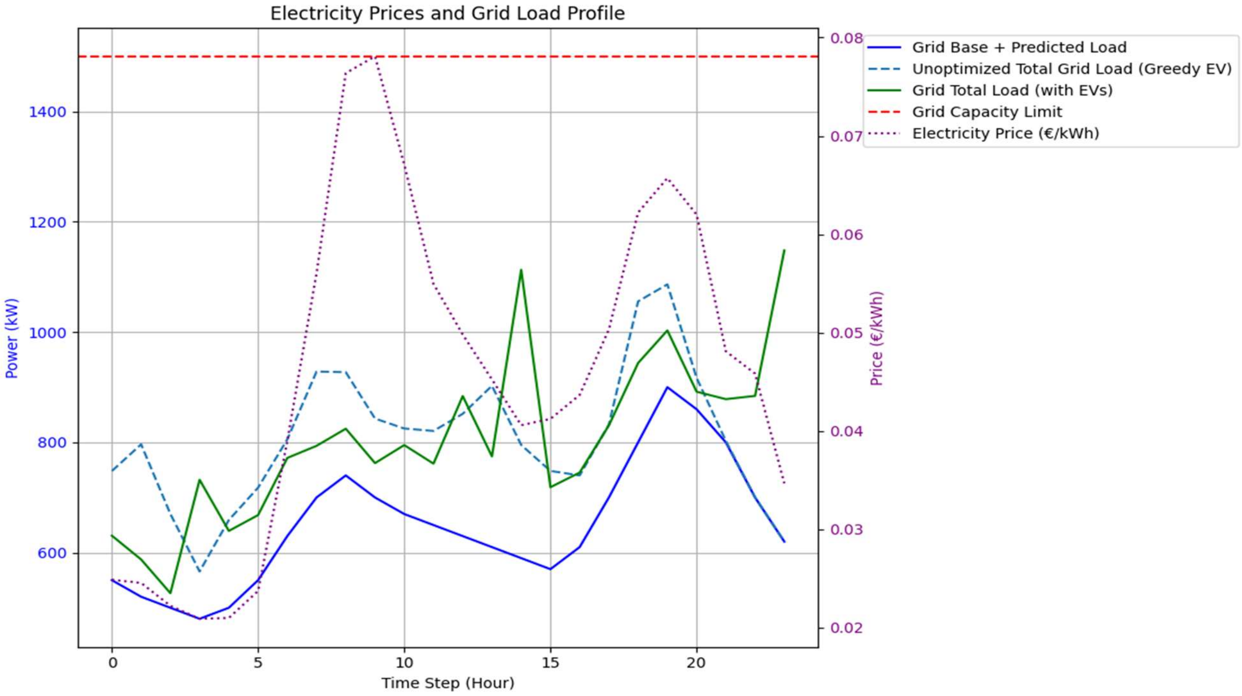


Figure 57: Comparison of Optimized and unoptimized charging of EV fleet

The solid GREEN line is the optimized total grid load with EVs compared to unoptimized total grid load shown in dashed (--) bluish green line. It is shown that SMART charging controller algorithm minimize the overall cost by charging the EVs during low price and participate in ancillary services if total plug-in time is more than the required charging time and minimizing battery degradation cost whilst respecting user comfort. It is noted at 3-5 hours, 14-15 hours and then at midnight when price is low more EVs are charged. During high price period it follows base load and only EVs with shorter plug-in duration are charged. Furthermore, minimum targeted SoC is set at 80% with adjustable tolerance level. Figure 58 shows the SoC of the individual EVs in the fleet over a period of 24 hours with vertical lines showing arrival and departure time. It can be noted that all EVs are charged to 80% SoC before departure time at low price while participating in the provision of ancillary services. The negative sign shows net profit and is subject to ancillary services price, electricity price, SoC set points and duration of plugged-in EVs.

```
   ancillary_service_up_price = 0.05 €/kW/hour for discharge regulation

   ancillary_service_down_price = 0.04 €/kW/hour for charge regulation
```

```
--- Optimization Results ---

Total Optimized Cost (including ancillary service revenue): €-445.00

Solver Status: optimal
```

