Impact of User-Driven Charging Behaviors and V2G Integration on the Dutch Low Voltage Grid

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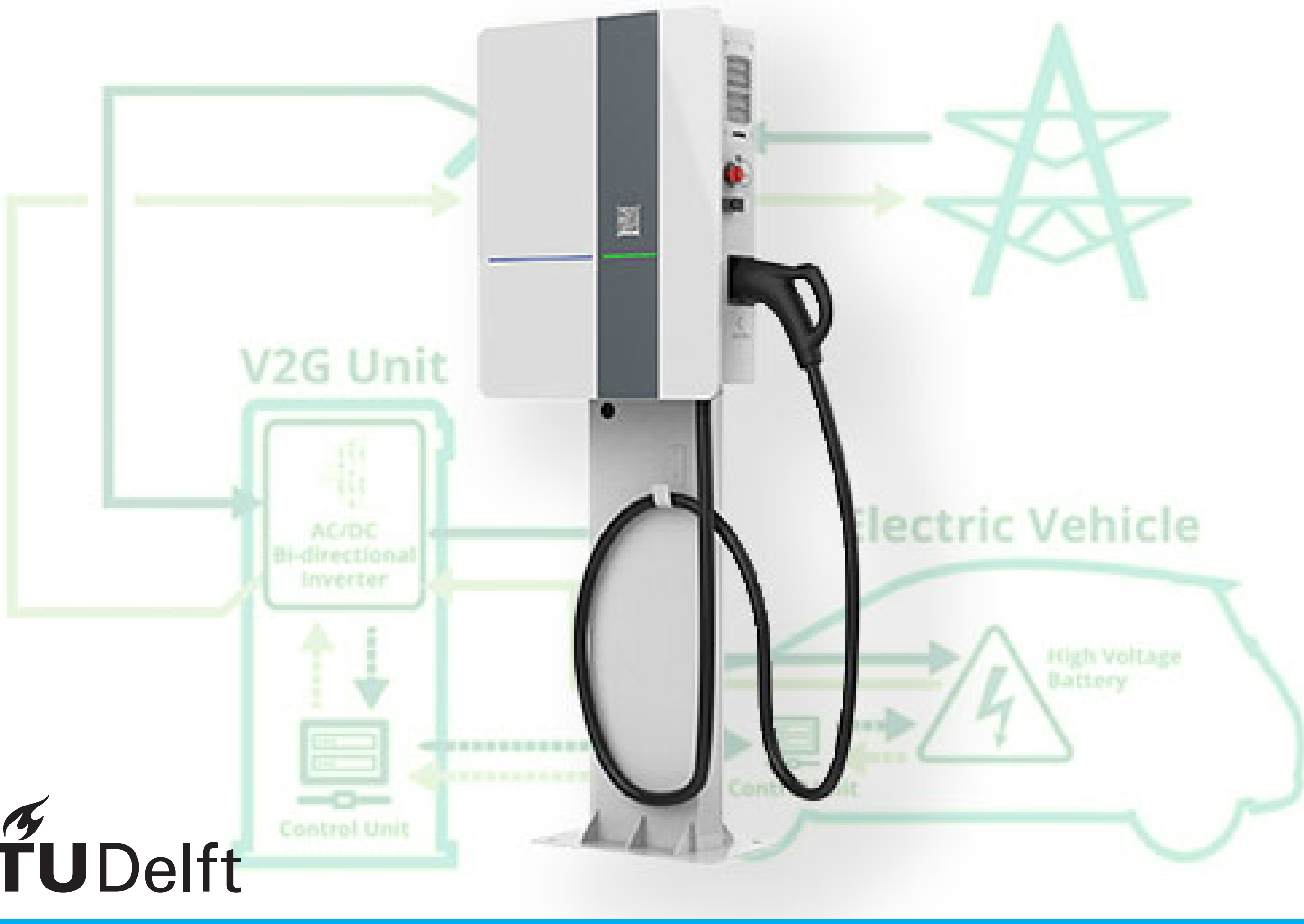

TU Delft

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by

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Preface

This thesis marks the completion of my Master's degree in Sustainable Energy Technology, a journey that has been both educational and life-changing. Over the past few years, I have had the privilege to study various aspects of sustainability, contributing in my small way to the larger goal of making the Earth a better place to live. My research focuses on integrating Vehicle-to-Grid technology and uncoordinated smart charging in the Dutch low-voltage grid. The aim is to better understand how real-world user behaviors impact grid stability and performance. By looking into uncoordinated charging patterns, this thesis sheds light on the challenges faced by distribution grids, especially in areas with a high number of electric vehicles. It also suggests ways to make the transition to electrified transportation smoother.

The last 11 months have been especially difficult, both academically and personally. Early being diagnosed with depression and ADHD, which made the work extremely challenging. However, with determination and the constant support of those around me, I regained my confidence and now proudly present this thesis. It not only focuses on the technical aspects of vehicle-to-grid integration but also explores the complexities of real-world conditions, where user behaviors, not ideal scenarios, dominate. The work takes a bottom-up approach to identify small but important issues that could arise during the transition, offering practical recommendations to improve grid stability as EV adoption increases.

I am deeply thankful to several people whose support was invaluable throughout this journey. First, I would like to sincerely thank my supervisor, Dr. Gautham Ram, for his continuous guidance and mentorship. I am also grateful to PhD candidate Álvaro, whose dedication and expertise helped me navigate the ocean of complexities of charging technology. Your support has been key in shaping this work. Wishing you good luck with your work with your PhD.

On a personal level, I owe a great deal to my parents and my girlfriend, Mrunmayi Kulkarni, for their unwavering love and encouragement. Their presence gave me the strength to keep moving forward, even in my darkest moments. I would also like to thank my close friends, Jayant Mulay, Vijay Venkatesh, and Maximilian Lagorio, for always standing by me and helping me stay strong during tough times.

This thesis is not just the result of technical work but is also a testament to resilience. It has reinforced my belief in the importance of community, perseverance, and the pursuit of knowledge. I look forward to applying these lessons as I continue to contribute to the field of sustainable energy.

Rohan Kadu
Delft, October 2024

Abstract

The rapid adoption of electric vehicles (EVs) poses significant challenges to low-voltage distribution grids, particularly in regions with high penetration rates like the Netherlands. As EVs increasingly draw power from and feed power back into the grid through technologies such as Vehicle-to-Grid (V2G) and mobile V2G, the stability and reliability of low-voltage grids are put to the test. This thesis investigates how uncoordinated charging behaviors, combined with real-world factors like commuting patterns, impact grid performance. The study focuses on key technical aspects such as grid congestion, voltage fluctuations, and transformer loading, aiming to understand the potential stress points in the grid.

Through a series of detailed simulations, the research explores different operational scenarios involving smart charging, V2G, and mobile V2G technologies. These simulations assess the grid's response to varying levels of V2G penetration, seasonal demand shifts, and commuting behaviors, providing a realistic analysis of the challenges that low-voltage grids face. The study models suburban Dutch grids, emphasizing real-world conditions such as the asynchronous nature of charging and discharging patterns and how they can lead to localized imbalances.

This research reveals the complex interactions between EV integration and grid performance, emphasizing that user-driven charging behaviors and the growing penetration of V2G solutions can lead to significant grid instability without proper coordination. The findings highlight the necessity for advanced grid management strategies, infrastructure reinforcements, and innovative charging solutions to mitigate these risks. By offering insights into the technical challenges of grid integration under various real-world conditions, this thesis contributes to a deeper understanding of the infrastructure requirements and operational strategies needed to support the transition to electrified transportation on a large scale.

Contents

1 Introduction

The world is currently facing an escalating climate crisis, characterized by rising global temperatures, frequent extreme weather events, and rapidly changing ecosystems that threaten environmental stability. In response, urgent measures are required to reduce greenhouse gas emissions, as outlined in the Paris Agreement, which aims to limit global temperature increases to well below 2°C above pre-industrial levels [1]. Among these measures, the transition to EVs is of paramount importance. As nations increasingly shift toward cleaner energy sources, EVs present a sustainable alternative to traditional fossil-fuel-based transportation. By reducing emissions from one of the most significant polluting sectors, widespread EV adoption is critical in meeting global climate goals and advancing a low-carbon future [2] .

The rapid integration of EVs is a vital element in global efforts to reduce carbon emissions and address climate change. While their deployment within power grids offers various benefits—such as enhancing grid stability and enabling more efficient energy management through smart charging and Vehicle-to-Grid (V2G) technologies—their impact on low-voltage grids remains a significant concern [3]. The low-voltage distribution network, which directly serves residential areas and local communities, is particularly susceptible to increased demand and voltage fluctuations resulting from widespread and simultaneous EV charging[4].

Despite advancements in smart grid management at higher grid levels, local networks face distinct challenges, including risks of localized overloads, uneven power distribution, and accelerated wear on grid infrastructure [5]. As EV adoption continues to rise, it is crucial to understand and address these challenges to ensure a smooth transition to electrified transportation without compromising the reliability and stability of local electricity supplies.

This thesis aims to evaluate the impact of smart charging, V2G, and mobile V2G technologies on low-voltage grids under various real-world scenarios. The analysis considers different commuting patterns (42% and 100% EV commuting), seasonal variations, and varying levels of V2G participation (with 50% and 100% of vehicles equipped with V2G technology or capable of discharging at home). By examining these conditions, this research provides a comprehensive assessment of the benefits and challenges associated with integrating these solutions into local distribution networks.

An introductory research overview is presented as follows. Section 1.1 provides an overview of EVs, focusing on their environmental benefits and growing global adoption. Subsequently, Section 1.1.1 delves into the adoption trends of EVs, highlighting key regions like the Netherlands and discussing the factors driving widespread adoption. Section 1.1.2 explains the importance of charging technologies, including fast charging and smart charging solutions, in supporting the expansion of EVs. The research question is outlined in Section 1.2, focusing on evaluating the integration of EVs into low-voltage distribution networks while maintaining grid stability. The thesis outline is presented in Section 1.3, summarizing the content and structure of each chapter. Lastly, this introductory chapter concludes with a discussion of the thesis motivation and contributions.

1.1. Electric Vehicles

The transportation sector is one of the largest contributors to global greenhouse gas (GHG) emissions, accounting for approximately 24% of global CO_2 emissions, with road transport responsible for around 75% of these emissions [6]. As the world moves toward decarbonization to combat climate change, EVshave emerged as a crucial technology in reducing GHG emissions from the transportation sector.

Unlike traditional internal combustion engine (ICE) vehicles, EVs produce zero tailpipe emissions[7]. This means that, during operation, EVs do not emit carbon dioxide (CO_2), nitrogen oxides (NO_x), or particulate matter (PM), which are harmful to both the environment and human health [8]. The shift from ICE vehicles to EVs can significantly reduce the direct emissions of pollutants in urban areas, where vehicular emissions contribute to poor air quality and adverse health outcomes.

Even when accounting for the emissions from electricity generation (known as ”well-to-wheel” emissions), EVs are significantly more efficient than ICE vehicles. Depending on the energy mix of the electricity grid, EVs can produce 30% to 70% less CO_2 over their lifecycle compared to gasoline or diesel vehicles [9]. In countries with a higher share of renewable energy, such as wind, solar, or hydropower, this reduction can be even more pronounced. For example, in countries like Norway, where renewable energy makes up over 90% of the electricity grid, the GHG emissions associated with EVs are reduced by as much as 70% [10]. As more countries invest in renewable energy sources to decarbonize their power grids, the overall lifecycle emissions of EVs will continue to decrease. By 2050, many developed nations aim to have fully decarbonized grids, further enhancing the environmental benefits of EVs [11].

EVs are also much more energy-efficient than traditional gasoline or diesel vehicles. EVs convert about 60-77% of the electrical energy from the grid into vehicle movement, whereas conventional vehicles only convert about 12-30% of the energy stored in gasoline into power at the wheels [12]. This increased efficiency results in a lower overall energy demand for transportation, further reducing the carbon footprint of road travel.

Beyond their role in reducing emissions, EVs can contribute to the stability and sustainability of energy systems through Vehicle-to-Grid (V2G) technology. V2G allows EVs to act as mobile energy storage units that can store excess renewable energy during periods of low demand and discharge it back into the grid during peak demand periods [13]. This technology supports the integration of renewable energy sources, which are often intermittent, by providing a flexible and distributed storage solution. In doing so, V2G can help smooth out fluctuations in the grid caused by variable renewable energy production, such as solar and wind power, further reducing the reliance on fossil fuel-based backup generators[14].

The global adoption of EVs has the potential to significantly reduce GHG emissions. According to the International Energy Agency (IEA), the widespread deployment of EVs could prevent the emission of up to 2.5 billion metric tons of CO_2 annually by 2050, which is roughly equivalent to the total emissions of India [15]. Additionally, reducing tailpipe emissions in cities will not only lower GHG emissions but will also result in cleaner air, improving public health outcomes, and reducing the societal costs of air pollution.

1.2. The Netherlands: A Global Leader in EV Adoption

The Netherlands has established itself as a global leader in EV adoption, recognizing the critical role these vehicles play in mitigating climate change. The Dutch government has implemented a comprehensive strategy that combines ambitious policy targets with substantial investments in infrastructure, making the Netherlands one of the most EV-friendly countries worldwide.

As part of its commitment to reducing greenhouse gas emissions, the Netherlands aims to achieve a fully carbon-neutral transportation system by 2050. A key milestone in this strategy is the planned phase-out of new gasoline and diesel vehicles by 2030, effectively mandating that all new cars sold after this date be zero-emission vehicles, predominantly electric [16]. This policy is integral to the Netherlands' broader climate goals, which include reducing national CO_2 emissions by 49% by 2030 compared to 1990 levels [17].

To support the rapid transition to EVs, the Netherlands has developed one of the most extensive charging infrastructures in Europe, with over 90,000 public charging points as of 2023 [18]. This network alleviates range anxiety and makes EV usage more practical, even in densely populated areas. Furthermore, the Dutch government offers a range of incentives to encourage EV adoption, including purchase subsidies, tax exemptions, and lower registration fees. These financial incentives, combined with the extensive charging network, have made EVs increasingly attractive to Dutch consumers. As a result, EVs accounted for more than 30% of all new car sales in the Netherlands in 2023 [19], with this figure expected to rise as the 2030 target approaches.

The Netherlands is also a pioneer in integrating EVs into its broader energy and mobility strategies[20]. Through the deployment of smart charging and V2G technologies, EVs can interact dynamically with the power grid, helping to balance supply and demand, store excess renewable energy, and reduce strain on the grid during peak hours [21]. This not only supports grid stability but also maximizes the environmental benefits of EVs by ensuring they are charged with green energy.

Building on its leadership in sustainable mobility, the Netherlands has seen significant growth in EV adoption. By 2023, registered EVs surpassed 400,000, representing approximately 15% of the total vehicle fleet[22]. This growth reflects a decade of strategic government efforts, including purchase subsidies, tax benefits, and substantial investments in public charging infrastructure.

Figure 1.1: Projected growth of the EV market share and total sales in the Netherlands [23].

As shown in Figure 1.1, the projected growth of the EV market share and total sales in the Netherlands illustrates the rapid pace of EV adoption. By 2035, the EV market share is anticipated to reach 88%, with the total number of EVs surpassing 5 million. This trajectory reflects the influence of government support, consumer demand, and technological advancements.

Technological innovations, particularly in battery technology, have been crucial in facilitating this transition. Advances in battery performance, increased vehicle range, and faster charging capabilities have addressed key concerns of potential EV buyers[24]. Moreover, the introduction of V2G technology is transforming EVs into dynamic components of the energy grid, enabling them to contribute to energy storage and distribution, and aligning with the Netherlands' broader goals of reducing carbon emissions[25].

However, this rapid adoption presents both challenges and opportunities for the Dutch power grid. The increasing penetration of EVs necessitates a deeper understanding. Ensuring grid stability and reliability will be critical as the country continues to advance toward its ambitious goals of electrification and sustainability. This requires strategic planning and the development of robust grid management solutions to accommodate the growing number of EVs and their integration into the national energy infrastructure.

1.3. Research Question

As EV adoption grows, especially in regions like the Netherlands, the potential challenges posed to local distribution grids become more pronounced. While solutions like smart charging, Vehicle-to-Grid (V2G), and advanced grid management strategies offer promising ways to mitigate grid stress, they often involve complexities such as highly coordinated behaviors or ideal conditions that are not always feasible in real-world scenarios. Additionally, the uncoordinated nature of individual user behavior and its cumulative effects on low-voltage grids remain under explored, despite being crucial to understanding the real-world impacts of EV integration.

This thesis aims to fill that gap by evaluating the effects of uncoordinated smart charging, V2G, and mobile V2G technologies driven by individual user behavior within the Dutch low-voltage grid. The primary objective is to assess how the lack of centralized coordination among EV users—each with unique driving and charging habits—affects grid stability, load management, and overall performance. By analyzing varying commuting patterns, seasonal influences, and different levels of V2G participation, this research provides a comprehensive understanding of the risks and benefits of this uncoordinated approach.

The impact of uncoordinated charging behaviors is anticipated to vary significantly based on grid topology, whether rural, urban, or suburban. However, in all cases, the consequences of uncoordinated user actions are likely to be substantial, potentially leading to grid instability. This study also distinguishes between two levels of power management: the local level and the central level. The local level focuses on individual chargers and charging behaviors, where uncoordinated actions can result in severe consequences for the grid. In contrast, the central level considers the collective operation of all system elements, with strategies such as curtailment mechanisms ensuring grid constraints are met.

The analysis centers on grid congestion resulting from uncoordinated charging and the deployment of mobile V2G solutions, exploring under what conditions these issues become critical and potential strategies for alleviating them.

The Dutch low-voltage grid serves as the focal point of this research due to its high EV adoption rates and extensive charging infrastructure, which present unique challenges and opportunities. Unlike studies that assume idealized conditions or coordinated charging, this thesis investigates more realistic, uncoordinated user behaviors that are expected to dominate in the near future, providing actionable insights directly relevant to the Netherlands' ongoing transition to electrified transportation.
The primary research question guiding this study is:

> *What is the impact of uncoordinated smart charging, Vehicle-to-Grid (V2G), and mobile V2G technologies, driven by individual user behavior, on dutch low-voltage distribution grids under different real-world conditions?*

In addition to the main research question, the following sub-questions are introduced:

1. *How does uncoordinated charging by individual users affect grid stability, congestion, and voltage levels in scenarios with high EV penetration in the Dutch low-voltage grid?*
2. *In what ways do individual user behaviors, such as different commuting patterns and seasonal charging habits specific to the Netherlands, influence the for grid congestion and voltage deviation?*

By addressing these questions, this thesis will provide valuable insights into the challenges and opportunities of integrating V2G into the Dutch power system. It will focus on user-driven factors that could either support or hinder grid stability, offering practical recommendations for improving the resilience of local distribution grids in the face of growing EV penetration.

1.4. Thesis Outline

The study begins by laying the theoretical foundation in Chapter 2, where a comprehensive literature review explores the role of smart charging and V2G technologies in low-voltage grid integration, highlighting how commuting patterns and seasonal variations impact grid performance. Moving into Chapter 3, the simulation setup is detailed, describing the key assumptions, grid models, integration of photovoltaic (PV) systems, and the use of day-ahead market data to simulate realistic charging conditions. In Chapter 4, the focus shifts to the formulation of the EV scheduling problem, outlining the methodologies used to optimize charging strategies for improved grid reliability and efficiency. Chapter 5 presents the results, analyzing how smart charging, V2G, and mobile V2G perform under different scenarios, revealing their distinct impacts on transformers, lines, and voltage stability, with mobile V2G emerging as the most balanced. Finally, Chapter 6 concludes the study by discussing key findings, offering recommendations for future research, and emphasizing the need for coordinated EV scheduling to ensure grid stability amidst growing EV penetration.

2 Literature Review

In the previous chapter, we discussed the role of EVs in reducing greenhouse gas emissions, focusing on global adoption trends and the Netherlands' leadership in EV uptake. The purpose of this section is to explore the impact of integrating EVs into low-voltage distribution networks, which serve as the critical connection point between local electricity supply and end-users. As EV adoption continues to accelerate, particularly in residential and rural areas, these networks face significant challenges related to voltage stability, load management, and infrastructure capacity. This section provides an overview of how increased EV charging demand, particularly from high-power chargers, can strain low-voltage grids and discusses various strategies to manage these issues, including grid reinforcement, smart charging, and energy storage solutions. By understanding these challenges and potential solutions, this section sets the foundation for assessing the broader implications of widespread EV adoption on local distribution systems.

2.1. Charging Technologies

Charging technologies are a cornerstone of the EV ecosystem, directly influencing their adoption by addressing key user concerns such as range anxiety and convenience. The variety of EV charging systems available plays an important role in meeting different user needs, ranging from daily commutes to long-distance travel. Each charging technology offers distinct benefits, and understanding these technologies is crucial for evaluating how they support the growing penetration of EVs. Furthermore, they serve as a foundation for more advanced systems like smart charging and V2G technologies [26].

EV charging technologies can be broadly categorized into three main types: slow (Level 1), fast (Level 2), and rapid or ultra-fast charging (DC fast charging). Slow charging, or Level 1, typically operates at 120 volts and can add approximately 3-5 miles of range per hour [26]. This method is most suitable for overnight charging at home or in residential areas where vehicles remain parked for extended periods. However, the extended time required to fully charge an EV using Level 1—often 12-24 hours—makes it less practical for users with busier schedules [27].

Fast charging, or Level 2, operates at 240 volts and can deliver around 10-30 miles of range per hour, significantly reducing charging time compared to Level 1, [28]. These chargers are commonly installed in public spaces such as parking lots, workplaces, or shopping centers. Although more efficient than Level 1, Level 2 chargers still require a few hours to fully charge an EV, depending on the battery size[29].

In contrast, rapid or ultra-fast charging, known as DC fast charging, can deliver 50-350 kW of power and can recharge an EV's battery to 80% capacity in approximately 20-40 minutes, adding hundreds of miles of range in a short time[26]. These systems are typically located along highways or major travel routes to support long-distance EV travel. While offering the greatest convenience, DC fast charging comes with higher installation costs—around $50,000 to $100,000 per station—and poses significant grid demands, particularly as EV adoption increases[30].

While fast charging offers substantial convenience, it also presents challenges, particularly regarding the strain it can place on the energy grid. To mitigate these issues, newer technologies such as smart charging and bidirectional charging are being developed. These innovations extend beyond simply improving charging speed. Smart charging, for instance, allows EVs to adjust charging times based on real-time electricity prices or grid load, reducing peak demand and grid stress. Bidirectional charging technologies, on the other hand, enable EVs to supply power back to the grid, which can help balance energy supply and demand, particularly during peak hours.

Smart Charging

Smart charging technology is a critical innovation for ensuring the large-scale adoption of EVs. As the number of EVs on the road grows, the demand for charging infrastructure and electricity increases significantly. Traditional grid infrastructure is often not equipped to handle the additional loads generated by widespread EV adoption, which could result in grid overloads or instabilities. Smart charging addresses these challenges by managing how and when EVs charge, using real-time data on electricity demand, grid capacity, and power availability to ensure efficient energy distribution. By optimizing charging sessions, smart charging plays a key role in maintaining grid stability, reducing energy costs, and facilitating the smooth integration of EVs into existing power networks [31].

A typical EV battery requires anywhere from 30 to 100 kWh to fully charge, depending on the vehicle's range and battery capacity. If unmanaged, widespread EV charging could increase peak electricity demand by 20-30% in some regions.According to Black D. [32], in California, where EV adoption is among the highest in the U.S., projections show that without smart charging, grid demand during peak hours could surge by as much as 25% by 2030, potentially destabilizing the grid during peak evening hours. Smart charging mitigates these risks by intelligently staggering charging sessions and aligning them with periods of lower electricity usage, often during the night when overall demand drops by 30-40%. This approach not only prevents grid stress but also increases the efficiency of energy use, reducing overall costs for consumers while maintaining grid stability [33].

Several key methods of smart charging have been developed to optimize energy consumption and ensure that EVs are smoothly integrated into the power grid. The primary methods include:

- **Controlled Charging**: In controlled charging, a centralized system dynamically adjusts the timing and power levels of EV charging sessions. According to Mahmood A. [34], during off-peak hours, EVs can charge at full power, when demand is 30-40% lower than peak times. In contrast, during peak periods , the system can reduce or delay charging to avoid overwhelming the grid. This method prevents grid overload by distributing power across various charging points based on the grid's capacity at any given time. Controlled charging is especially beneficial in environments with high EV density, such as residential complexes and large commercial buildings. Studies show that in such environments, controlled charging can reduce peak demand by up to 25%, significantly improving grid stability [35].

- **Dynamic Load Management (DLM)**: DLM is essential in high-demand environments, such as public or commercial charging hubs, where multiple EVs are plugged in simultaneously [36]. DLM systems monitor the total electrical load in real-time and allocate available power across several charging points, ensuring that the grid is not overloaded. According to Kimmel A. [37] in a commercial fleet charging scenario involving 50 EVs, DLM can prevent peak loads from exceeding 80-90% of grid capacity, while still providing adequate charging for all vehicles. By dynamically adjusting the power supplied to each vehicle, DLM reduces the risk of localized blackouts and ensures efficient energy distribution. This method can reduce peak load by up to 40% in high-demand areas, ensuring that the grid remains stable even during times of heavy use.

The scalability of smart charging technology is another significant advantage. In regions with high EV adoption, where the number of vehicles on the road is projected to grow exponentially in the coming years, the strain on local grids could require costly infrastructure upgrades if unmanaged. For example, in Europe, some countries are preparing for a future where EVs could constitute 30-40% of total vehicles by 2035 [38]. Without smart charging, this could lead to a doubling of electricity demand during peak hours, potentially requiring billions of euros in grid expansions. However, smart charging systems offer a scalable solution that can adapt to increasing demand without the need for significant investments in grid capacity [39]. By controlling charging times and rates, smart charging reduces peak loads and allows existing infrastructure to support a greater number of vehicles.

Smart charging also contributes to grid resilience by enabling utility providers to manage energy flows more effectively. By smoothing out peaks in demand and ensuring a more balanced load throughout the day, smart charging reduces the likelihood of grid failures or power outages [40]. For example, in regions where renewable energy sources such as solar or wind power are abundant, smart charging can be programmed to align EV charging with periods of high renewable energy generation. By charging during times of high solar output or strong winds, smart charging reduces reliance on fossil fuels, lowering the carbon footprint of EVs while supporting broader sustainability goals.

In addition to improving grid stability, smart charging can lower electricity costs for consumers. Studies show that by optimizing charging times and reducing demand during peak hours, smart charging can lower electricity costs by 20-30% compared to unmanaged charging [41]. For large commercial fleets or public charging stations, this translates into significant savings over time. For instance, a company operating a fleet of 100 EVs could save up to $100,000 annually in electricity costs by implementing smart charging systems that reduce demand during peak hours [42].

Vehicle-to-Grid (V2G)

V2G technology is a transformative innovation in EV adoption, providing crucial benefits for grid stability, renewable energy integration, and economic incentives for EV owners. V2G enables bi-directional energy flow, allowing EVs to not only draw power from the grid but also return stored energy when needed. This capability is essential for balancing electricity supply and demand, particularly during peak periods, which reduces stress on the grid and improves overall efficiency [14].

With millions of EVs on the road, their combined storage capacity could reach hundreds of gigawatt-hours (GWh). According to Alsharef M. [43], if just 10% of 1 million EVs in a region participate in V2G, they could provide up to 10 GWh of electricity back to the grid—enough to power approximately 200,000 homes for a day. This distributed storage capacity allows V2G to act as a buffer during peak electricity consumption, reducing reliance on fossil-fuel-based peaker plants, which are costly and contribute significantly to greenhouse gas emissions [14].

V2G's ability to provide distributed energy storage offers significant economic advantages. As EV adoption increases, electricity demand will rise, particularly during peak hours when EV owners typically charge their vehicles. Without V2G, this increased demand could necessitate costly grid infrastructure upgrades to prevent overloads. In the paper by Chen G. [44] suggests that, the U.S. grid may require between $100 billion and $200 billion in upgrades by 2040 to accommodate EV demand. However, V2G could reduce this required investment by up to 30%, as EVs can discharge energy back into the grid during peak demand, flattening demand curves and reducing the need for expensive expansions.

An important application of V2G is its role in enhancing renewable energy integration. Renewable energy sources such as wind and solar are variable, often generating energy during times when demand is low, such as at night or midday. V2G enables EVs to store surplus renewable energy during these periods and discharge it back into the grid when demand peaks. For instance, wind farms may over-produce energy at night, while solar farms generate excess energy during the day. V2G can absorb this energy, making it available when it is most needed, reducing the reliance on fossil-fuel generation. In regions with high renewable energy adoption, V2G could reduce carbon emissions by up to 25% by minimizing the need for conventional peaking plants and reducing energy curtailment [45].

Mobile V2G, a more flexible extension of traditional V2G, amplifies the potential of this technology by offering greater mobility and adaptability. Unlike stationary V2G systems, mobile units can be deployed anywhere they are needed, making them especially beneficial in regions with underdeveloped charging infrastructure. This mobility enables energy services to reach remote or rural areas that may otherwise be excluded from V2G programs, ensuring broader participation. For instance, in locations where the grid is weak or unable to meet peak demand, mobile V2G units can be deployed to provide additional capacity and prevent blackouts. Furthermore, these mobile systems can act as temporary energy sources during emergencies or large-scale events, helping to stabilize grids that face unexpected stress from high demand or natural disasters [46].

In disaster response, mobile V2G offers a crucial solution by supplying on-demand power to critical infrastructure. Following natural disasters such as hurricanes, earthquakes, or floods, mobile V2G units can quickly be mobilized to power essential services, including hospitals, emergency shelters, and communications networks [43]. For example, after a major grid outage caused by a natural disaster, mobile V2G units could be dispatched to provide several megawatts of power to key facilities, reducing reliance on diesel generators, which are both carbon-intensive and challenging to maintain during crises. This added resilience is especially important in disaster-prone regions, where the ability to restore power swiftly can be lifesaving.

The role of mobile V2G in supporting renewable energy adoption is also noteworthy. These units can be deployed near renewable energy sources, such as wind farms or solar arrays, to store excess energy when generation is high but demand is low. By capturing surplus energy during periods of peak production—such as sunny afternoons for solar power or windy nights for wind power—mobile V2G units can transport this stored energy to urban centers or areas with higher demand [45]. This not only helps balance the grid but also reduces the curtailment of renewable energy, which is often wasted when there is insufficient storage capacity. In regions where renewable energy generation frequently exceeds demand, mobile V2G can significantly reduce wasted energy and improve overall grid efficiency.

For EV owners, mobile V2G opens up new economic opportunities. Much like stationary V2G systems, mobile units allow EV owners to sell excess energy back to the grid during peak periods when electricity prices are highest [47]. However, mobile V2G offers even greater flexibility by enabling EV owners to position their vehicles in locations where demand is greatest. For instance, fleet operators or individual owners can move mobile V2G units to high-demand areas, such as urban centers during peak times, to provide energy directly to the grid. This mobility enhances revenue potential, with mobile V2G units able to supply energy where it is most valuable, generating substantial income for operators. For example, a fleet of mobile V2G units deployed during a major city event could supply megawatts of power, earning tens of thousands of dollars over the course of a single high-demand period [44].

2.2. Low-Voltage Distribution Networks and EVs

The rapid growth of EV (EV) adoption is placing substantial stress on low-voltage distribution grids, particularly due to uncontrolled charging—charging without the use of smart technologies or grid coordination systems such as V2G. Uncontrolled charging leads to significant increases in power demand during peak hours and has a measurable impact on voltage levels across the grid, causing both voltage fluctuations and demand surges that affect overall grid stability [48, 49].

In areas where uncontrolled charging is the dominant mode, voltage instability becomes a critical issue. Voltage drops of 5% to 8% are common in neighborhoods with moderate EV penetration, and these drops can exceed 10% in areas where adoption rates surpass 30% [50]. These voltage drops are particularly problematic in low-voltage grids, which are designed to handle steady, predictable loads. Sudden voltage dips affect line voltage regulation and cause deviation from the nominal voltage , leading to operational inefficiencies in electrical appliances and devices connected to the grid.

Moreover, the voltage fluctuations impact the efficiency of EV charging itself. When voltage sags occur, EV chargers experience reduced power throughput. In an uncontrolled charging scenario, this results in increased charging times, with studies reporting a 20% increase in charging duration due to suboptimal voltage levels [49]. According to Nalo N., Bosović A. and Musić M.A [51] 10% voltage drop from 230V to 207V can extend EV charging times by 10%, resulting in an additional 3 kWh of energy consumed per session. In a neighborhood with 100 EVs charging simultaneously, this can lead to an extra 300 kWh per event, increasing load on transformers and causing 1-2% efficiency loss for every 5°C rise in operating temperature, accelerating thermal degradation of grid components. This ultimately leads to higher operational temperatures, particularly in grid components not designed for such prolonged peak loads, increasing the risk of thermal degradation and failure.

The effects of uncontrolled charging are most pronounced during peak demand periods, when residential demand for electricity overlaps with EV charging. In regions with significant EV penetration, such as the Netherlands, peak load surges due to uncontrolled charging have been shown to increase overall neighborhood demand by 30% to 50% [48]. This surge in demand stresses distribution transformers, which must operate well beyond their rated capacity during these hours. Continuous overloading reduces transformer efficiency and accelerates aging factors such as oil degradation and winding insulation breakdown, leading to reduced transformer lifespans.

In addition to voltage issues, grid congestion becomes a significant problem in areas with high rates of uncontrolled charging. Grid congestion refers to the inability of the grid to meet local demand due to physical limitations of the distribution infrastructure. In low-voltage networks, congestion results in load imbalances where different phases of the network carry uneven loads, further aggravating voltage instability [52]. Phase imbalances in three-phase distribution systems can result in neutral current buildup, which increases the risk of overheating in conductors and can lead to neutral point shifts, negatively affecting voltage regulation across all phases [53].

Rural areas are particularly vulnerable to these effects, given that grid infrastructure in such regions is often older and less capable of handling the concentrated loads generated by uncontrolled EV charging. Simulation studies in rural networks have demonstrated that the addition of 20 to 30 EVs in a neighborhood can cause voltage drops of up to 10%, significantly impacting both power quality and the operational stability of the grid [49]

In areas with high EV penetration, uncontrolled charging can cause voltage drops of up to 10% and increase peak demand by 30% to 50%, leading to grid congestion and inefficiencies. Without smart charging or V2G, transformers and conductors face prolonged overloading, accelerating thermal degradation and reducing their lifespan by up to 50%, which significantly increases maintenance costs and the risk of grid failure[54].

2.3. Smart Charging and Its Impact on Low-Voltage Grids

As EV adoption accelerates, the growing strain on low-voltage (LV) grids has become a critical issue, particularly in areas with high EV penetration. Smart charging has emerged as an essential tool for managing this increased demand. Unlike uncontrolled charging, which leads to sudden demand spikes and voltage instability, smart charging systems can smooth demand curves by optimizing charging times based on real-time data and grid conditions. Research shows that smart charging can reduce peak loads by 30-50%, alleviating pressure on distribution transformers and preventing localized voltage drops, which in some high-EV penetration areas can otherwise reach up to 10% [55]. By distributing the load more evenly throughout the day, smart charging minimizes the need for expensive grid reinforcements, delaying infrastructure upgrades by several years in congested urban networks [56].

Figure 2.1 provides a comprehensive overview of the components involved in EV charging scheduling, highlighting three primary elements: Dynamic Pricing Schemes, Optimization Techniques, and Optimization Objectives. These components are critical to optimizing charging patterns and improving grid stability. Dynamic Pricing Schemes, such as Time of Use (TOU) pricing, Real-Time Pricing (RTP), and Critical Peak Pricing (CPP), incentivize EV owners to charge their vehicles during off-peak hours when electricity demand is lower. This alignment of economic incentives with grid requirements helps flatten the demand curve. Studies have shown that TOU pricing alone can reduce peak demand by 15-25%, encouraging users to avoid charging during high-demand periods [57]. However, challenges such as the avalanche effect, where large numbers of EVs begin charging simultaneously in response to lower prices, remain an issue. This can lead to an amplified grid load, increasing demand by up to 15 times in high-EV penetration areas [58].

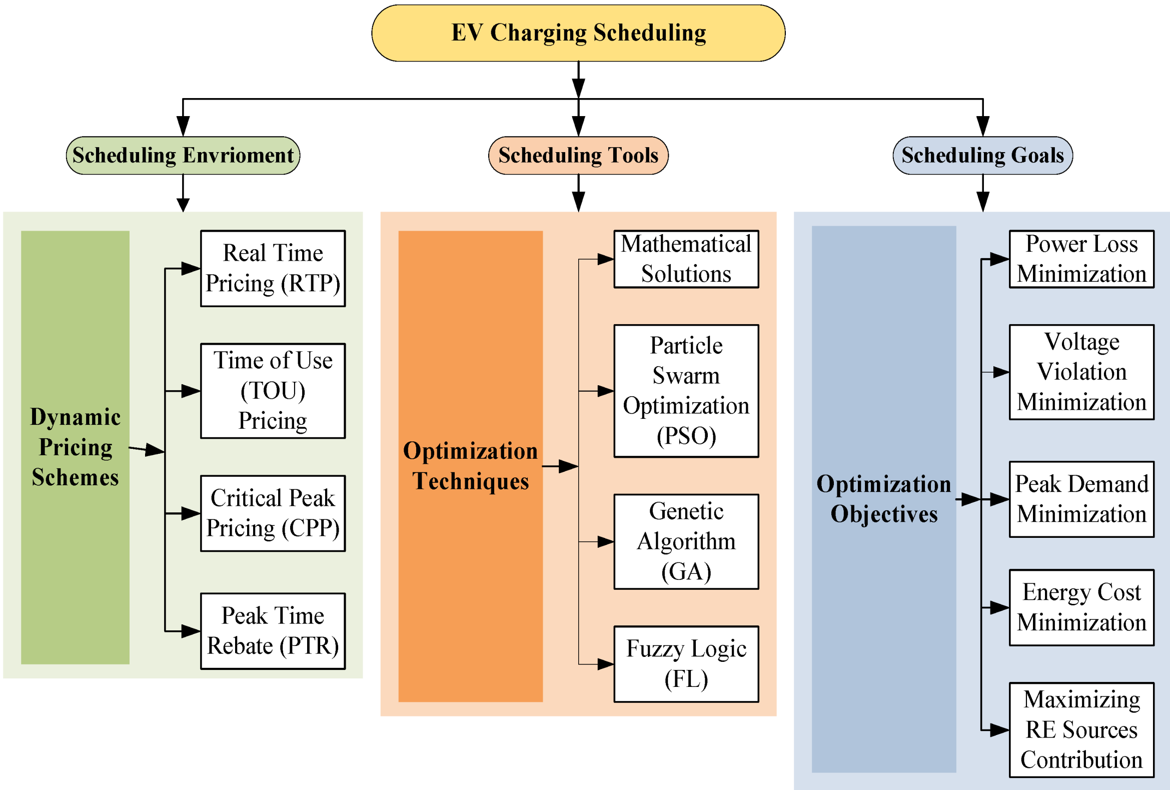

Figure 2.1: EV Charging Scheduling Framework [59]

To address these challenges, several studies have integrated demand response mechanisms into smart charging models. These systems dynamically adjust charging times or rates based on real-time grid conditions, preventing localized overloads caused by the avalanche effect. Predictive algorithms, often powered by machine learning, can forecast grid load conditions with 95% accuracy, allowing charging sessions to be staggered and distributed more efficiently [44]. Research indicates that when smart charging is combined with demand response strategies, peak demand can be reduced by up to 70%, significantly reducing the likelihood of grid overloads [60].Such systems not only stabilize the grid but also reduce electricity costs for EV users by up to 20%, aligning economic incentives with grid reliability [56].

Additionally, price-based optimization models, such as those that utilize day-ahead market prices, have gained significant attention in the literature. These models optimize charging schedules by purchasing electricity when prices are low and reducing or even selling power back to the grid when prices rise. This approach, often referred to as arbitrage, can generate cost savings of up to 20% for EV owners, while contributing to grid stability by preventing overloads during high-demand periods [60].Incorporating these price signals into charging strategies ensures that EVs charge when there is excess capacity in the grid, reducing the strain on critical components such as transformers and distribution lines.

While the benefits of smart charging are well-documented, many studies highlight the importance of considering real-world user behavior and environmental factors, which can significantly affect the performance of smart charging systems. For example, seasonal variations in electricity demand—such as increased heating loads in winter—can alter grid conditions and complicate the optimization of charging schedules. In colder months, energy consumption can increase by as much as 30%, placing additional strain on the grid. If not accounted for, these seasonal factors can lead to suboptimal charging schedules that fail to alleviate grid stress during peak periods [61]. Furthermore, the diversity of urban, suburban, and rural driving patterns introduces additional variability into charging demand, which many generalized models fail to capture.