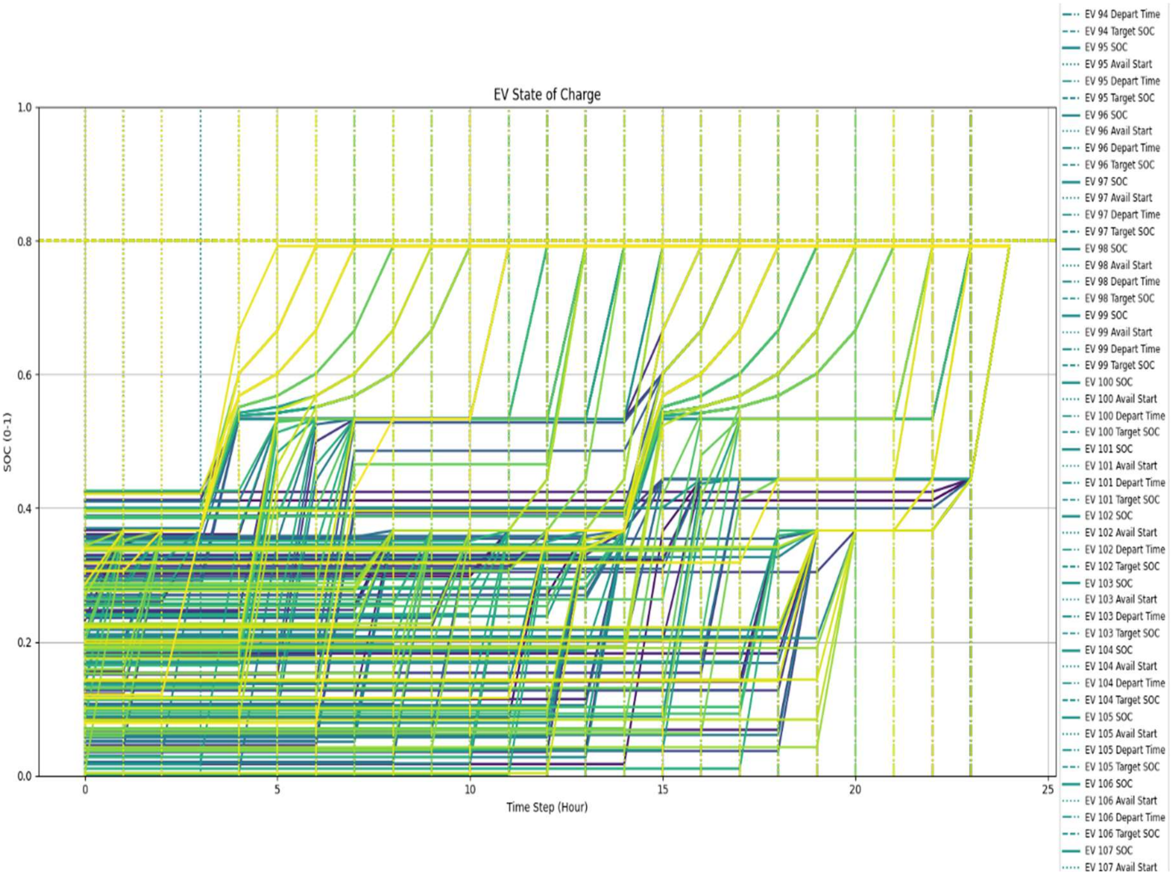


Figure 58: Initial and final SoC with plug-in and plug-out time all EVs

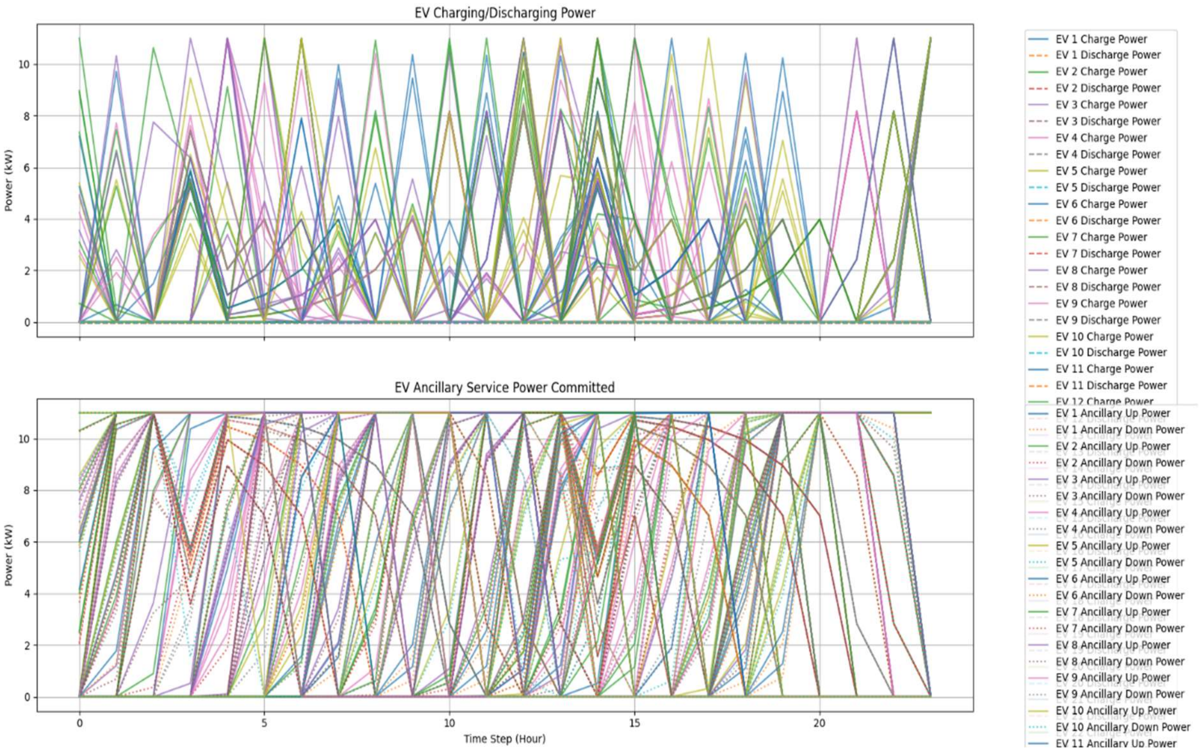


Figure 59: Provision of ancillary services during charging and discharging

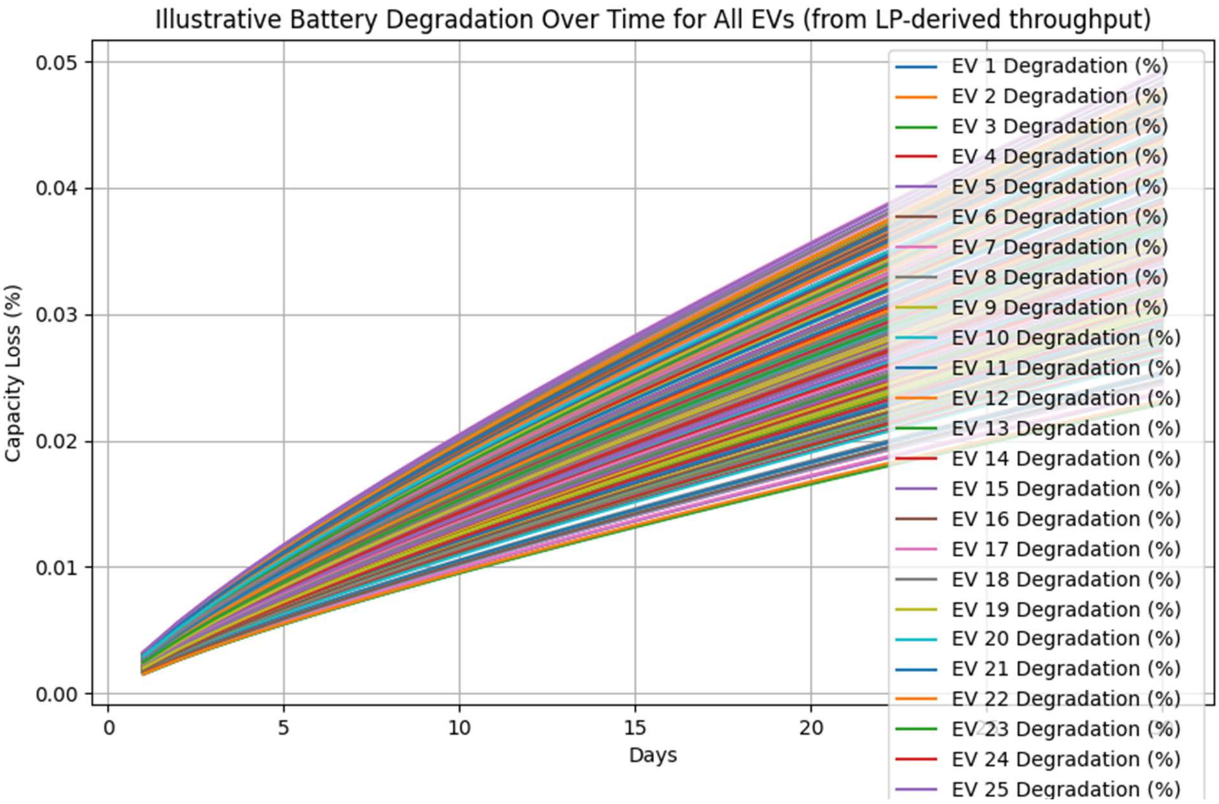


Figure 60: Battery degradation projection for next 30 days based on daily throughput calculated from optimization

8 Discussion and Recommendations

To meet net-zero target it is imperative for governments to continue supportive policies and incentives to accelerate deployment of EVs. IRA, the EU Net Zero Industry Act, China's 14th Five-year plan, India's PLI, The Finnish Climate Act (revised 2022) and Sweden's Climate Leap programs have accelerated transition to carbon neutral societies that has also contributed in the economic growth of these countries. However, recent change in policy from many countries like USA and Sweden have discouraged the consumers to spend on expensive EVs notably in slow growth period despite decrease in inflation. Moreover, volatility in market due to uncertainty caused by new trade barriers can further decrease economic growth and consumer spending, and investment in renewable sector. It is argued that the purpose of incentives is to make emerging technologies competitive compared to its counterparts therefore decrease in incentives for renewable technologies is justified. US has also withdrawn from