Incorporating these real-world variables into smart charging optimization is critical for ensuring the scalability of these systems. Studies confirm that smart charging models that account for SOC dynamics, user behavior, and environmental factors can provide a more robust and scalable solution to the growing challenges faced by low-voltage grids in the era of mass EV adoption.

2.4. V2G Technology and Its Integration into Low-Voltage Grids

V2G technology enables bidirectional energy flow, allowing EVs to function as distributed energy resources, which contributes to low-voltage grid stability through services like frequency regulation, load balancing, and voltage support. By utilizing the storage capacity of EV batteries, V2G allows vehicles to not only draw power from the grid but also feed electricity back into it. This capability is particularly valuable for low-voltage grids, which are often more susceptible to demand and supply fluctuations. For example, in frequency regulation, V2G-equipped EVs can rapidly inject or absorb power to help maintain grid frequency within operational limits, which is essential for preventing widespread blackouts [62]. Additionally, load balancing is enhanced as EVs can discharge power during peak demand periods, easing grid strain and flattening the load curve [63]. V2G technology also provides voltage support by supplying reactive power, which can improve power quality and mitigate voltage dips in local grids [64].

Studies on V2G scenarios reveal both positive and negative impacts on voltage stability, transformer loading, and power quality in low-voltage distribution networks. V2G technology can enhance grid stability, but it also introduces challenges that require careful management. One key area of impact is voltage stability; when EVs discharge power back into the grid, they can help regulate voltage levels during high demand or low generation periods. However, without proper coordination, V2G operations can cause voltage fluctuations, leading to instability in local grids [65]. Regarding transformer loading, V2G offers advantages by distributing loads more evenly throughout the day. For instance, during peak periods, EVs can discharge stored energy, reducing the strain on transformers and potentially extending their lifespan. On the downside, frequent bidirectional power flows could accelerate transformer aging, particularly in older infrastructure, if not carefully managed [66]. In terms of power quality, V2G can provide reactive power support and reduce harmonics, which improves overall power quality. However, uncoordinated V2G activities might lead to power imbalances, voltage sags, and harmonic distortion, especially in grids with high EV penetration [67].

Widespread adoption of V2G technology faces significant challenges related to grid coordination, bidirectional inverter technology, and regulatory barriers, all of which must be addressed for successful integration. One of the primary hurdles is grid coordination, as effective V2G deployment requires real-time communication between EVs, charging infrastructure, and grid operators. This coordination is critical for managing power flows, preventing grid congestion, and ensuring that V2G activities do not destabilize local grids. Without sophisticated management systems and reliable communication protocols, large-scale V2G could lead to imbalances and inefficiencies, posing risks to grid stability [68].

Another challenge lies in the development of cost-effective and reliable bidirectional inverters, which are essential for enabling EVs to both charge and discharge power. While these inverters are crucial to V2G functionality, current models are expensive, and ongoing research is focused on improving their efficiency, durability, and affordability. Enhancements in inverter design, particularly regarding power conversion efficiency and long-term reliability, are necessary to make V2G a viable large-scale solution [69]. Regulatory barriers also present significant obstacles. V2G introduces complexities around energy pricing, grid access, and compensation for energy fed back into the grid. Existing regulations often do not fully support bidirectional power flows, and there is a lack of universal standards for integrating V2G into national grids. For V2G to scale, regulatory frameworks need to evolve to address grid access rights, tariffs, battery degradation compensation, and data privacy concerns tied to the communication between EVs and grid operators [70].

2.5. Mobile V2G: A New Frontier in Grid Integration

Mobile V2G technology has emerged as a promising concept that could significantly enhance grid flexibility by enabling EVs to function as mobile energy resources, dynamically supporting the grid wherever they are connected. Traditional V2G systems typically rely on stationary EVs discharging power at fixed locations like homes or designated charging stations. In contrast, mobile V2G leverages the inherent mobility of EVs to offer grid services across different locations, increasing the responsiveness and adaptability of energy management. Research indicates that mobile V2G can improve grid flexibility by providing services such as frequency regulation, peak shaving, and emergency power supply, especially in areas with fluctuating demand or limited infrastructure [71]. For example, EVs equipped with mobile V2G capabilities can address temporary energy needs during events or act as distributed backup generators during localized outages.

One of the significant advantages of mobile V2G is its ability to balance energy supply and demand more dynamically, which is particularly useful in grids with high renewable energy penetration. By moving to where energy is needed most, EVs can contribute to more effective load balancing and facilitate the integration of intermittent renewable sources like solar and wind [64]. Despite its potential, large-scale implementation of mobile V2G presents challenges, including the need for real-time communication systems, standardized bidirectional charging infrastructure, and regulatory frameworks that accommodate the mobile nature of these energy resources [72]. Mobile V2G technology introduces significant unpredictability to low-voltage grids, potentially affecting grid stability due to the dynamic availability and mobility of EVs. While mobile V2G provides the flexibility to support the grid from various locations, this mobility also creates challenges in predicting energy availability and usage patterns. Unlike stationary V2G systems, mobile V2G is influenced by the movement and behavior of EV users, which can be inconsistent and difficult to forecast. This unpredictability can result in voltage fluctuations, imbalanced power flows, and additional strain on grid infrastructure, particularly in low-voltage networks [73]. For example, if a group of EVs leaves a particular area during peak demand times, the anticipated grid support may disappear, leading to voltage drops. On the other hand, a sudden surge in EVs returning to charge at the same location could overload local transformers, causing grid instability and potential failures [74].

Simulation models of mobile V2G scenarios reveal that while this technology can enhance grid performance, it can also strain grid stability, especially in low-voltage networks, depending on factors like EV distribution and coordination. On the positive side, these models show that mobile V2G can alleviate grid congestion by discharging power during peak hours, reducing transformer stress and helping prevent overloads. However, the unpredictability introduced by the movement and varying availability of EVs creates significant challenges [74]. For example, irregular charging and discharging patterns can lead to localized voltage instability and imbalances in power distribution. Additionally, when large numbers of EVs return to a single area and begin charging simultaneously, it can lead to grid congestion, voltage drops, and power quality issues. The effectiveness of mobile V2G in either mitigating or exacerbating these impacts depends heavily on the coordination and control mechanisms in place. This underscores the need for advanced, real-time control strategies and predictive algorithms that can dynamically manage the fluctuating nature of mobile V2G resources.

2.6. Role of Commuting Patterns in EV Integration Studies

Studies modeling EV charging behavior often rely on real-world commuting data, focusing on arrival and departure times to predict and optimize charging demand. These models are key to improving grid management, charging infrastructure planning, and load balancing by understanding the temporal and spatial dynamics of commuter-driven charging behavior. Charging demand tends to follow the daily routines of drivers, making commuting patterns, such as when and where drivers park and charge their vehicles, essential for accurate modeling. Research shows that morning and evening commute patterns create predictable spikes in charging demand, particularly in residential areas [75]. This insight enables the design of smart charging strategies, such as delayed charging or time-of-use pricing, which can help prevent grid overload [76]. Furthermore, these models are instrumental in identifying optimal charging station locations and integrating renewable energy sources by aligning charging behaviors with periods of peak renewable generation [77].

Research analyzing varying levels of commuting participation, such as 42% versus 100%, highlights significant implications for grid management and EV charging strategies. These studies show that partial participation scenarios produce distinct charging demand patterns, which are critical to consider for maintaining grid stability. The load profile of EV charging varies considerably depending on the level of commuting participation. For instance, in a 100% participation scenario, peak loads are much more concentrated and predictable compared to lower participation levels, like 42%. Reduced participation results in more dispersed charging, which can ease peak congestion but also introduces challenges in accurately forecasting loads [78]. On the other hand, scenarios with nearly full participation lead to more intense and concentrated demand spikes, particularly during morning and evening commuting hours [79]. This necessitates tailored grid management strategies, such as demand response programs and dynamic pricing, that align with the specific commuter participation levels.

Moreover, different participation rates affect the deployment and effectiveness of V2G strategies and smart charging infrastructure. Mixed participation scenarios are particularly challenging, as they require more adaptive solutions to balance loads efficiently [80]. These findings underscore the need for flexible, data-driven approaches in grid management as EV adoption continues to rise.

Despite advancements in EV research, significant gaps remain in understanding how different commuting scenarios interact with V2G systems and smart charging strategies. These gaps underscore the need for further investigation into how diverse commuting behaviors impact grid stability, V2G efficiency, and the integration of renewable energy sources.

While there has been progress in modeling the interplay between commuting patterns, V2G systems, and smart charging, several critical areas remain underexplored. For instance, many existing models lack detailed analysis of mixed and dynamic commuting scenarios, such as fluctuating levels of remote work or hybrid commuting, which can substantially alter charging demand profiles [80]. Furthermore, the effectiveness of V2G strategies is not fully understood in situations where real-world commuting behaviors introduce unpredictability in grid support availability. For example, most studies assume a stable number of vehicles available for V2G during peak demand, but they often overlook the variability in commuter participation and vehicle availability [79]. Another research gap lies in the integration of smart charging strategies with V2G systems in environments where commuting participation is inconsistent. The interaction between smart charging algorithms and V2G under dynamic conditions remains insufficiently studied, particularly regarding how these systems can adapt to sudden shifts in commuter behavior [81]. Additionally, there is a need for more comprehensive evaluations of how varying charging behaviors influence the integration of renewable energy sources, such as optimizing charging schedules to coincide with peak solar or wind generation periods.

2.7. Seasonal Variations and Their Impact on EV Grid Integration

Temperature variations and seasonal shifts in energy demand significantly impact both grid operations and EV performance. pan. Additionally, seasonal energy demand fluctuations challenge grid stability, influencing charging behavior and the integration of renewable energy sources.

Seasonal energy demand shifts also play a significant role in grid operations. For example, in winter, increased energy consumption for heating coincides with peak EV charging times—typically in the evening—intensifying the strain on grid capacity [82]. In summer, the demand from air conditioning combined with EV charging requires careful load balancing to prevent grid congestion. These seasonal variations further influence renewable energy integration. Solar energy generation peaks during summer, potentially aligning better with midday EV charging, while wind energy tends to be more abundant in winter, offering different opportunities for balancing grid demand.

To mitigate the impacts of temperature fluctuations and seasonal demand shifts, grid operators must plan for infrastructure enhancements and implement effective demand response programs. Smart charging strategies, V2G systems, and advanced battery thermal management are critical for maintaining both EV performance and grid reliability under varying temperature and seasonal conditions.

3
Simulation Setup and Case Studies

After exploring different aspects of charging technology in Chapter 2. In this chapter, we present the key assumptions, simulation grids, and modeling parameters that form the foundation of our analysis of EV integration and charging strategies within low-voltage grids. We begin by outlining the main assumptions used to simplify system interactions. Next, we describe the simulation grids, including their topology and grid-specific parameters. Finally, we explore the integration of EVs, charger distribution, and the role of Day-Ahead Market prices in optimizing charging and discharging strategies. These elements collectively define the operational environment used to assess the impact of different EV charging strategies on grid performance.

3.1. Main Assumptions

The following assumptions were made to model and simulate the impact of EVs, charging strategies, and related grid dynamics within this thesis. These assumptions simplify complex system interactions and enable the application.

- **Active Power Consideration**: Reactive power effects are neglected due to the significant presence of power electronics in PV panels and charging stations. The average power factor is assumed to be close to unity, focusing the analysis solely on active power flows.
- **Three-Phase Connections and Chargers**: All EV chargers, regular loads, and charging stations are modeled as three-phase connections to ensure balanced phase distribution and avoid grid imbalances. This assumption also improves simulation convergence.
- **Fixed Grid Topology**: The grid topology remains unchanged throughout the study. Restructuring or reinforcement of grid infrastructure is outside the scope, allowing the focus to remain on current grid conditions.
- **Ideal PV System Operation**: PV systems are modeled with optimal tilt and consistent generation, disregarding factors like cloud coverage, rain, or dust. This provides a stable power output for the analysis.
- **Perfect System Knowledge**: Regular load and solar panel behavior are assumed to be known with 100% accuracy, while information on EV connections becomes available only at the moment of connection. This includes perfect knowledge of energy prices, vehicle trips, and EV availability throughout the simulation.
- **Constant Power Assumption**: Both regular loads and charging stations are modeled with constant power behavior. While this simplifies the analysis, it may impact simulation precision.

- **Day-Ahead Market Energy Prices**: Energy prices are based on the Day-Ahead Market, allowing for better optimization in the charging process. Differences between Day-Ahead and Intraday prices are considered negligible.
- **Curtailment Limited to Charging Stations**: In case of grid issues, only charging stations are curtailed. Regular residential and industrial loads are considered inflexible and cannot be curtailed without requiring compensation from the Distribution System Operator (DSO).
- **Private EVs Exclusively Modeled**: The study focuses solely on private EVs, excluding semi-public and public charging stations, to provide a detailed analysis of individual user behavior.
- **User-Centric Simulation Perspective**: Simulations are conducted from the perspective of individual users rather than grid operators, emphasizing the impact of uncoordinated charging strategies.

These assumptions collectively streamline the analysis, enabling a targeted investigation of the key factors influencing the integration of EVs and their charging strategies within low-voltage grids. By narrowing the focus, this research provides actionable insights while acknowledging the limitations inherent in modeling such a complex system.

3.1.1. Simulation Grids

The simulations are performed on two suburban grids obtained from Enexis Groep. These grids exhibit a radial topology, which is typical for suburban electrical networks. Figures 3.1 and 3.2 show the grids used for the simulation.

The grid parameters, such as the number of nodes, buildings, lines, and PV installations, are summarized in Table 3.1. These parameters provide a comprehensive comparison between the heavy suburban and light suburban grids, reflecting the differences in infrastructure density and PV penetration levels.

Table 3.1: Comparison of grid parameters between heavy suburban and light suburban setups

Parameter	Heavy Suburban	Light Suburban
Nodes	2809	2553
Buildings	885	809
Lines (m)	2636	2483
PV Installations	133	122

3.1.2. Simulation Parameters

The simulation parameters for the winter and summer seasons are compared in Table 3.2. Both simulations have a timestep duration of 15 minutes, allowing for consistent data collection and comparison. The winter simulation runs from January 5th to January 10th, while the summer simulation spans from June 15th to June 20th. These time ranges are chosen to represent seasonal extremes, offering insight into grid performance under varying environmental conditions.

Table 3.2: Simulation Parameters for Winter and Summer Seasons

Parameter	Winter	Summer
Time Step Duration	15 min	15 min
Simulation Period	05-01 00:00:00 – 10-01 00:00:00	15-06 00:00:00 – 20-06 00:00:00

Figure 3.1: Light Suburban Grid

3.2. Load Modelling

The residential and commercial loads used in the model, provided by Enexis Groep, are represented as low-voltage (LV) loads, capturing typical energy consumption behaviors across the Netherlands based on data from the Dutch Energy Data Exchange (NEDU) [83]. While NEDU profiles provide detailed insights into daily energy consumption patterns, the actual power consumption at any given time is modeled using a specific formula that accounts for the total annual consumption, the consumption profile at that time, and the number of time steps. In this study, the time step is 15 minutes, meaning the consumption is calculated four times per hour. The formula used to determine the power at time t is expressed as:

$$\text{Power}_t = \frac{\text{Total Annual Consumption} \times \text{Consumption Profile}_t}{\text{Total Number of Time Steps}} \tag{3.1}$$

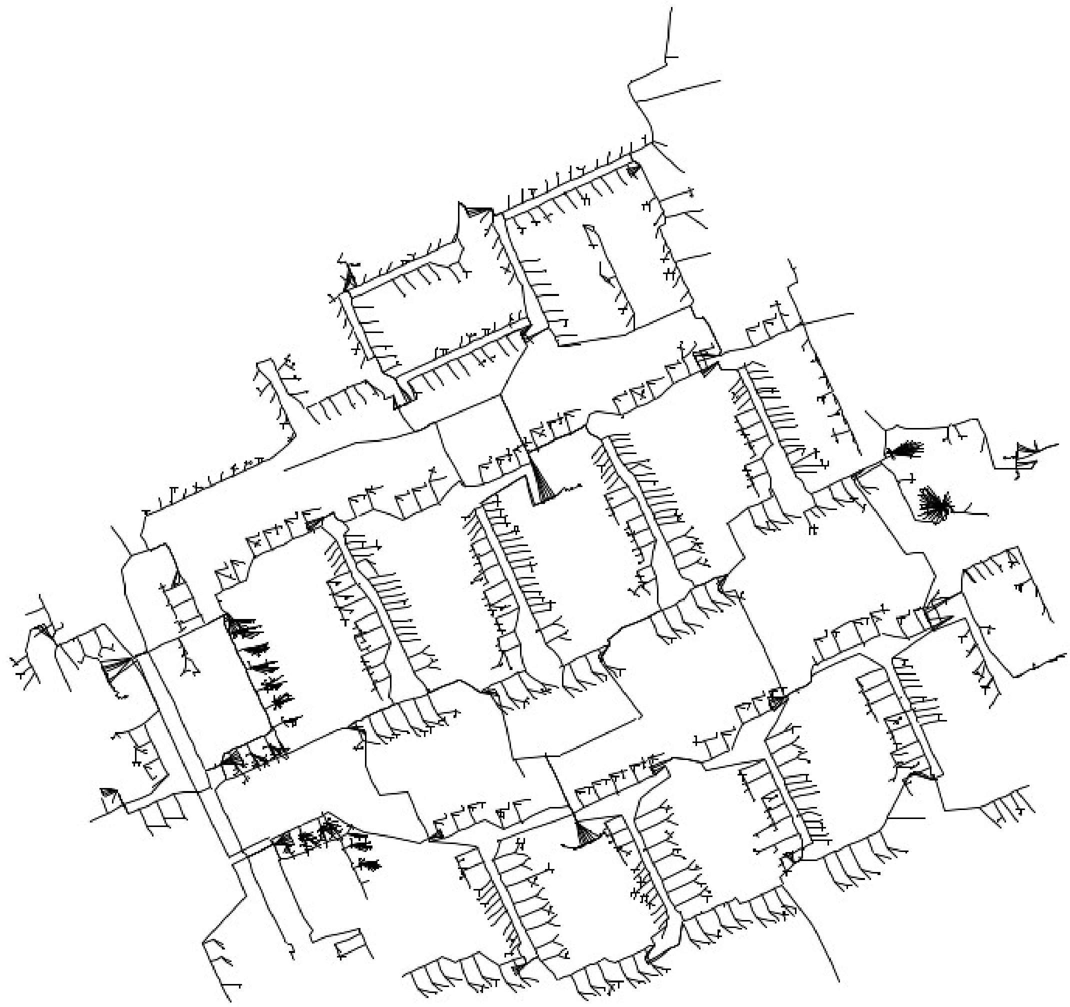

Figure 3.2: Heavy Suburban Grid

This equation distributes the total annual consumption over the year based on the NEDU profiles and the 15-minute time intervals. The consumption profile from NEDU provides the relative usage pattern throughout the day, and the formula converts this pattern into a power profile for each time step.

For small households with relatively steady consumption, the E1A profile provides the basis for the calculation. The power profile, as shown in Figure 3.3, is calculated by applying Equation (3.1) to the E1A consumption profile, with the total annual consumption distributed across the time steps.

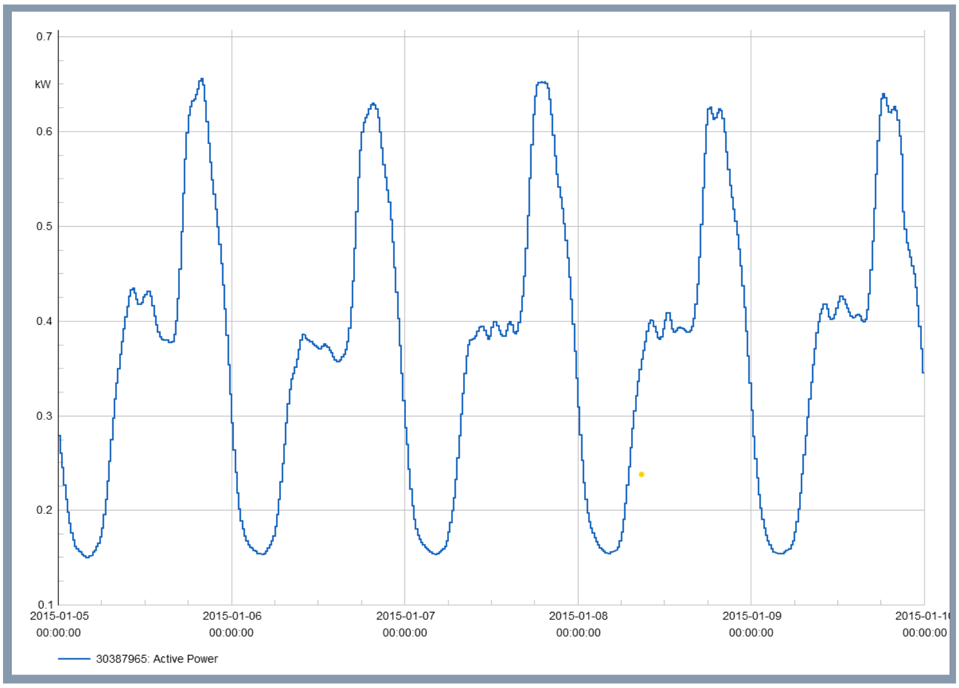

Figure 3.3: E1A Load

Similarly, the E1C profile reflects households that shift their energy usage to off-peak hours due to lower electricity tariffs, particularly between 9:00 PM and 7:00 AM. As illustrated in Figure 3.4, the power profile shows higher energy demand during these hours, calculated using the same formula and time-step adjustment.

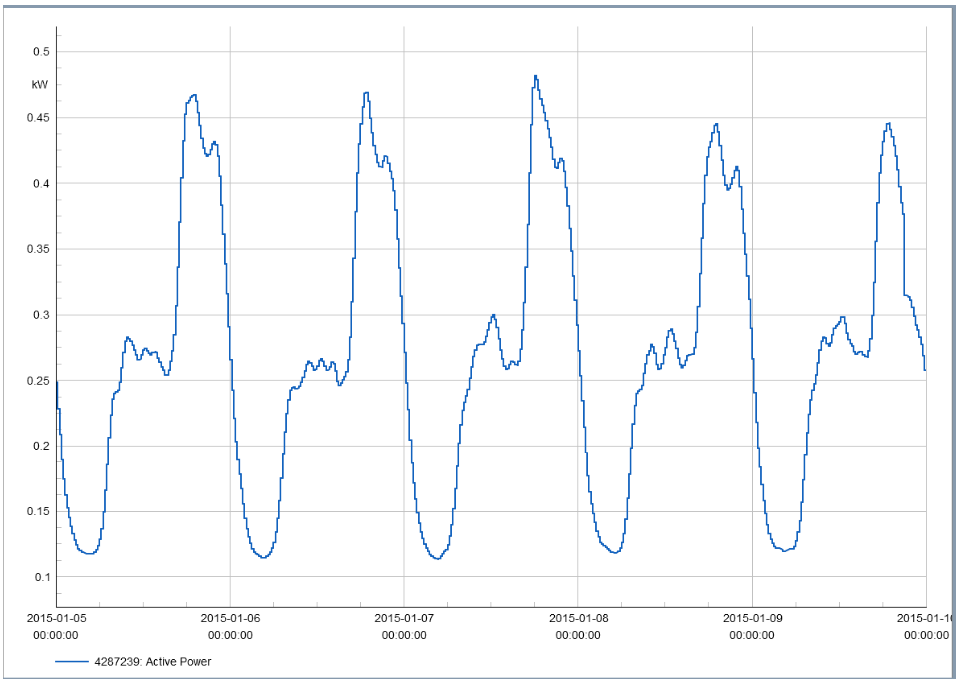

Figure 3.4: E1C Load

For commercial users, the model applies the NEDU profiles in a similar manner. The E2A profile represents small commercial consumers with moderate energy demand, while the E2B profile captures larger commercial users with more intensive energy use. In both cases, the power profiles, shown in Figures 3.5 and 3.6, are calculated by applying the same formula to the respective consumption profiles provided by NEDU.

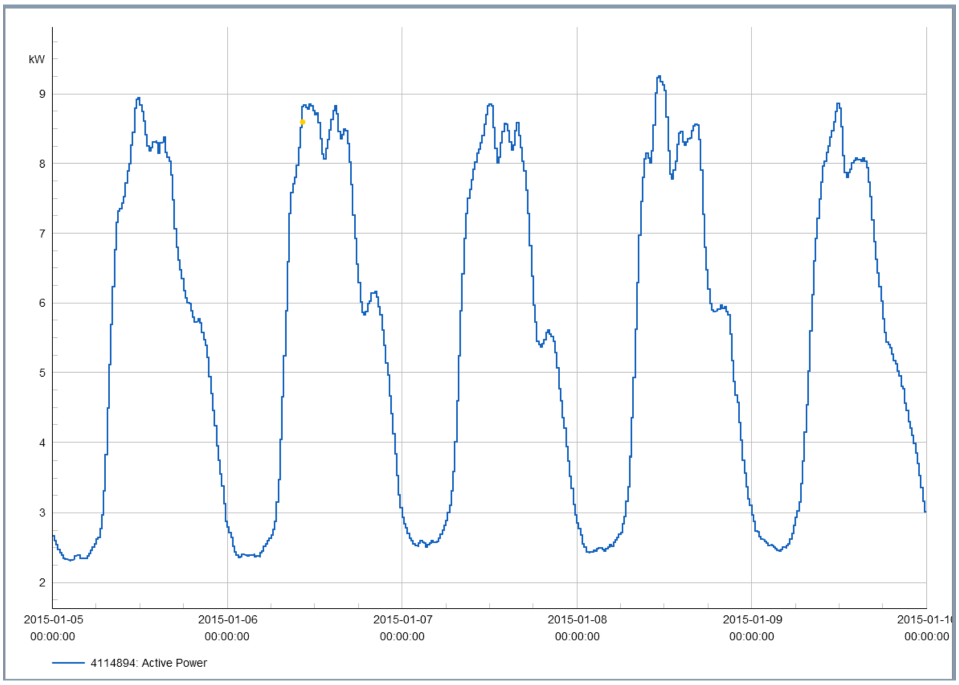

Figure 3.5: E2A Load

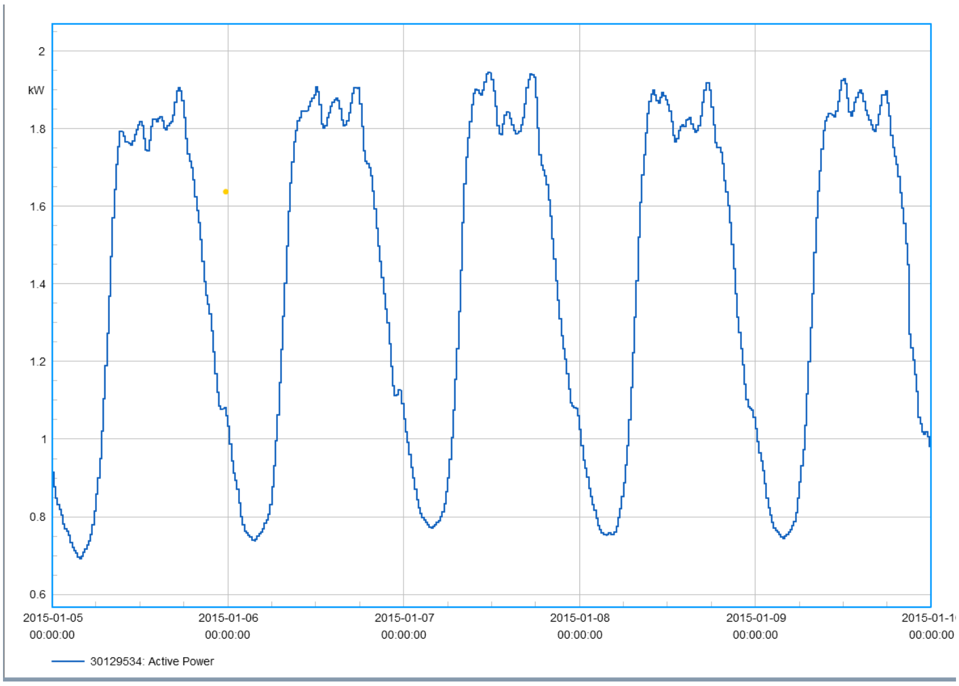

Figure 3.6: E2B Load

3.3. Photovoltaic Generation

To accurately model photovoltaic (PV) generation within the grid, a solar calculation model is utilized. In this study, DIgSILENT PowerFactory was employed to simulate the behavior of PV systems, incorporating inputs like PV module specifications, inverter characteristics, site conditions, and meteorological data (solar irradiance and temperature).

3.3.1. Solar Calculation Model

The solar calculation model in DIgSILENT PowerFactory computes the DC power output from the PV modules using the following formula:

$$P_{\text{DC}} = G \times A \times \eta_{\text{PV}} \times [1 - \alpha \times (T - T_{\text{ref}})] \tag{3.2}$$

where:

- G is the global irradiance (W/m²)
- A is the area of the PV modules (m²)
- η_{PV} is the efficiency of the PV modules
- α is the temperature coefficient of the PV panels (%/°C)
- T is the module temperature (°C)
- T_{ref} is the reference temperature (10°C for winter, 20°C for summer)

The generated DC power is then converted into AC power using the inverter, applying an efficiency factor η_{inv} as follows:

$$P_{\text{AC}} = P_{\text{DC}} \times \eta_{\text{inv}} \tag{3.3}$$

PowerFactory integrates these calculations dynamically in simulations, considering hourly or sub-hourly profiles for irradiance and temperature. This results in accurate modeling of PV output during load flow and dynamic analyses.

3.3.2. Panel Specifications

For this simulation, the SunPower SPR-X21-345 solar panel was used. This panel is recognized for its high efficiency and robust performance, with a rated output of 345 watts and an efficiency of 21.5%. The SunPower SPR-X21-345 is a reliable choice in scenarios where space is limited but high energy production is required. Figure 3.7 provides the detailed specifications of the SunPower SPR-X21-345 panel.

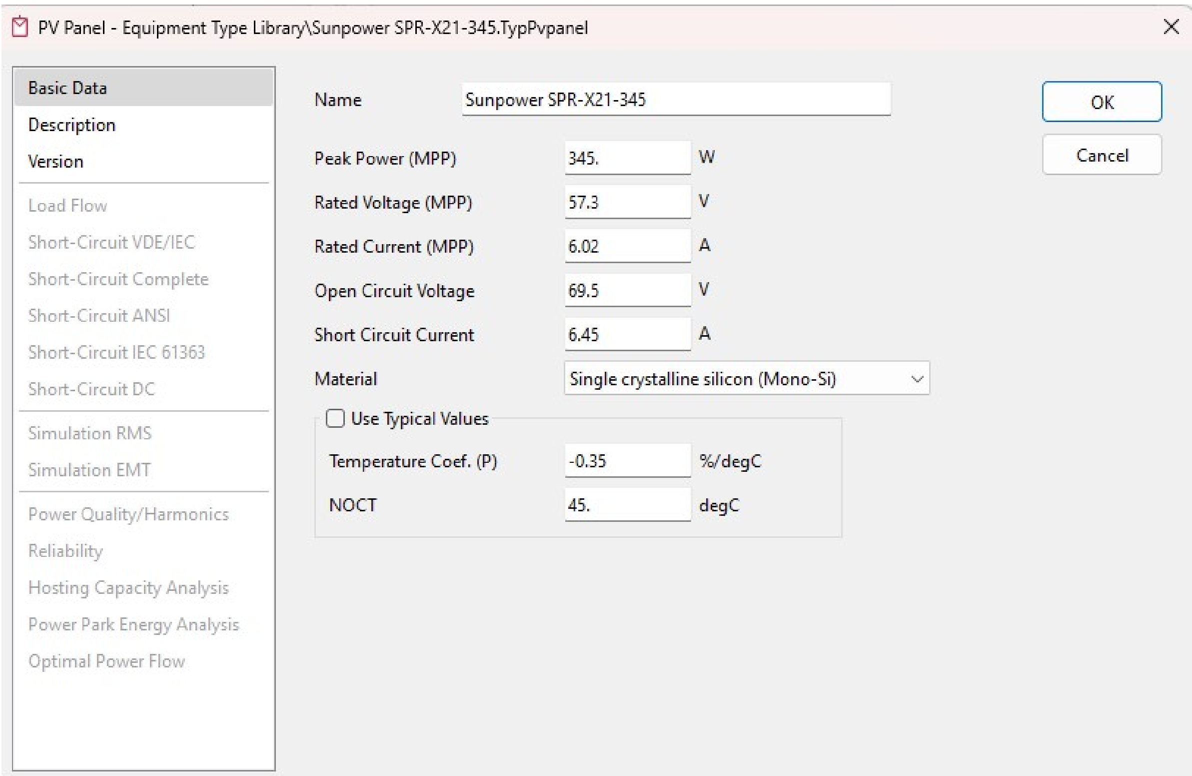

Figure 3.7: Specifications for SunPower SPR-X21-345 Panel

3.3.3. Environmental Data

The irradiance data used for this study is derived based on the geographic coordinates (latitude and longitude) of the node where the PV system is connected. The global irradiance data is modeled using the Adnot-Bourges et al. model, while diffuse irradiance is estimated using the Louche et al. model.

The Adnot-Bourges et al. model is a statistical approach that estimates global solar irradiance by considering historical data, geographic location, seasonal patterns, and climatic conditions. It is designed to provide hourly estimates of irradiance, making it suitable for detailed PV performance analysis.

The Louche et al. model specializes in calculating diffuse irradiance—sunlight scattered by atmospheric particles such as clouds and aerosols. This model uses empirical relationships between various atmospheric parameters (e.g., cloud cover, humidity) to deliver accurate predictions of diffuse irradiance on both hourly and daily scales.

Both models complement each other by providing a comprehensive assessment of solar irradiance, enabling more accurate simulations of PV output under varying environmental conditions.

Based on the given data, PV panels in the grid have been modeled based on two setups: residential PV and workplace/commercial PV, differentiated by the number of panels and the number of inverters. Table 3.3 highlights the differences in PV modeling for these setups. It can be observed that PV generation is higher in commercial setups compared to residential loads, and PV generation is more significant in summer than in winter.

Table 3.3: Number of panels and inverters for residential and commercial setups

Type	Number of Panels per Inverter	Total Number of Inverters
Residential	8	1
Commercial	8	2

3.4. EV Modeling

The integration of EVs into the grid plays a central role in this study, with a specific focus on 80% EV penetration within suburban low-voltage distribution grids. The goal of EV modeling is to assess the impacts of high EV adoption on grid stability, load management, and charging behavior, specifically within suburban environments.

Charger Types and Distribution

In the model, EVs are distributed across three types of chargers based on the availability and usage patterns in suburban areas. These categories are:

- **Home Chargers**: Chargers located at the user's residence, predominantly used for overnight charging.
- **Semi-Public Chargers**: Chargers located in shared spaces, such as workplaces or parking garages.
- **Public Chargers**: Publicly accessible chargers located in commercial areas like shopping centers and parking lots.

Suburban grids are modeled with a majority of EVs charging at home, reflecting the residential nature of the area. The breakdown of charger types used in the model is shown in Table 3.4, where 50% of EVs use home chargers, 25% use semi-public chargers, and 25% use public chargers.

Table 3.4: EV Charger Distribution in Suburban Grids

Grid Type	Home Charger (%)	Semi-Public Charger (%)	Public Charger (%)
Suburban	50	25	25

This distribution reflects the typical charging behavior of suburban EV users, who primarily charge their vehicles at home during off-peak hours.

The total number of electric vehicle chargers for a given EV penetration level can be calculated using the following equation:

$$N_{c,\text{tot}} = N_{c,\text{hh}} + N_{c,\text{sp}} + N_{c,\text{p}} \tag{3.4}$$

Here, $N_{c,\text{tot}}$ represents the total number of chargers, while $N_{c,\text{hh}}$, $N_{c,\text{sp}}$, and $N_{c,\text{p}}$ correspond to the number of home, semi-public, and public chargers, respectively.

To generate a robust dataset, a Monte Carlo simulation is employed, producing one week of charging information for 200 chargers per type. This data is obtained through random sampling of real-world measurements combined with assumptions about EV types and charging patterns. The key objective is to convert the number of EVs into the required number of chargers, ensuring sufficient coverage for the growing EV fleet.

The calculation of home chargers is shown in the following equation:

$$N_{c,\text{hh}} = ev \times N_{\text{car,hh}} \times N_{\text{hh}} \times c_e \times N_{ce,\text{hh}} \tag{3.5}$$

where:

- ev is the EV penetration rate, expressed as a percentage of the total vehicle population.
- $N_{\text{car,hh}}$ is the average number of cars per household, assumed to be 1.6 for different grid types.
- N_{hh} is the total number of households, typically derived from grid data.
- c_e represents the average number of charging events per car per week, set at 4 for all grids.
- $N_{ce,\text{hh}}$ is the percentage of home chargers, as listed in Table 3.4.

Similar calculations are applied for semi-public ($N_{ce,\text{sp}}$) and public ($N_{ce,\text{p}}$) chargers, with each type's percentage distribution defined in the same table.

In total, 10 different types of EVs were used to develop the EV fleet dataset [84]. This dataset captures the charging behavior and characteristics of a wide range of vehicles, providing critical insights into charger demand across different types of charging spaces. Key behavioral parameters include the arrival time (t_{arr}), parking duration (t_{parking}), and the distance covered (d_{cov}) by the EVs, all of which vary depending on whether it is a weekday or weekend.

3.5. Day-Ahead Market

The Day-Ahead Market prices, obtained from the ENTSO-E Transparency Platform, are integral to optimizing charging schedules for EVs and implementing V2G technologies. These prices are forecasted based on anticipated electricity supply and demand for the upcoming 24-hour period and are provided in EUR/kWh for the Dutch bidding zone BZN|10YNL.

Day-Ahead Market pricing data enables strategic charging and discharging decisions, allowing EV charging to be scheduled during off-peak times when electricity prices are lower, which reduces costs for EV owners and alleviates grid stress. In addition, this pricing data is used to optimize V2G operations, where EVs can return stored energy to the grid during high-demand periods when electricity prices peak. This bidirectional energy exchange not only enhances grid stability but also offers financial benefits to EV owners.

Two figures are used to illustrate the trends in Day-Ahead Market prices. Figure 3.8 represents price trends reflecting the winter period with increased demand due to heating requirements.

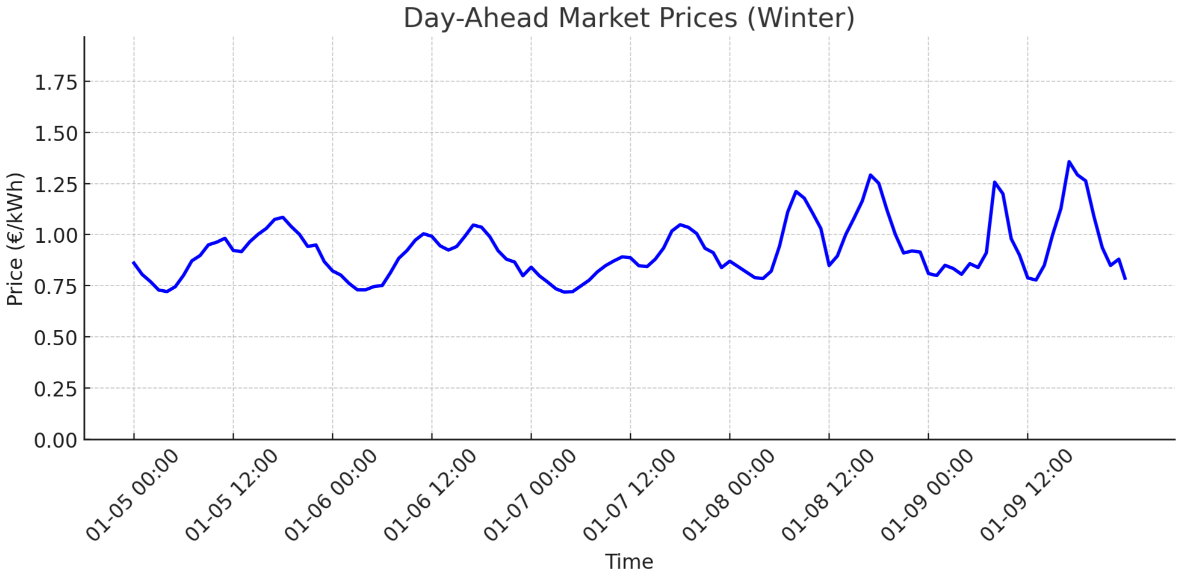

Figure 3.8: Day-Ahead Market prices for winter period

Figure 3.9 shows the fluctuations in prices, highlighting summer conditions with variable renewable energy generation.