Paris agreement and has ended EV mandate because according to the current administration it has increased the price of energy putting an extra burden on consumers. Also, EVs are competitive to its counter internal combustion engine cars without incentives due to emissions tax therefore consumers should have a choice under the principles of free market economy. US has also declared energy emergency paving the way for coal and hydrocarbon energy sources that according to many experts can increase greenhouse emissions and will reverse the progress made over the last many years but according to US officials it will increase investment in energy intensive industry of artificial intelligence that require stable and reliable power, and will reduce inflation that would ultimately increase consumer spending and thus increase economic growth. Also, the renewable technology is mature enough to compete with conventional power sources and a need to increase flexible power generation with high inertia is critical to accommodate high penetration of renewable energy sources while ensuring system stability and security of supply.

EU has cautious optimism and is criticised for stringent regulation that slows the innovation and adoption of new technology. Existing regulations are not supportive for energy storage technologies as it taxed twice – during charging and discharging. More supportive policies and regulations can certainly increase the pace of EV adoption and investment in energy storage systems. Recent EU announcement of reducing red tape and introduction of standard regulations for companies to operate in whole Europe is encouraging however its impact is yet to be seen. This will increase the competition in EV market that will bring down the price of EVs. Nevertheless, there is always a debate to not compromise the public safety and quality of products that has a direct relation with the cost. It is one of the reasons the price of an EV in EU is comparatively high despite recent sharp decrease in battery prices. On the brighter side the EVs made in Europe are reliable, safe and more efficient. Decrease in inflation in medium to long term with lower interest rates will enable more borrowing and investment in renewable sector that will be a stimulus for the economy and ultimately it will increase consumer spending. Consequently, people will buy more EVs as according to a recent survey majority of young and middle age people want to buy an EV instead of internal combustion engine car. One of the main reasons is the availability of charging infrastructure especially bidirectional high-speed chargers available for long drives that also enable V2G technology. With V2G ownership cost of EVs and energy bills reduce significantly and aggregated volume of EVs can provide stability to grid in the form of ancillary services.