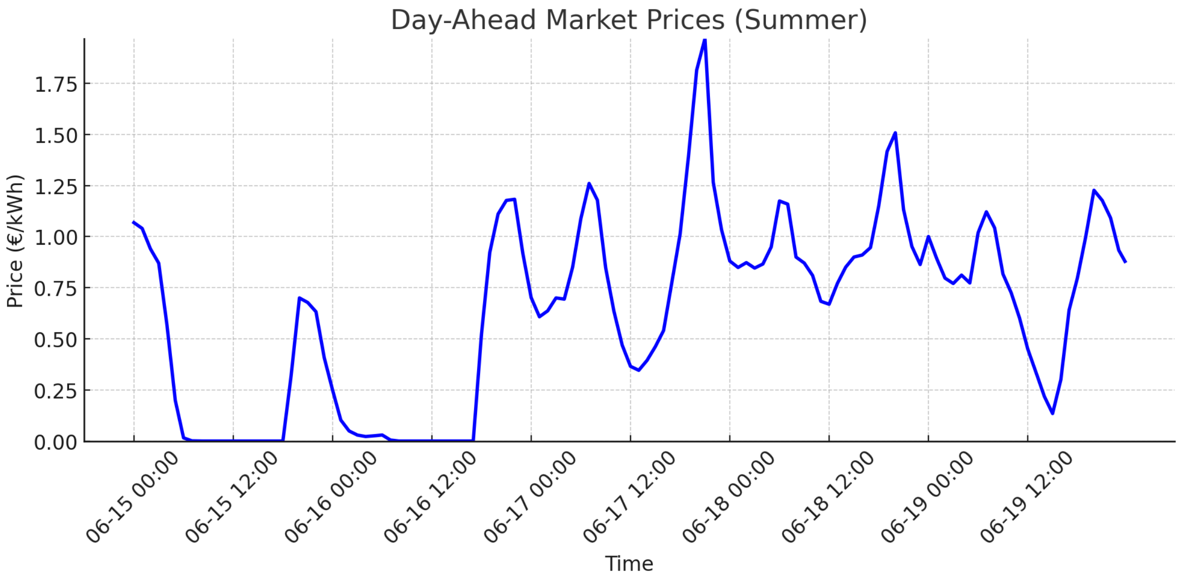

Figure 3.9: Day-Ahead Market prices for summer period

In order to simplify the problem, negative pricing has not been considered in this analysis. If negative prices occur in the Day-Ahead Market, they are limited to a minimum value of 0. This approach reduces the complexity of optimization and ensures that charging and discharging strategies are based on non-negative price values, which still aligns with the goals of minimizing costs and supporting grid stability.

4

EV scheduling

In this Chapter the optimization model developed in this thesis aims to provide efficient EV charging schedules by simulating a wide range of real-world scenarios. A total of 48 unique simulations were conducted, each integrating different combinations of parameters to reflect various EV commuting patterns, V2G participation, seasonal variations, and grid conditions.

Key Factors Considered in the Simulations

Commuting Patterns:

- Two distinct commuting patterns were modeled: one reflecting a realistic scenario where 42% of vehicles follow typical commuting schedules [85], and an extreme scenario where 100% of vehicles are assumed to be in use.
- This distinction allows for evaluation under both normal and peak usage conditions, offering insights into how varying levels of EV availability impact grid interactions and charging opportunities.

V2G Participation:

- Scenarios were designed with both 50% and 100% V2G participation.
- The 50% scenario represents a situation where half of the EV fleet is equipped and willing to participate in V2G operations, contributing power back to the grid during high-demand periods.
- The 100% scenario assumes full participation, enabling an analysis of the maximum potential impact of V2G on grid stability and peak load management.

Seasonal Variations:

- Seasonal variations were accounted for by conducting simulations in both winter and summer conditions.
- Winter typically involves higher household heating demand and reduced photovoltaic (PV) energy generation, while summer features increased cooling demand and higher PV energy output.
- Understanding how EV charging behavior adjusts to these seasonal shifts is crucial for optimizing energy usage year-round.

Each of the 48 simulations represents a unique combination of the above factors, reflecting the complex interplay between EV behavior and grid performance under different conditions. This structured approach ensures a comprehensive evaluation of optimal EV charging strategies across various real-world scenarios. Figure 4.1 below summarizes the representation of these different parameters across the 48 scenarios.

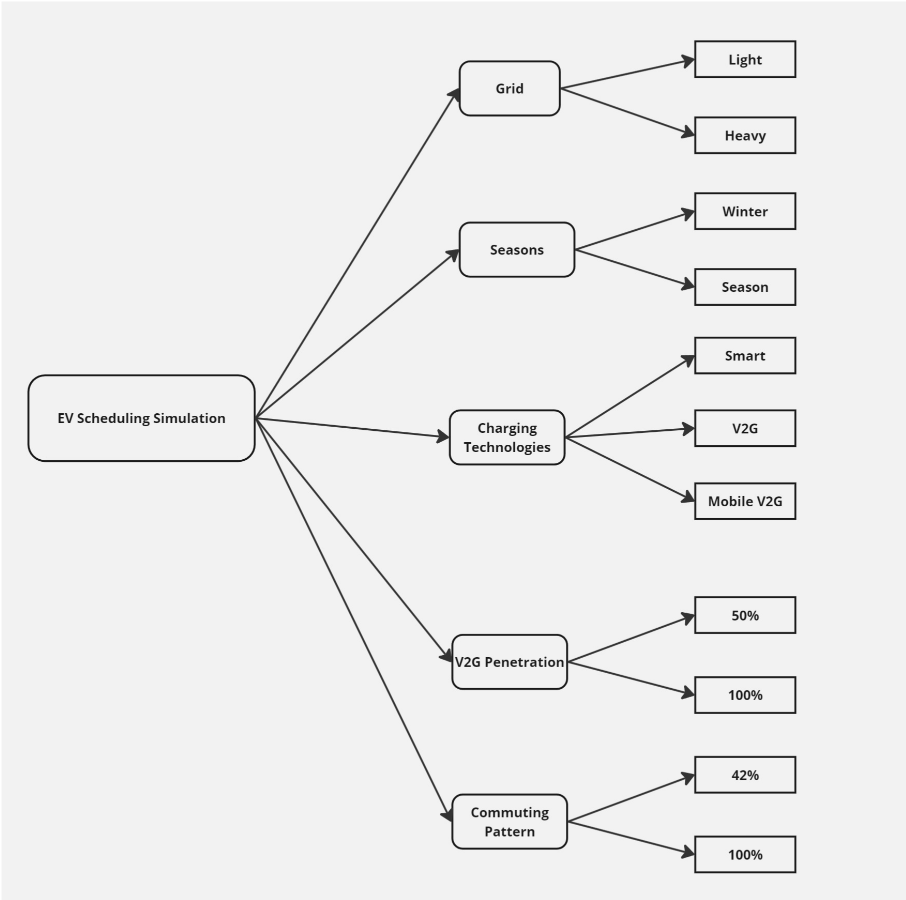

Figure 4.1: Summary of Simulations performed

4.1. Problem Formulation

The objective of the Smart Charging, V2G, and Mobile V2G models is to optimize the charging and discharging schedules of electric vehicles (EVs) at various locations while maximizing revenue through electricity arbitrage. The models differ in their handling of charging, discharging, and vehicle availability based on location (home, work, or mobile charging stations). The variables used for this are given in Table 4.1.

Objective Function
For all three models, the objective function aims to maximize net profit by buying electricity when prices are low and selling it back to the grid when prices are high:

$$\text{Total Revenue} = \sum_{t \in T} \sum_{r \in R} \left[P_{\text{sellHome}_{t,r}} \cdot \Delta t \cdot P_{\text{price}_t} \cdot E_{\text{sell}} - P_{\text{buyHome}_{t,r}} \cdot \Delta t \cdot P_{\text{price}_t} \right] \tag{4.1}$$

where:

- $P_{\text{sellHome}_{t,r}}$: Power sold to the grid at time t from location r.
- $P_{\text{buyHome}_{t,r}}$: Power bought from the grid at time t for location r.
- P_{price_t}: Price of electricity at time t.
- E_{sell}: Efficiency factor accounting for losses when selling electricity back to the grid.
- Δt: Duration of the time step.

Table 4.1: Variables used in the Smart Charging, V2G, and Mobile V2G models.

Variable	Description
$P_{\text{sellHome}}(t,r)$	Power sold to the grid at time t from location r.
$P_{\text{buyHome}}(t,r)$	Power bought from the grid at time t for location r.
$P_{\text{price}}(t)$	Price of electricity at time t.
E_{sell}	Efficiency factor accounting for losses when selling electricity back to the grid.
Δt	Duration of the time step.
$P_{\text{chEV}_{t,r}}$	Power used to charge the EVs at location r at time t.
$P_{\text{dchEV}_{t,r}}$	Power discharged from the EVs at location r at time t.
$\text{PV}_{t,r}$	Power generated by photovoltaic systems at location r at time t.
$L_{t,r}$	Residential load at location r at time t.
$P_{\text{maxPeakHome}_r}$	Maximum allowable peak power for location r.
P_{grid}	Maximum grid capacity for selling electricity back to the grid.
$P_{\text{ch}_{t,k}}$	Maximum charging power for EV k at time t.
$P_{\text{dch}_{t,k}}$	Maximum discharging power for EV k at time t.
$A_{t,k}$	Availability of EV k at time t. $A = 1$ (home), $A = 2$ (work/mobile), $A = 0$ (transit).
$\text{SOC}_{t,k}$	State of charge of EV k at time t.
$\text{TE}_{t,k}$	Trip energy consumed by EV k at time t.
BatCap_k	Battery capacity of EV k.
η_{chEV}	Charging efficiency of the EV battery.
η_{dchEV}	Discharging efficiency of the EV battery.

Shared Constraints
The following constraints apply to Smart Charging, V2G, and Mobile V2G:

1. **Power Balance**
This constraint ensures that the power balance at each residential location holds, accounting for energy bought from and sold to the grid, EV charging/discharging, residential loads, and photovoltaic (PV) generation:

$$P_{t,r}^{\text{buyHome}} - P_{\text{sellHome}_{t,r}} = P_{\text{chEV}_{t,r}} - P_{\text{dchEV}_{t,r}} - \mathrm{P}_{PV\,t,r} + L_{t,r} \tag{4.2}$$

where:

- $P_{\text{buyHome}_{t,r}}$: Power purchased from the grid at location r.
- $P_{\text{sellHome}_{t,r}}$: Power sold to the grid from location r.
- $P_{\text{chEV}_{t,r}}$: Power used to charge the EVs at location r.
- $P_{\text{dchEV}_{t,r}}$: Power discharged from the EVs at location r.
- $\mathrm{P}_{PV\,t,r}$: Power generated by photovoltaic systems at location r.
- $L_{t,r}$: Residential load at location r at time t.

2. **Maximum Power Constraints**
To prevent grid overloading, the power bought or sold at each location must remain below the grid capacity:

$$P_{\text{buyHome}_{t,r}} \le P_{\text{grid}_r} \tag{4.3}$$

$$P_{\text{sellHome}_{t,r}} \le P_{\text{grid}} \tag{4.4}$$

where:

- P_{grid}: Maximum grid capacity for selling electricity back.

Charging and Discharging Constraints
The availability of EVs at home or work impacts their charging and discharging capabilities. The availability function $A_{t,k}$ takes different values depending on whether the vehicle is at home, work, or in transit:

- $A_{t,k} = 1$: EV is connected to the grid and available for charging or discharging.
- $A_{t,k} = 2$: EV is connected at a work or mobile location and only available for partial charging.
- $A_{t,k} = 0$: EV is in transit and not available for charging or discharging.

1. **Smart Charging**
In the Smart Charging model, EVs are only allowed to charge but not discharge. Charging constraints ensure that an EV can only charge if it is connected:

$$P_{\text{chEV}_{t,k}} \leq P_{\text{ch}_{t,k}} \cdot A_{t,k} \quad \text{if } A_{t,k} = 1 \tag{4.5}$$

$$P_{\text{dchEV}_{t,k}} = 0 \quad \text{if } A_{t,k} = 1 \text{ or } A_{t,k} = 2 \tag{4.6}$$

2. **Vehicle-to-Grid (V2G)**
In the V2G model, EVs can charge and discharge, providing flexibility to sell electricity back to the grid when prices are high:

$$P_{\text{chEV}_{t,k}} \leq P_{\text{ch}_{t,k}} \cdot A_{t,k} \quad \text{if } A_{t,k} = 1 \tag{4.7}$$

$$P_{\text{dchEV}_{t,k}} \leq P_{\text{dch}_{t,k}} \cdot A_{t,k} \quad \text{if } A_{t,k} = 1 \tag{4.8}$$

3. **Mobile Vehicle-to-Grid (V2G+)**
In the Mobile V2G model, EVs can charge or discharge not only at home and work locations but also at mobile charging stations:

$$P_{\text{chEV}_{t,k}} \leq P_{\text{ch}_{t,k}} \cdot A_{t,k} \quad \text{if } A_{t,k} = 1 \text{ or } 2 \tag{4.9}$$

$$P_{\text{dchEV}_{t,k}} \leq P_{\text{dch}_{t,k}} \cdot A_{t,k} \quad \text{if } A_{t,k} = 1 \tag{4.10}$$

State of Charge (SOC) Dynamics
1. **Smart Charging Model**
In Smart Charging, the EV is only allowed to charge (no discharging). The SOC equation accounts for energy consumed during trips and the power gained from charging:

$$\text{SOC}_{t,k} = \begin{cases} \text{SOC}_{t-1,k} - \frac{\text{TE}_{t,k}}{\text{BatCap}_k} & \text{if in transit (i.e., } A_{t,k} = 0) \\ \text{SOC}_{t-1,k} + \frac{P_{\text{chEV}_{t,k}} \cdot \eta_{\text{chEV}} \cdot \Delta t}{\text{BatCap}_k} & \text{if charging, } A_{t,k} = 1 \text{ or } 2 \end{cases} \tag{4.11}$$

2. **Vehicle-to-Grid (V2G) Model**
In the V2G model, EVs can both charge and discharge based on grid requirements:

$$\text{SOC}_{t,k} = \begin{cases} \text{SOC}_{t-1,k} - \frac{\text{TE}_{t,k}}{\text{BatCap}_k} & \text{if in transit (i.e., } A_{t,k} = 0) \\ \text{SOC}_{t-1,k} + \frac{P_{\text{chEV}_{t,k}} \cdot \eta_{\text{chEV}} \cdot \Delta t}{\text{BatCap}_k} & \text{if charging, } A_{t,k} = 1 \\ \text{SOC}_{t-1,k} - \frac{P_{\text{dchEV}_{t,k}} \cdot \Delta t}{\eta_{\text{dchEV}} \cdot \text{BatCap}_k} & \text{if discharging, } A_{t,k} = 1 \end{cases} \tag{4.12}$$

3. **Mobile Vehicle-to-Grid (Mobile V2G) Model**
In Mobile V2G, EVs can charge and discharge at home, work, and mobile charging stations:

$$\mathrm{SOC}_{t,k} = \begin{cases} \mathrm{SOC}_{t-1,k} - \frac{\mathrm{TE}_{t,k}}{\mathrm{BatCap}_k} & \text{if in transit (i.e., } A_{t,k} = 0) \\ \mathrm{SOC}_{t-1,k} + \frac{P_{\mathrm{chEV}_{t,k}} \cdot \eta_{\mathrm{chEV}} \cdot \Delta t}{\mathrm{BatCap}_k} & \text{if charging, } A_{t,k} = 1 \text{ or } 2 \\ \mathrm{SOC}_{t-1,k} - \frac{P_{\mathrm{dchEV}_{t,k}} \cdot \Delta t}{\eta_{\mathrm{dchEV}} \cdot \mathrm{BatCap}_k} & \text{if discharging, } A_{t,k} = 1 \end{cases} \quad (4.13)$$

The SOC of the EV battery must remain within certain limits to ensure proper operation:

$$\mathrm{SOC}_{t,k} \geq 0.2, \quad \mathrm{SOC}_{t,k} \leq 0.8 \quad (4.14)$$

Equations 4.1 to 4.14 define the key constraints and objectives in the Smart Charging, V2G, and Mobile V2G models.

5

Results and Analysis

5.1. EV scheduling using Python

The Results obtained from EV scheduling is mentioned in this section where in we have plotted required charging power (for all EVs)comparing it across different v2g participation and commutation pattern.

5.1.1. Smart Charging

In scenarios where smart charging is used. Figures 5.1 and 5.2 illustrate the charging power demanded from the grid under light and heavy grid conditions, respectively.

In the light suburban grid scenario (Figure 5.1), the interaction between EVs and the grid is influenced by both commuting behavior and seasonal variations. When 42% of vehicles are commuting, the interaction with the grid remains moderate, with less pronounced peaks compared to the scenario where 100% of vehicles are commuting. Fewer vehicles in use result in lower and more stable power demands, with minimal fluctuations during the 42% commuting scenario.

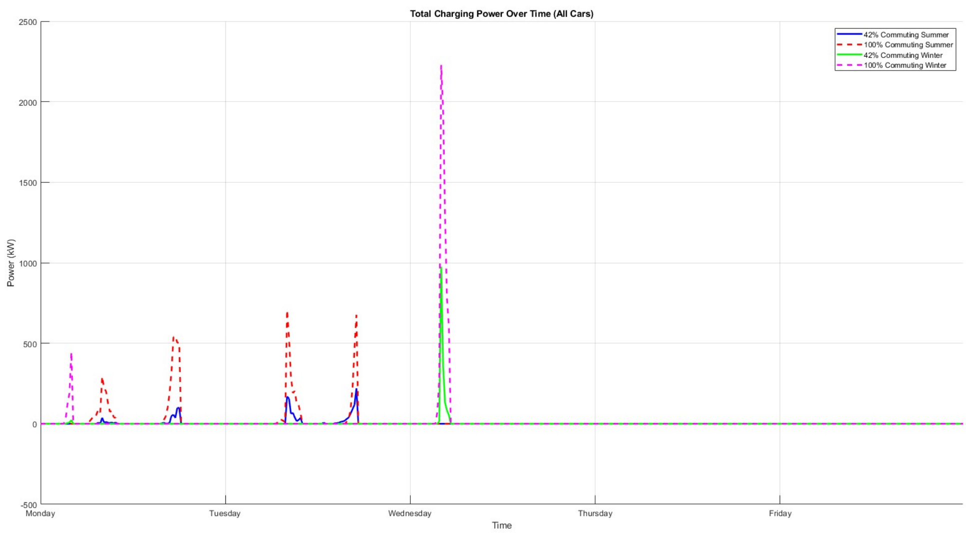

Figure 5.1: Charging power demanded from the grid in the light suburban grid scenario.

However, when 100% of vehicles are commuting, the demand on the grid increases, particularly after daily commuting, resulting in more pronounced peaks.This is because the energy required to carry out the trip increases (T.E increases). Due to this when compared with the prices we see difference in the charging patterns for summers and winters.

Seasonal variations also play a significant role. In summer, higher solar generation allows for power to be sold back to the grid, reducing net demand. Users are more likely to charge their vehicles during off-peak hours when prices are lower. In contrast, during winter, the grid faces a substantial increase in demand, with peaks reaching up to 2200 kW at midnight due to lower prices.Hence we see a single peak when the prices are the lowest.

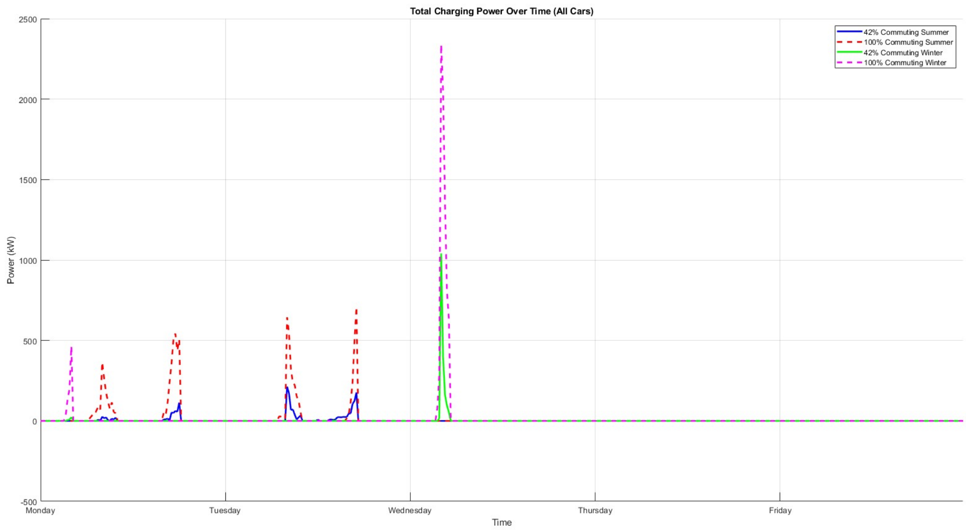

Figure 5.2: The charging power demanded from the grid in the heavy suburban grid scenario.