Battery degradation is the main concern for EV owners to participate therefore it is essential to use accurate models to calculate its economic impact. There is generally a trade-off using models with high accuracy that are non-linear at computational cost versus linear models that are fast simple but lack accuracy compared to real battery degradation process. We proposed semi-empirical models to calculate battery degradation compensation and keeps the overall model simple. Battery technology has improved significantly in last ten years and Li-ion batteries tend to recover to its original state of charge if used under suitable conditions. It is not advised to overestimate battery degradation, and instead a higher compensation is proposed in the form of incentives to encourage V2G participation. EV owners have shown concern because of too many stakeholders in V2G implementation and respective regulations. It is therefore essential to make V2G regulations simple suitable for EV owners and a consensus between involved stakeholders. It is however concluded that EV owners are comfortable with their energy supplier for V2G if it performed under the guidelines of OEM and any damage is covered by their insurance company.

EV owner’s data is critical to improve model accuracy and its ability to predict aggregated volume of battery capacity at given time which would ultimately help aggregators to participate in energy market with certainty to maximize the profits. However, there are concerns regarding the misuse of this data that can give an undue advantage to a company, and can risk the safety of users. It is therefore recommended to formulate processes to ensure user privacy only necessary data for analysis is shared anonymously. Cyber security is also a concern that can have dire consequences especially with SMART charging in which information is shared between many EVs and aggregators.

It can provide a gateway to hackers to enter in the system and manipulate the behaviour of the system in such a manner that can trip power system and cause blackouts. It is important to consider this aspect and place necessary layers of control to reduce the risk.

It is further recommended to study the system behaviour on a larger network for instance IEEE 9-Bus or IEEE European Test Feeder, which is a 906-bus distribution system with EV profiles used in these simulations. To have more realistic findings these EVs can be spread on the network as per EV charging infrastructure in Nordic countries. It is recommended to expand the solution for large datasets of EVs with different scenarios to calculate its impact on the network in the event of a failure – worst case scenario. Load flow analysis, discrimination analysis especially for microgrids capable of operating in island mode. SMART charging reduces the risk of overloading network lines however it is vital for study its effect beforehand.

Nordpool has moved to a 15-min market for balancing power, aFFR, mFFR and for ancillary services to be part of larger EU balancing market. Shorter timescale is a huge potential for V2G provided large aggregated volume that can replace expensive generation. OpenEMS has developed an opensource system that can aggregate EVs, stationary energy storages and DER that can communicate with DSOs to participate in energy market. TSOs and DSOs can compute economic dispatch simultaneously considering bids of aggregated volume of EVs to make the final decision. As discussed in this report optimization of EV charging profiles using SMART charging and load flow to verify the impact of EVs on the network is crucial to integrate V2G.

Another aspect is lack of standards for vehicle integration into grids. At current Bidirectional DC charging standards are ready and stable however Bidirectional AC charging is still under development. First commercial V2G DC chargers were introduced in 2024 but no AC EVSE are available yet. Further to discussion, no V2G DC-upload compatible cars are commercially available. Cars with V2G AC-upload ready are available. There is a need for standardised equipment from different EV manufacturers and charging OEMs is required that can communicate with each other to fast fact its implementation. For instance, in Norway the government has implemented new regulations that will enable charging of EVs from any charging station regardless of their make. So now Tesla chargers can be used to charge any vehicle.