The heavy suburban grid (Figure 5.2) shows similar trends but with greater capacity to handle the increased load. Even though the heavy grid can accommodate larger loads, peak commuting times still present challenges, particularly in winter. The contrast between the stable periods during 42% commuting and the stress during 100% commuting is significant, especially in colder months.

5.1.2. Vehicle-to-Grid (V2G)

In the light suburban grid scenario with 42% commuting, depicted in Figure 5.3, the impact of V2G participation is evident. At 50% V2G participation, the grid experiences moderate peaks, with charging power reaching around 1500 kW. As V2G participation increases to 100%, these peaks become more pronounced, especially during synchronized discharging periods when EVs discharge simultaneously to capitalize on high electricity prices.

In the 100% commuting scenario (Figure 5.4), the grid faces greater challenges. With full commuting, vehicle availability is more evenly distributed, leading to substantial discharging peaks of up to 4500 kW during peak times. Correspondingly, the charging power demand rises to around 2000 kW at midnight. This synchronized behavior significantly amplifies the grid's load, underscoring the critical role of V2G participation in maintaining grid stability under full commuting conditions.

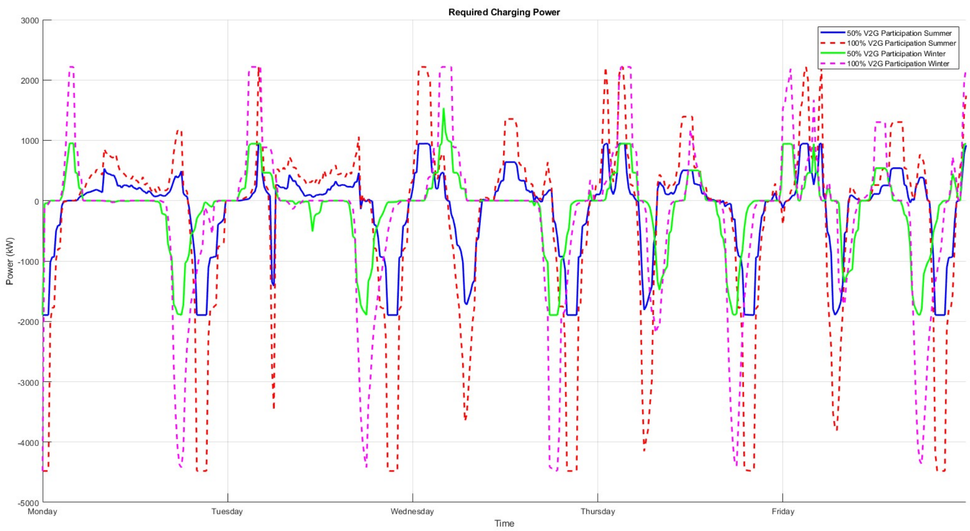

Figure 5.3: Charging power demand in the light suburban grid scenario with 42% commuting.

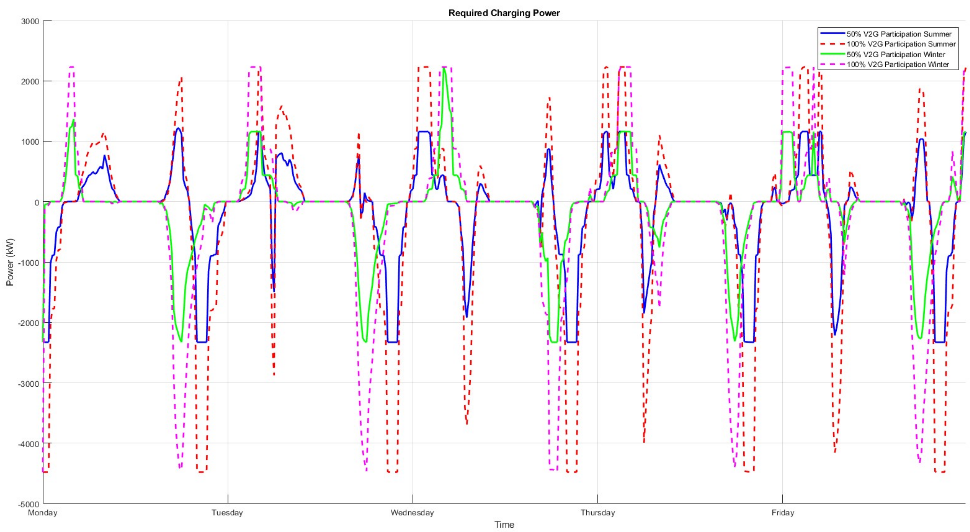

Figure 5.4: Charging power demand in the light suburban grid scenario with 100% commuting.

From the results of heavy suburban grid shown in Figures 5.5 and 5.6, we observe that the fluctuations are more effectively managed, due to the grid's higher capacity. While the peaks in both commuting scenarios are similar to those in the light grid, the heavy grid's robustness allows it to absorb these fluctuations without significant stress.

5.1.3. Mobile Vehicle-to-Grid (V2G+)

The introduction of mobile V2G technology in the light suburban grid, which allows vehicles to charge outside of home, presents notable differences. In the 42% commuting scenario (Figure 5.7), mobile V2G significantly reduces the required charging power compared to traditional V2G, with peak demand

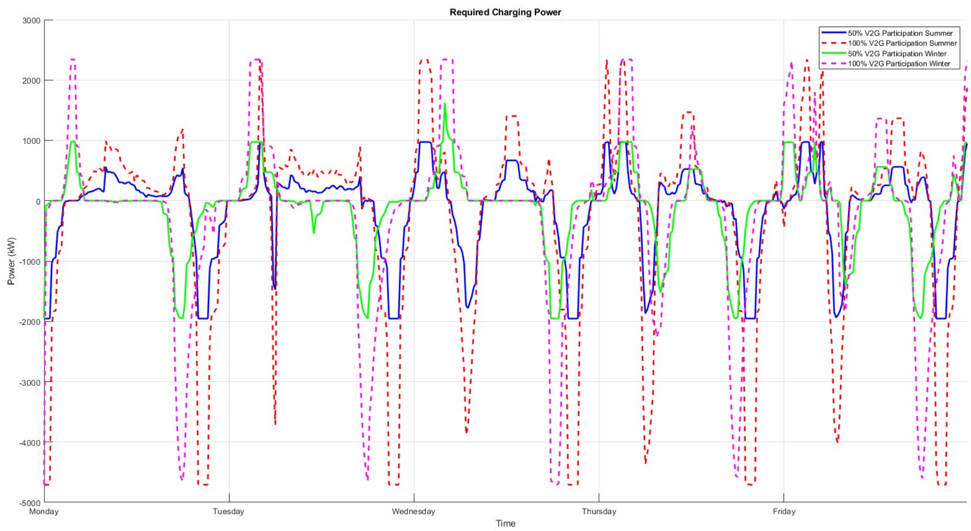

Figure 5.5: Charging power demand in the heavy suburban grid scenario with 42% commuting.

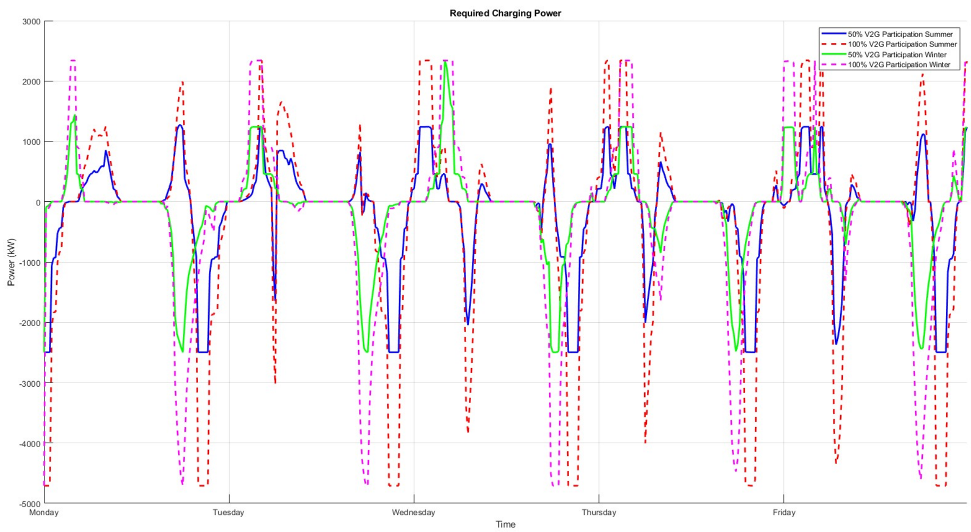

Figure 5.6: Charging power demand in the heavy suburban grid scenario with 100% commuting.

around 1000 kW. This results in a shorter and more distributed peak, enhancing the grid's ability to manage the load.

Under the 100% commuting scenario (Figure 5.8), the differences between mobile V2G and traditional V2G become more pronounced. The peak charging power required by the grid rises to around 2200 kW, but this is still lower than in a non-mobile V2G scenario. The ability to charge at various locations reduces the strain on the grid during peak times.

In the heavy suburban grid, mobile V2G demonstrates its advantages, particularly in high-commuting scenarios. For the 42% commuting scenario (Figure 5.9), mobile V2G results in a reduced peak charging demand compared to traditional V2G, with the grid's required charging power peaking at around 1500 kW.

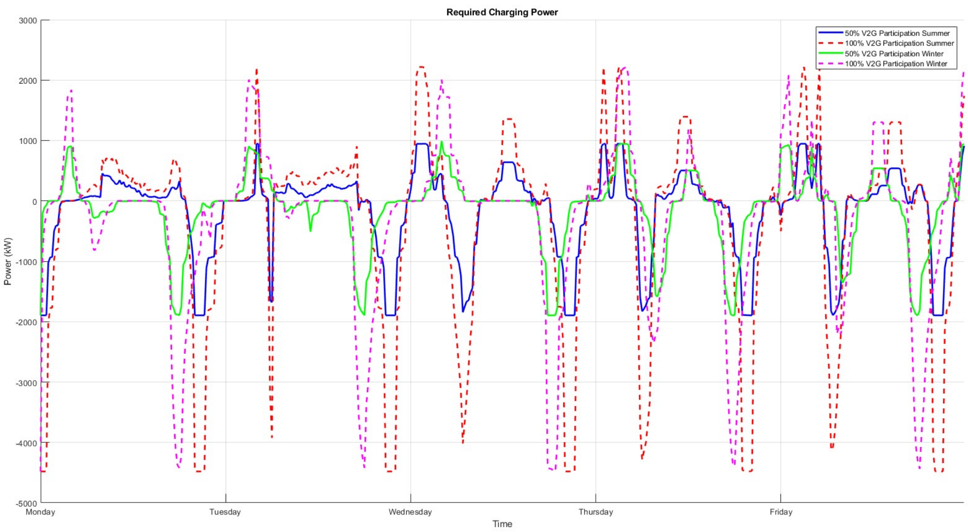

Figure 5.7: Charging power demand in the light suburban grid scenario with 42% commuting.

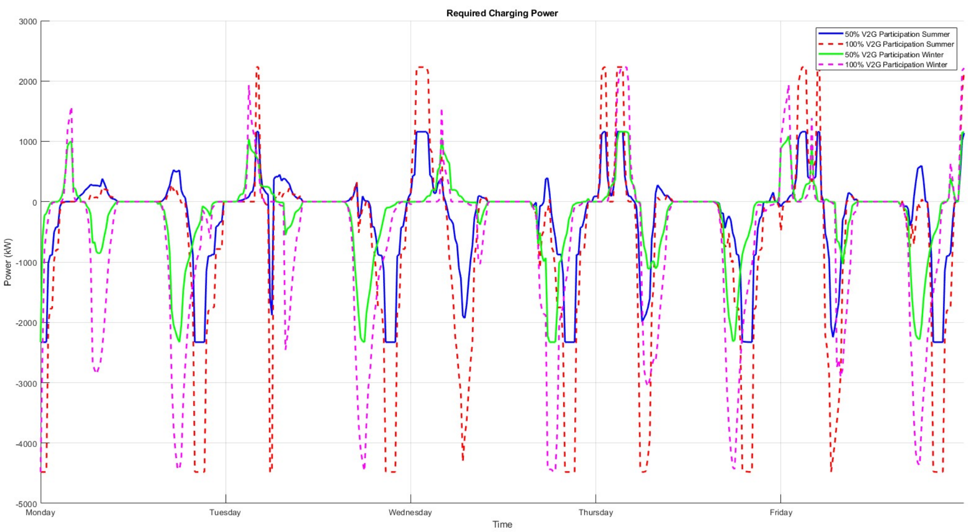

Figure 5.8: Charging power demand in the light suburban grid scenario with 100% commuting.

When commuting increases to 100% (Figure 5.10), the grid experiences a peak charging demand of around 2200 kW, which is again lower than in a non-mobile V2G setup. The peak discharge power reaches up to 4500 kW, reflecting the high participation rate and the grid's reliance on mobile V2G during peak periods.

Figures 5.7 through 5.10 highlight the benefits of mobile V2G technology in reducing peak charging demands while still enabling significant energy contributions during peak discharge periods. The flexibility offered by mobile V2G allows for a more distributed and manageable load on the grid, especially in high-commuting scenarios.

The summary of findings, including the impact of commuting patterns, seasonal variations, and V2G participation on grid stability and demand, is presented in Table 5.1. This table highlights the key differences across smart charging, traditional V2G, and mobile V2G scenarios.

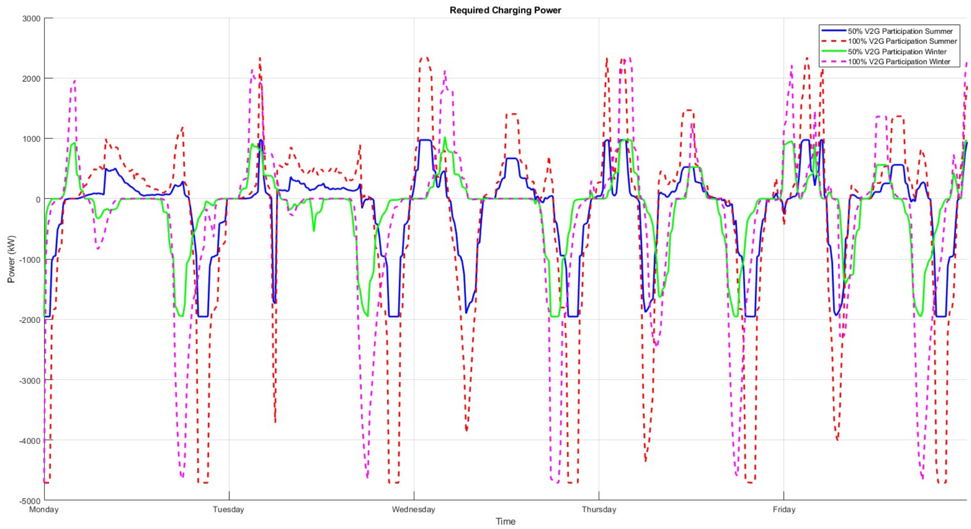

Figure 5.9: Charging power demand in the heavy suburban grid scenario with 42% commuting.

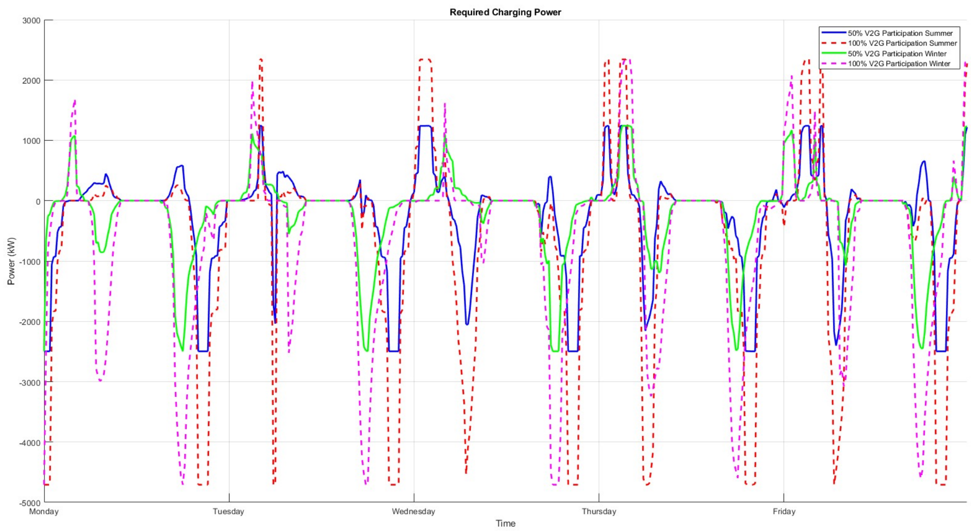

Figure 5.10: Charging power demand in the heavy suburban grid scenario with 100% commuting.

5.2. Impact of Charging Technologies on grid

To comprehensively assess the impact of high EV penetration on the grid, we will analyze key components, including lines, nodes, and transformers. A central metric in our analysis is the *Duration Magnitude Product* (DMP), which provides a clear indication of grid stress by combining both the severity and duration of violations. Specifically, DMP is calculated by determining the percentage by which a parameter exceeds its limit, then multiplying this by the duration of the violation.

For example, if a transformer experiences a loading violation of 115%, the DMP would be calculated as:

$$(115 - 100) \times \text{duration}$$

meaning the excess 15% is multiplied by the duration of time the violation persists.

Table 5.1: Summary of Results

Factor	Smart Charging	Traditional V2G	Mobile V2G
Commuting Pattern	- 42% commuting results in lower grid interaction with moderate peaks. - 100% commuting increases demand, with peak loads up to 2200 kW in winter for light grids.	- 42% commuting shows moderate discharging peaks (up to 1800 kW for light grids). - 100% commuting causes significant grid stress, with discharging peaks reaching 4500 kW in light grids.	- 42% commuting reduces peak charging demands to around 1000 kW. - 100% commuting shows reduced peaks compared to traditional V2G, with charging demands around 2200 kW and discharging peaks up to 4200 kW.
Seasonal Variation	- Summer reduces grid demand due to increased solar generation. - Winter increases demand significantly, especially in mid-week (2200 kW peak for light grids).	- Summer allows for more energy selling back to the grid. - Winter causes higher peaks in discharging (4500 kW) and charging (2000 kW) due to heating and EV needs.	- Summer sees reduced charging demands due to distributed charging. - Winter shows increased demands, but peaks remain lower than traditional V2G (e.g., 2200 kW peak charging in heavy grids).
V2G Participation	- N/A (discharge not utilized in smart charging).	- 50% participation: moderate grid impact. - 100% participation: high stress on grid, especially under full commuting (up to 4500 kW discharge).	- 50% participation: manageable peaks, better load distribution. - 100% participation: lower peaks than traditional V2G, indicating more efficient grid management (e.g., 2200 kW peak charging for heavy grids).

By summing the DMP values across all components for each scenario or case, we gain a comprehensive view of the overall grid impact under varying conditions.This visualizations will help highlight when and where the grid is most stressed.

5.2.1. Impact due to commutation pattern

Transformer

Figure 5.11 illustrates the DMP values for different commuting scenarios in a light suburban grid, where the blue bars represent 42% commuting and the red bars represent 100% commuting. In the case of smart charging, as the commuting percentage increases, the energy demand rises sharply. Since smart charging involves only charging without any discharge of power back to the grid, the entire energy demand falls on the transformer, resulting in higher DMP values for 100% commuting. This increased energy demand directly translates to higher stress on the transformer, as there is no discharge mechanism to alleviate the load, leading to more significant Overloading.

However, the introduction of V2G technology changes this dynamic. In V2G, vehicles not only charge but also discharge power back to the grid, thereby reducing the net power demand on the transformer. As shown in Figure 5.11, the increase in the DMP when compare to 100% is not that significant. This is not just because of the discharging but the power is constantly being exchanged with the external grid. While this reduces the net energy demand, it also introduces sharp and higher spikes in transformer stress due to the continuous back-and-forth flow of power. These spikes are a result of vehicles

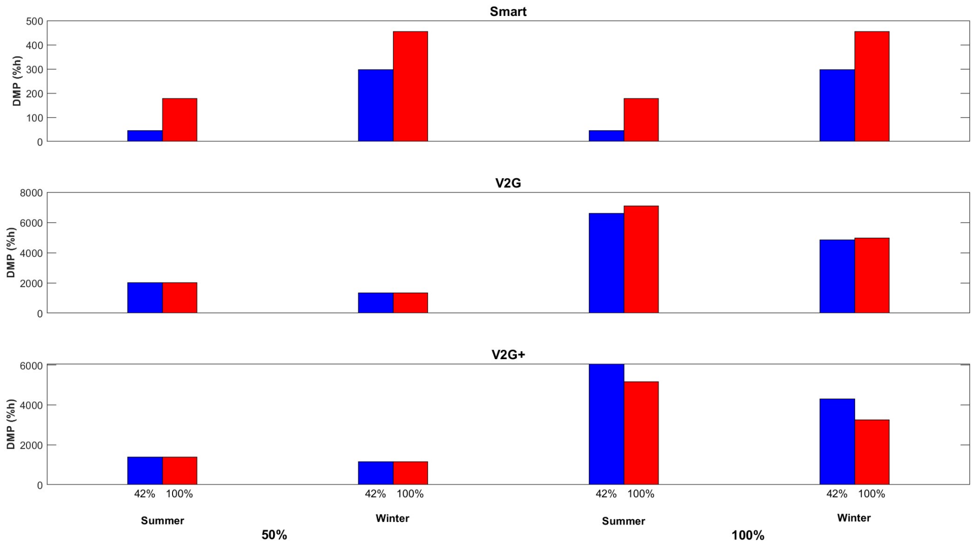

Figure 5.11: DMP values for different commuting scenarios in a light suburban grid.

frequently discharging into the grid, which causes the transformer to cycle between charging and discharging states more rapidly. This creates additional stress points for the transformer, especially in mobile V2G scenarios where power exchange is even more dynamic. In mobile V2G, we see higher peaks for 42% commuting scenrios is because the vehicles are able to bring back energy externally to the grid .

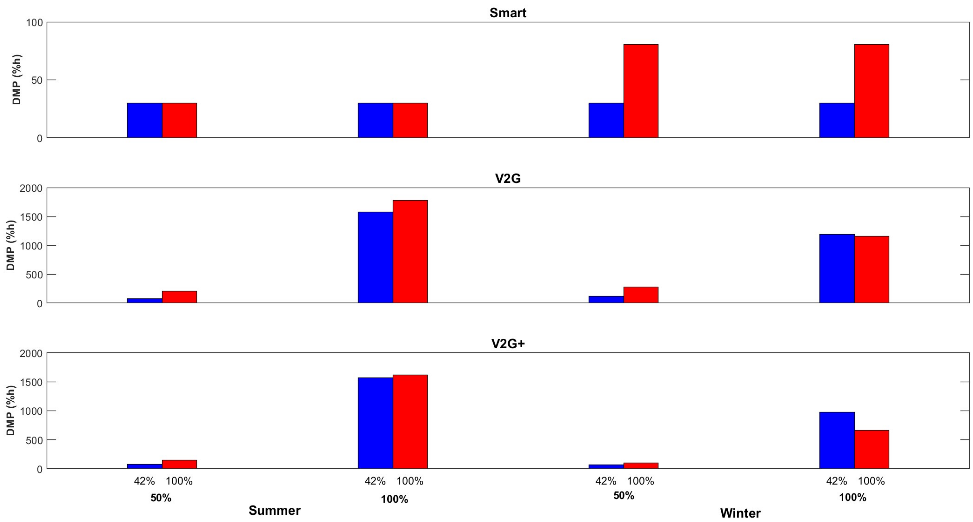

Figure 5.12: DMP values in a heavy suburban grid with 100% V2G participation.

Figure 5.12 further illustrates these trends in a heavy suburban grid. As seen with the light suburban grid, smart charging in the heavy suburban grid leads to high DMP values, particularly with 100% commuting, as the transformer is required to meet the increased energy demand without any discharge relief. However, the introduction of V2G and mobile V2G technologies significantly alters the DMP values.

The DMP values, as observed in both light and heavy suburban grids, are heavily influenced by commuting patterns and the charging technology in use. In smart charging, the lack of discharging capabilities results in higher DMP values as commuting increases due to the higher energy demand. In

V2G and mobile V2G systems, the transformer stress is mitigated by the vehicles' ability to discharge, but sharp spikes in DMP values are introduced due to the constant power exchange with the grid. As shown in Figure 5.12 and supported by the data in the appendix, this power exchange plays a critical role in determining transformer stress, particularly under high commuting and high V2G participation scenarios.

Line

Figure 5.13 illustrates that in a light suburban grid under smart charging conditions, an increase in commuting leads to higher DMP values, which mirrors the rise in line loading of the grid. This occurs because the increased energy demand for charging EVs during peak commuting times has a significant impact on the grid. The greater the number of commuters, the more energy is drawn from the grid, which stresses the transformers and the overall grid infrastructure.

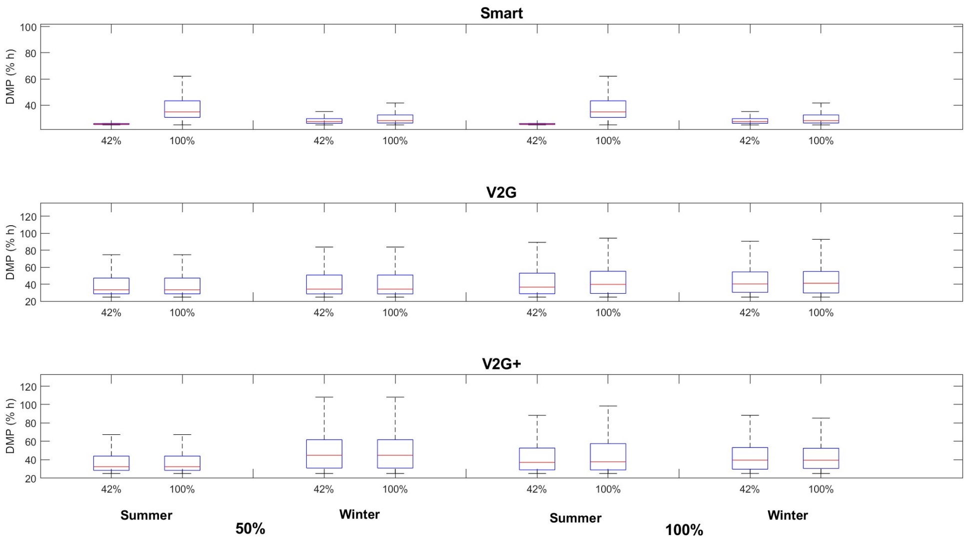

Figure 5.13: DMP values of Line for different commuting scenarios in a light suburban grid.

However, when V2G technology is introduced, the relationship between commuting patterns and line loading becomes more complex. The distinction between different commuting levels begins to blur due to the discharging capability of the EVs. Even though the energy demand increases due to more trips and commuting, the overall impact on the grid is mitigated by the ability of the EVs to discharge power back into the system. As the availability of EVs in the grid increases, their participation in both charging and discharging becomes more frequent. However, the key factor driving the increased line loading is not simply the availability of EVs but rather the charging and discharging behavior of vehicles located farther from the grid, such as car 31. These vehicles, positioned at the periphery of the network, experience lower nodal voltages, which leads to higher current demand during charging. The lower the nodal voltage, the more current is required, resulting in increased line loading.Where the charging and discharging of distant vehicles cause significant current surges due to their greater distance from the transformer. Therefore, while V2G helps balance energy demand, it also contributes to increased line loading, especially when vehicles located far from the grid are involved. This highlights the need for grid reinforcement, particularly in areas with long distribution lines, to mitigate the effects of low nodal voltages and high current demands.

This effect is clearly seen in the winter scenario with 50% V2G participation, where 100% commuting results in equal higher magintude DMP values than the 42% commuting scenario. The discharge from EVs helps to reduce the overall load on the grid, meaning that higher commuting does not necessarily lead to higher DMP values when V2G is involved. A similar trend is observed in mobile V2G systems, where 50% V2G participation in summer also leads to lower DMP values despite the higher commuting levels. This is due to the extra energy brought externally from grid.

In Figure 5.14, a similar trend is observed in the heavy suburban grid. However, the grid in this scenario is relatively more stable, and the line overloading primarily occurs when there is significant V2G participation, such as with 50% V2G in summer. In these cases, the energy demand from EVs is lower overall due to reduced charging requirements, especially in relation to the lower load demand during the summer season. As a result, the DMP values reflect the grid's ability to handle higher levels of commuting when discharging technology is in use.

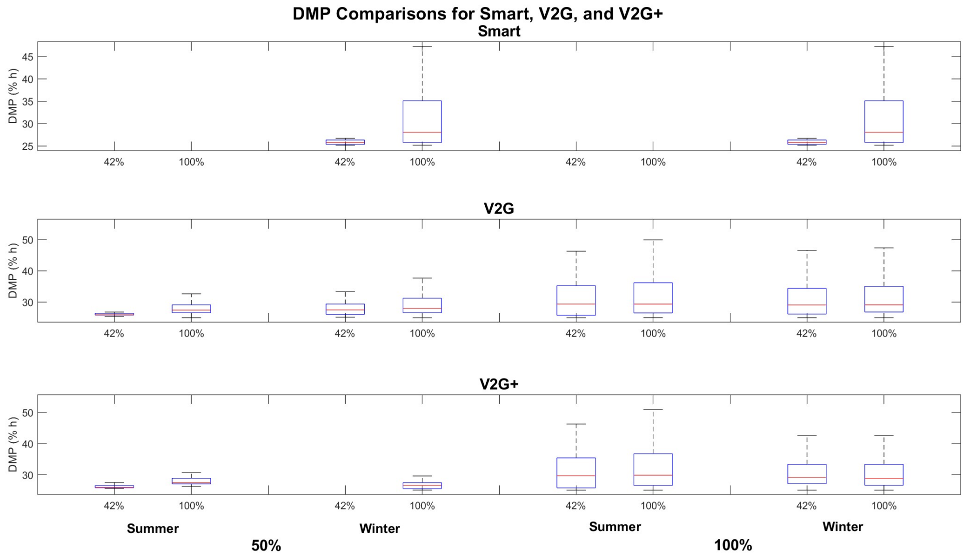

Figure 5.14: DMP values of Line for different commuting scenarios in a heavy suburban grid.

This suggests that the line loading is not solely dependent on commuting patterns but is also significantly influenced by the availability of vehicles for discharging and the grid's overall load requirements. The grid becomes less sensitive to commuting fluctuations when V2G or mobile V2G systems are in place, as the discharging from EVs helps to alleviate some of the stress caused by increased energy demand from commuting. Therefore, the line loading, when compared solely to commuting, becomes relatively indifferent in V2G systems, as the discharge capabilities and energy management through vehicle-grid interaction play a more dominant role in managing grid stress.

Node

Figure 5.15 illustrates how smart charging impacts node voltages in a low-voltage grid under varying commuting patterns. As the commuting pattern increases from 42% to 100%, there is a clear rise in undervoltage occurrences. This increase is attributed to the heightened energy demand required for commuting, which intensifies the load on the grid during peak hours. The median undervoltage values also escalate, indicating a general decline in voltage levels across the network due to the additional charging requirements of a larger number of EVs.

In the V2G scenario, similar findings to smart charging are observed, with undervoltage levels rising as the commuting pattern increases. However, a distinctive observation in V2G is the occurrence of overvoltages when EVs discharge energy back to the grid. This suggests that the energy supplied by the EVs is significant compared to the grid's demand, leading to voltage levels exceeding acceptable limits. Despite this, the median undervoltage values remain relatively constant, indicating that while overvoltages become more prominent with increased V2G participation, undervoltages do not worsen significantly beyond a certain threshold.

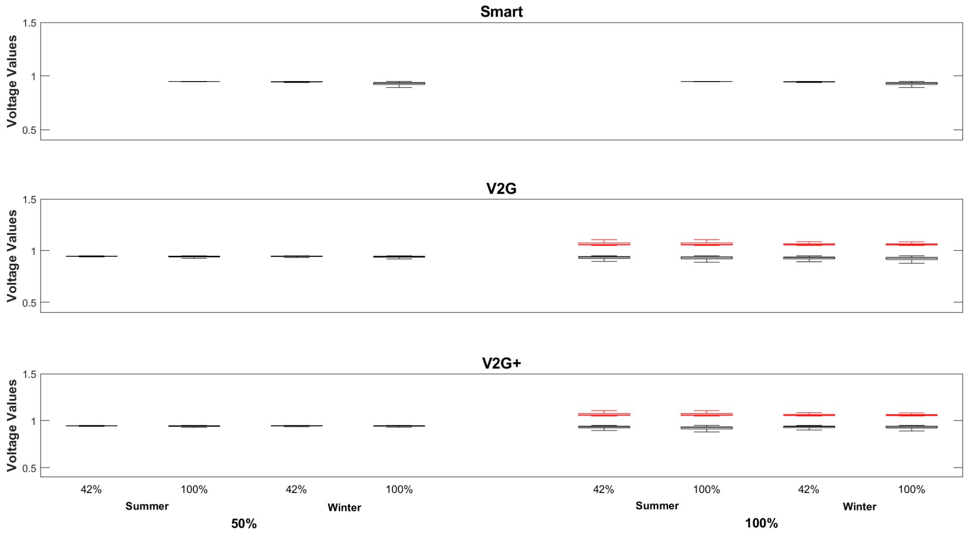

Figure 5.15: Node Voltages in heavy suburban grid different commuting patterns

A similar pattern is seen in the combined V2G and mobile V2G scenarios. The simultaneous charging and discharging activities contribute to both undervoltage and overvoltage issues, highlighting the importance of careful management of V2G operations to maintain voltage stability in the grid.

Figure 5.16 presents the impact of node voltages in a light suburban grid. The results align with those of the heavy grid, where heavy commuting leads to undervoltage problems under smart charging strategies. The increased number of EVs charging simultaneously imposes a substantial load on the grid, causing voltage drops below acceptable levels.

In the V2G and mobile V2G scenarios depicted in Figure 5.16, a similar trend of overvoltages emerges due to EV discharging. Interestingly, an anomaly is observed during the winter season with 100% commuting, where the variability in electricity prices results in less significant undervoltage and overvoltage issues compared to the 42% commuting pattern. This trend is caused by the reduced availability of EVs for discharging and the influence of price signals, which lead to fewer charging and discharging cycles. As a result, the grid experiences less stress in terms of voltage fluctuations during this period.

Overall, the analysis shows that in low-voltage grids, the charging and discharging behaviors of EVs significantly affect node voltage levels. Increased commuting patterns exacerbate undervoltage issues under smart charging due to higher energy demand. In V2G and mobile V2G scenarios, while undervoltages remain relatively stable, overvoltages become more frequent as EVs discharge energy back to the grid.

5.2.2. Impact due to V2G participation

Transformer

The integration of V2G technology places an increasing operational burden on transformers, particularly as participation rises from 50% to 100%. In light suburban grids, this effect is clearly visible. As seen in Figure 5.17, during summer with 42% commuting, the DMP for 50% V2G participation sits at approximately 1,500%h. However, when V2G participation reaches 100%, the DMP climbs sharply to around 6,000%h, representing a fourfold increase. This indicates that the increasing scale of V2G participation places significant stress on transformers, pushing them toward operational limits as the bidirectional flow of energy intensifies.

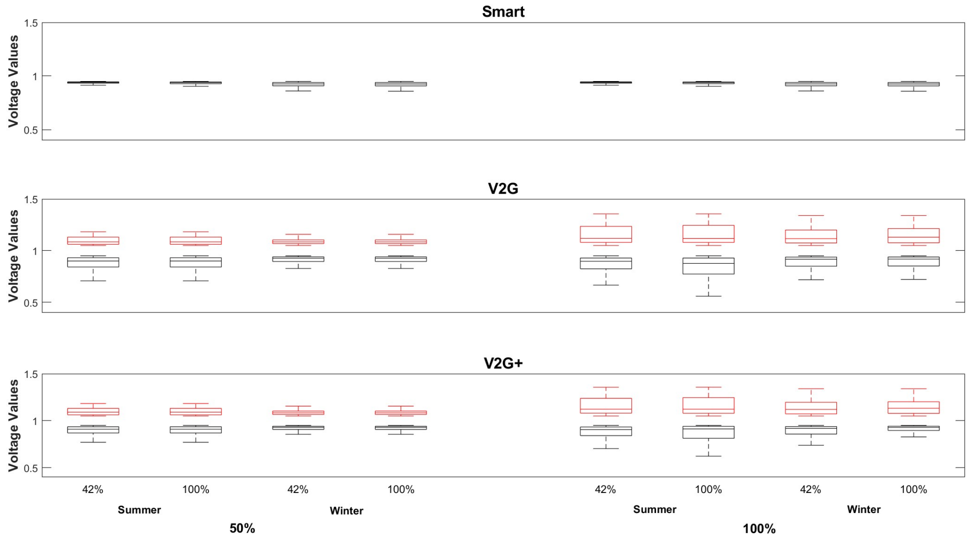

Figure 5.16: Node Voltages in Light suburban grid different commuting patterns.

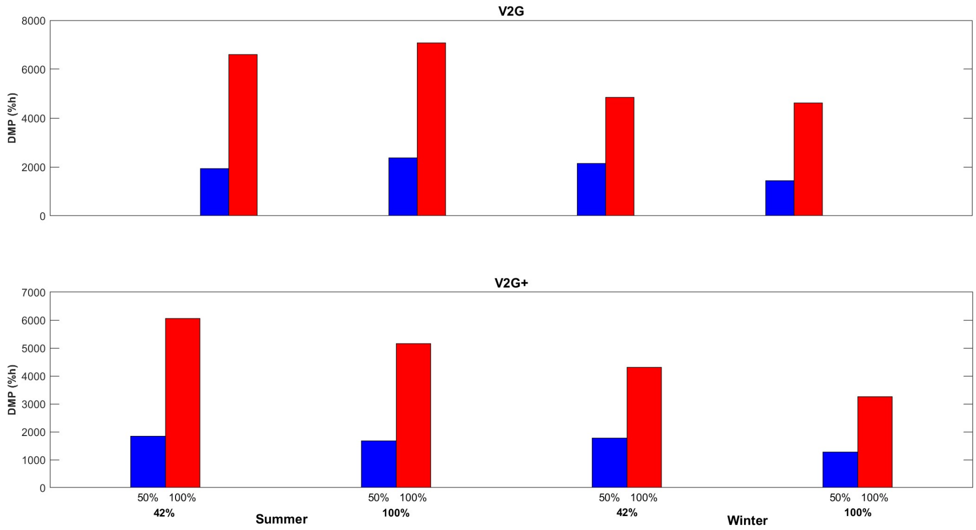

Figure 5.17: DMP values of transformer for different V2G participation level in a light suburban grid.

The stress is even more pronounced in heavy suburban grids. Here, the DMP values are significantly higher, reflecting the amplified energy demands of these regions. As seen in Figure 5.18, the DMP remains relatively low at around 200%h under 50% V2G participation during summer with 42% commuting. However, once V2G participation reaches 100%, the DMP surges to approximately 1,600%h, representing an eightfold increase. The same pattern holds in winter, with the DMP jumping from 250%h at 50% V2G to 1,500%h at 100%. These results highlight the severe vulnerability of transformers in heavy suburban grids, where increased V2G participation puts an even greater strain on infrastructure.

The key driver behind this increase in transformer stress is the power exchange between electric vehicles and the external grid. V2G technology allows electric vehicles to not only consume power from the grid but also discharge power back into it. This bidirectional energy flow, particularly during charging and discharging cycles, significantly amplifies the load on transformers, accelerating Overloading. As V2G participation rises, the frequency and volume of these energy exchanges increase, which contributes to the dramatic rise in DMP values observed across both light and heavy suburban grids.