9 Conclusion

In conclusion, Finland is leading by example by setting up ambitious net-zero targets to become carbon neutral by 2035. Transport sector in Nordic countries contributes the highest green-house gases and thus electrification of transport sector is critical in achieving sustainability targets. Since Russia-Ukraine conflict Europe is facing an energy crisis because of the disruption in gas supply from Russia. EU member states has to rely on expensive LNG from spot market because of the shortage in supply, and additional cost of liquification and transportation. As indicated in Mario Draghi's report old and inefficient fossil fuel plants set the electricity price despite a smaller share in the energy mix due to the structure of EU energy market that rely on marginal price. Therefore, increase in gas prices increased electricity prices that affects consumers due to high energy consumption lifestyle mainly because of the cold weather and energy intensive industries – production, AI datacentres, EVs – slowing EU economic growth. Furthermore, more than 40% of EU electricity network – notably distribution network – is more than 40 years old and lacks capacity to integrate renewable energy resources located further away from the areas of high electricity demand. Also, intermittent nature of renewable energy resources adds more uncertainty in the equation that causes price volatility because of redispatch problem utilising expensive generators at spot price. Fingrid in its financial statement indicated the reason for price volatility is due to intermittent renewable energy production and lack of flexibility in power system. Moreover, Fingrid calls for more investment in flexible energy sources and storage technologies to improve reliability and stability of the power system and to cater variation in RES production.

Vehicle-to-Grid (V2G) is a promising technology that can address these challenges. Nordic countries in Europe have the highest EV adoption. This is due to the favourable policies and incentives on EVs that made EVs more cost effective compared to its counter internal combustion engine vehicles and high investment in charging infrastructure that enabled long travels. Addition of electric vehicles further increase the load on grid and if not managed smartly can cause high demand during peak hours which could lead overloading and high prices. Aggregated volume of these dispersed storage resources can provide flexibility in power system by offsetting the peak-to-valley arbitrage that would also enable high penetration of RES production and provision of ancillary services for instance voltage or frequency support to network operator. In this report we have studied and developed a model that estimates the EV demand for both home and public charging using using Monte Carlo and gaussian mixture model respectively. Total EV demand is estimated by convex problem formulation that is solved in python using MOSEK solver in cvxpy. NREL battery degradation model is integrated in our model and is run in parallel to keep model linear. A cost factor is calculated by calibrating of NREL battery degradation model that is fed in the optimization problem. By using V2G SMART charging algorithm this EV demand is optimized to minimize the grid load, electricity price and battery degradation cost while increasing ancillary services revenue without compromising the user comfort. The results show that with SMART charging more than 40% charging cost of an EV fleet can be reduced. This model is further enhanced from user point of view, tested and validated using charging data of 200 EVs with different initial SoC, arrival and departure time, and Finland's 2025 average hourly electricity price. The results show significant reduction in overall charging cost, reduction in battery degradation cost while increasing ancillary services revenue of the EV fleet. Results show net revenue gain because of the power committed to ancillary services and minimal battery degradation. The model then further calculates the battery degradation based on the resulting throughput and projects battery degradation for next 30 days for each EV using advanced NREL Li-ion battery model. Based on the results it can be concluded that V2G enables high penetration of renewable energy specially wind power, provides flexibility in power system to cater RES variation, reduces peak load from operators' point of view, reduces charging cost for EV owners by allocating charging during low price (valley filling), reduces ownership cost by providing ancillary services with minimal effect on battery life and most importantly reduces carbon footprint. User data is critical in implementing SMART charging that can be challenging considering EU privacy laws.

In summary, opportunities and challenges of V2G in Nordic countries in current energy crisis and its role in achieving net zero target, modelling of V2G scheme including estimation of EV demand, charging schemes using time of use tariff and smart charging, battery deterioration, charging stations capable of providing active/reactive power, and associated business models are discussed. With proper planning, coordination between government, academia, public and private sector risk of integrating high volume of EVs and RES can be converted into opportunities. EVs in the Nordic countries will increase exponentially in next decade along with offshore wind energy to meet decarbonization goals. Also, Nordic countries have announced to move to 15 minutes time resolution for balancing power and grid services. Therefore, V2G has a huge potential and target market because of shorter timeframe. Nonetheless, continuation of favourable policies, regulation and incentives are critical in deploying high number of EVs to decarbonize transport sector that is the biggest source of carbon emissions in the Nordic countries.

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11 Appendices

1. V2G SMART charging algorithm with NREL battery degradation model

Python code

https://github.com/Manxr/V2G.git