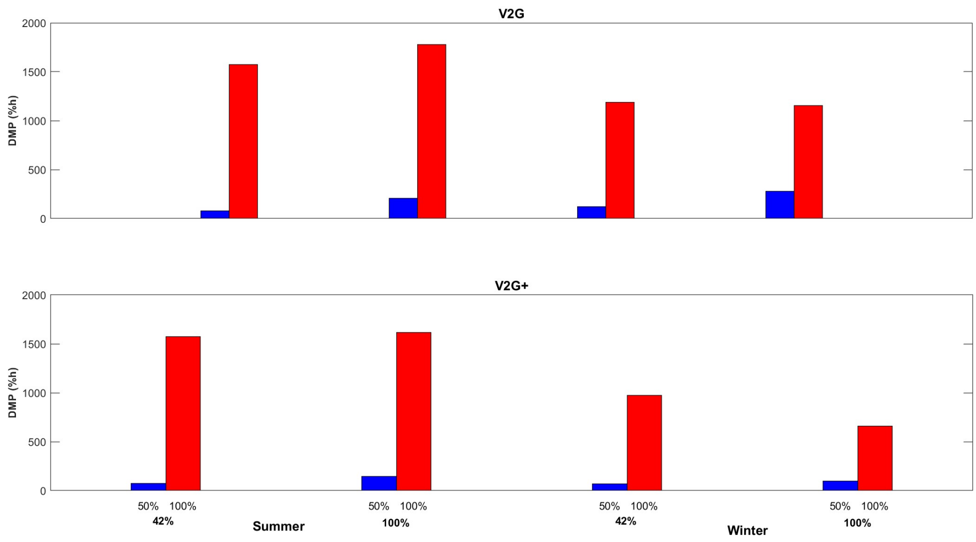

Figure 5.18: DMP values of transformer for different V2G participation level in a heavy suburban grid.

Essentially, the more vehicles involved in energy exchange, the more stressed the grid becomes.

While mobile V2G technology offers a potential solution, the benefits are somewhat limited. Vehicles that charge at external locations, such as workplaces, instead of relying on the local grid, do reduce the frequency of energy exchanges, alleviating some stress on transformers. However, as many vehicles still discharge power back into the grid during non-working hours—especially in the evening—the reduction in transformer stress remains modest. Although mobile V2G prevents continuous grid interaction during the day, its impact on overall grid stress remains limited.

Line

Increasing V2G participation from 50% to 100% leads to a notable rise in Median DMP values across various grid types, seasons, and commuting patterns. In the heavy grid, as illustrated in Figure 5.19, during summer with a 42% commuting pattern, the Median DMP increases from 30 to 38, reflecting a 26.7% rise. For the same grid type during summer but with a 100% commuting pattern, the Median DMP rises from 30 to 36, indicating a 20% increase. During winter, the Median DMP also rises by 20% across both commuting patterns. The light grid follows a similar pattern (Figure 5.20), though the increases are slightly smaller, particularly in summer with a 42% commuting pattern, where the Median DMP grows by 15.6%. Under all other conditions, the increase remains steady at 20%, indicating a consistent rise in grid stress as V2G participation reaches 100%.

This trend points to a direct relationship between increased V2G activity and heightened grid pressure. The uniform rise in Median DMP values, regardless of grid type, season, or commuting patterns, suggests that the expansion of V2G participation consistently elevates grid strain, with potential implications for grid management and infrastructure stability.

Further evidence supporting these conclusions comes from transformer and line loading data. For example, in the case of 42% commuting during winter, both V2G and mobile V2G scenarios exhibit greater variability in grid stress at 50% participation, with a wider range of maximum and minimum loading values. However, at 100% participation, the median loading values are higher, demonstrating greater overall stress despite the fluctuations being more pronounced at lower participation levels. This indicates that while stress variability may be higher at 50% participation, the total load on grid infrastructure intensifies significantly as V2G participation reaches 100%.

In the heavy suburban grid, the increase in V2G participation correlates with a higher frequency of grid violations, such as transformer overloads and line congestion, signaling potential risks of grid instability

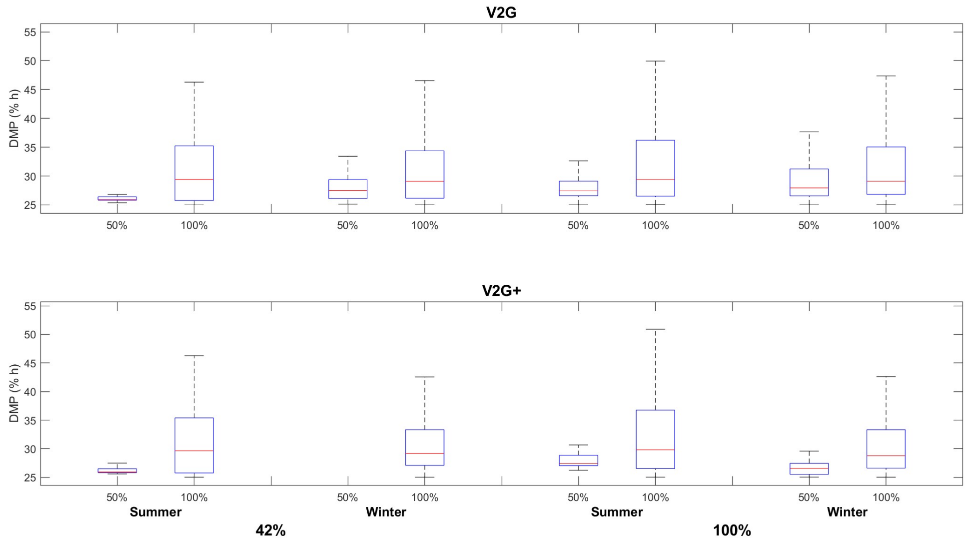

Figure 5.19: DMP values of line for different V2G participation level in a heavy suburban grid.

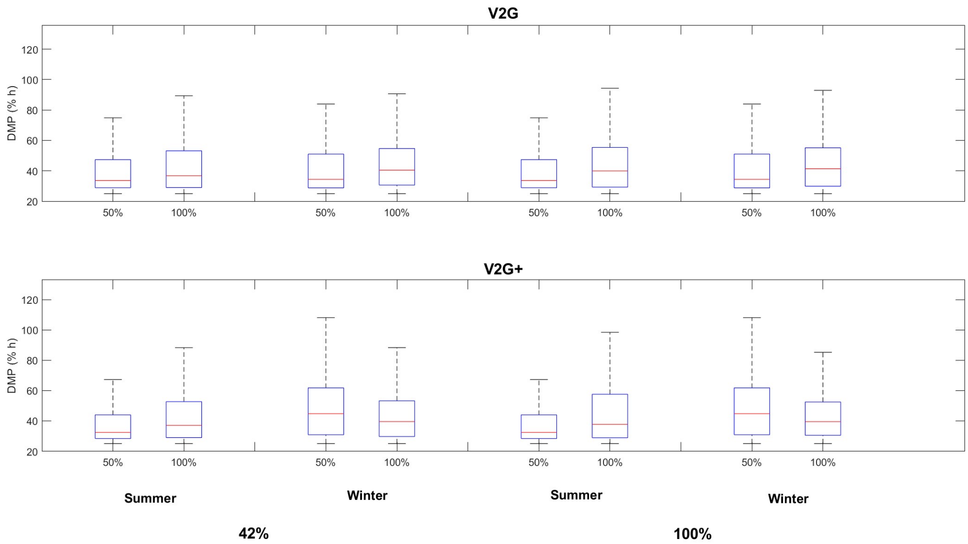

Figure 5.20: DMP values of line for different V2G participation level in a light suburban grid.

and failure. The consistent increase in stress across the grid, as indicated by transformer and line data.

Node

Figure 5.21 illustrates the node voltage profiles in a heavy suburban grid under different scenarios. As V2G participation increases from 50% to 100%, a clear trend emerges: both undervoltage and overvoltage issues become more common. This increase in voltage instability is linked to the higher number of EVs that can charge and discharge simultaneously, putting additional stress on the grid. The interaction between EV charging and discharging during peak hours amplifies these voltage fluctuations, which becomes particularly noticeable as more vehicles participate in V2G.

In the smart charging scenario, as the commuting pattern shifts from 42% to 100%, there is a notable rise in undervoltage occurrences. The increased energy demand from more vehicles charging during

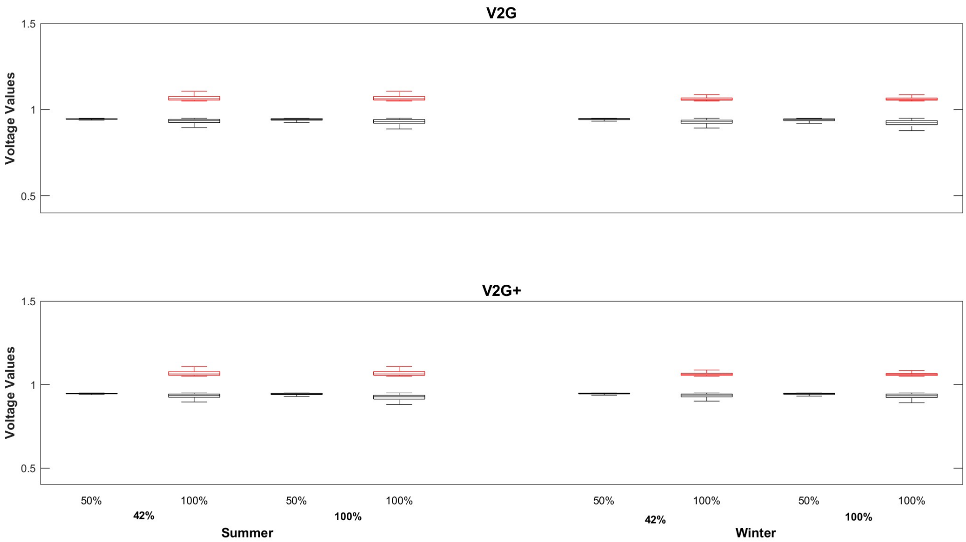

Figure 5.21: Node voltage profiles in the heavy suburban grid under varying V2G participation and commuting patterns.

peak periods causes voltage drops across the grid. Median undervoltage levels also increase, reflecting a broader decline in voltage stability due to the additional charging load. As more EVs require power during the same hours, the grid's capacity to maintain stable voltages diminishes, leading to more frequent undervoltage events.

In both the V2G and mobile V2G scenarios, increasing V2G participation worsens both undervoltage and overvoltage issues. The simultaneous charging of EVs leads to undervoltages, while discharging activities cause overvoltages, resulting in greater voltage swings throughout the grid. However, the mobile V2G scenario shows a slightly reduced impact compared to standard V2G. This difference is likely due to mobile V2G's ability to distribute the charging load across multiple locations, potentially easing some of the voltage instability by avoiding overloading residential areas during peak times.

Figure 5.22 shows a similar trend in the light suburban grid, with increasing commuting patterns leading to more severe undervoltage problems. As more EVs charge at the same time during peak hours, the grid faces greater strain, causing voltage levels to dip below acceptable thresholds. The increase in concurrent EV charging activities imposes a heavy load on the grid, leading to widespread undervoltage issues similar to those seen in the heavy suburban grid.

In the V2G and mobile V2G scenarios depicted in Figure 5.22, both undervoltage and overvoltage problems become more pronounced with higher V2G participation. As in the heavy grid, the charging of EVs causes undervoltage issues, while discharging leads to overvoltage fluctuations. Interestingly, an anomaly is observed in the mobile V2G scenario with 100% V2G participation and daily commuting. In this case, undervoltage issues are less severe compared to the 42% commuting pattern. This reduction in undervoltages is due to EVs being able to charge at work locations during the day, which helps balance the grid's energy demand and reduces the load on residential nodes during the evening peak. By charging away from home, EVs return with lower energy needs, easing the demand on residential areas and thus lowering the frequency of undervoltages.

Despite the improvement in undervoltages, overvoltages caused by discharging activities remain consistent. Since the total amount of energy discharged back to the grid does not change significantly, the risk of overvoltage continues, particularly when EVs feed excess energy back into the grid during off-peak hours. Seasonal variations also play a role in voltage stability, particularly in the winter season with 100% commuting in the light suburban grid. During this period, fluctuations in electricity prices and EV availability reduce the severity of undervoltage and overvoltage issues compared to the 42% commuting pattern. Price signals encourage EVs to charge and discharge in a way that results in fewer

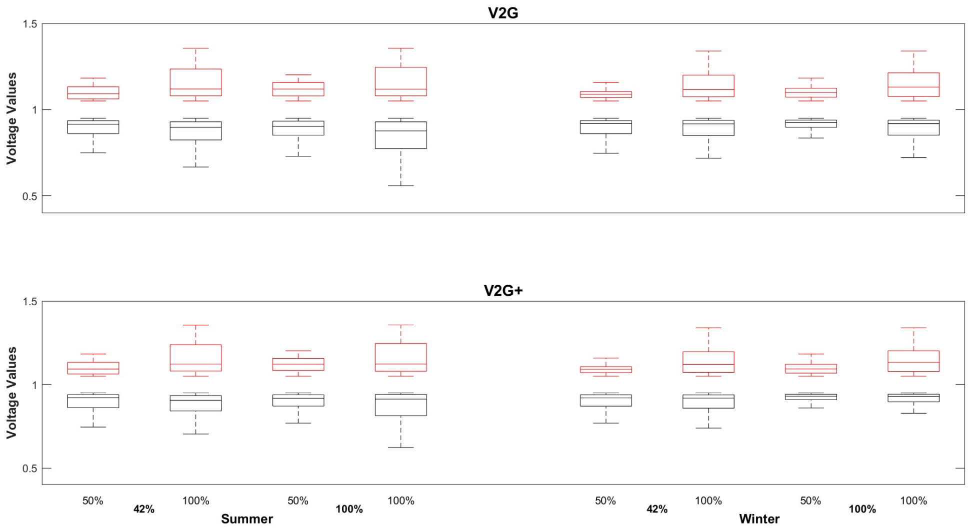

Figure 5.22: Node voltage profiles in the light suburban grid under varying V2G participation and commuting patterns.

cycles, thereby placing less stress on the grid. In the mobile V2G scenario, the ability of EVs to charge at multiple locations further spreads the load, contributing to the reduction in voltage fluctuations.

5.2.3. Impact due to Seasonal variation

Transformer

As Figure 5.23 illustrates, in the heavy suburban grid, the Smart Charging scenario shows consistent transformer DMP values of 40 %h in both summer and winter for the 42% commuting pattern. However, at 100% commuting, the DMP rises from 80 %h in summer to 90 %h in winter, reflecting a 12.5% increase in transformer stress during the colder months. This suggests that while Smart Charging effectively handles lower commuting levels, winter causes higher transformer stress at full commuting capacity, likely due to increased heating demands.

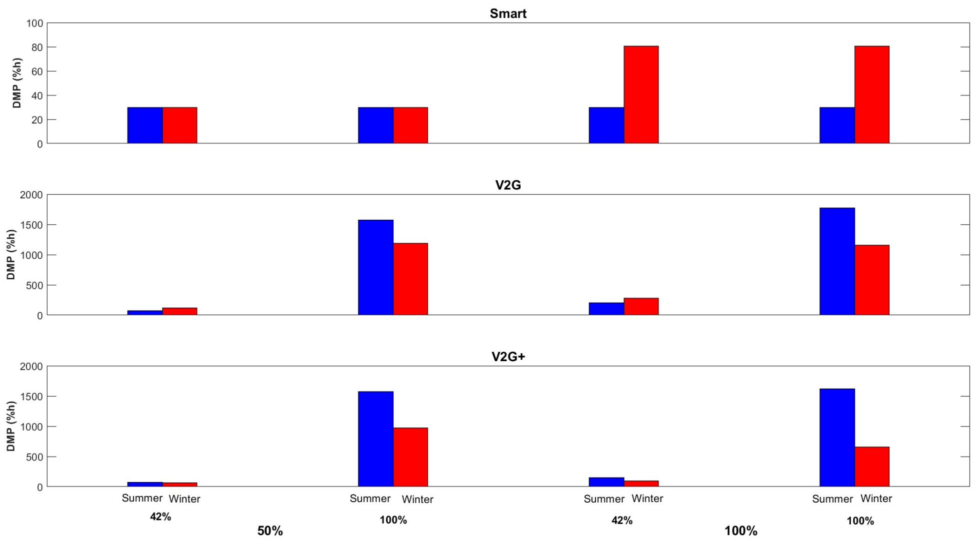

Figure 5.23: Transformer DMP values in the heavy suburban grid for different seasons

For V2G, a significant pattern emerges, particularly in the 42% commuting scenario, where transformer stress is higher in winter than summer. The DMP increases from 200 %h in summer to 210 %h in winter, a 5% rise in stress during winter. This is notable, as V2G typically exerts more stress during summer due to higher solar generation and frequent charging/discharging. However, in this case, the heavy suburban grid faces additional transformer loading challenges in winter, likely driven by heating needs and reduced solar input.

At 100% commuting, Figure 5.23 shows that summer-induced transformer stress becomes more pronounced. The DMP increases to 1600 %h in summer compared to 1400 %h in winter, reflecting a 14.3% rise. This aligns with expected trends, where summer, driven by peak solar production and V2G interactions, leads to greater transformer strain.

In the V2G+ scenario, as Figure 5.23 further demonstrates, winter proves more stressful for transformers at 42% commuting. The DMP doubles from 20 %h in summer to 40 %h in winter, indicating a 100% rise. This suggests that even with the dynamic capabilities of V2G+, winter conditions, with heightened heating demand and less solar power, significantly increase transformer loading.

At 100% commuting, the trend reverses again, with summer causing more transformer stress. The DMP reaches 1400 %h in summer, compared to 1200 %h in winter, representing a 16.7% increase. This follows the pattern observed with V2G, where higher commuting and solar activity during summer exacerbate the demands on transformers.

In the light grid, as depicted in Figure 5.24, Smart Charging reveals an inverse trend, with winter consistently causing more transformer stress than summer. At 42% commuting, the DMP jumps from 120 %h in summer to 250 %h in winter, a 108.3% increase. Similarly, at 100% commuting, the DMP rises from 280 %h in summer to 400 %h in winter, a 42.9% increase in transformer stress during winter. This highlights that Smart Charging struggles to manage transformer loading effectively in the light grid during the winter, likely due to lower solar generation and higher heating demand.

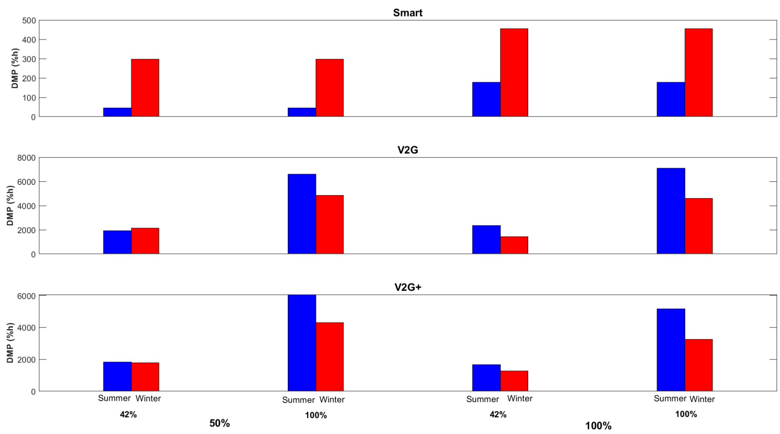

Figure 5.24: Transformer DMP values in the light grid for different seasons.

For V2G, transformer stress remains considerably higher in summer. At 100% commuting, the DMP reaches 5000 %h in summer, compared to 4600 %h in winter, reflecting an 8.7% increase in summer stress. At 42% commuting, the summer DMP is 2000 %h, compared to 2200 %h in winter, showing a 10% rise in winter stress. Although summer induces higher stress overall, winter still poses significant challenges to transformer loading, particularly under lower commuting conditions.

Similarly, Figure 5.24 shows that in the V2G+ scenario, summer continues to cause more stress at 100% commuting, with the DMP rising from 3500 %h in winter to 4000 %h in summer, reflecting a 14.3% increase. At 42% commuting, winter slightly exceeds summer, with DMP values of 2000 %h in winter compared to 1800 %h in summer, indicating an 11.1% rise. Although V2G+ performs better overall, both summer and winter present transformer loading challenges, with summer causing slightly more stress at higher commuting levels.

Line

As Figure 5.25 illustrates, in the heavy suburban grid, line loading increases significantly during winter, especially in the Smart Charging scenario. Under the 42% commuting pattern, DMP rises from 25 %h in summer to 30 %h in winter, reflecting a 20% increase in line stress. This trend becomes more pronounced at 100% commuting, where DMP jumps from 25 %h in summer to 40 %h in winter, a 60% rise. These results indicate that Smart Charging faces substantial challenges in maintaining line stability during winter, particularly as commuting levels increase. The added heating demand in colder months is a major factor, contributing to heightened grid stress despite efforts to optimize charging times.

For V2G, Figure 5.25 shows that winter continues to be more challenging for line loading, though the increase in stress is less extreme. Under the 42% commuting pattern, DMP rises from 30 %h in summer to 35 %h in winter, marking a 16.7% increase in stress on the lines. At 100% commuting, DMP climbs from 40 %h in summer to 45 %h in winter, reflecting a 12.5% increase in line loading during the colder months. Despite V2G's potential to alleviate stress through energy discharge, the increased heating demands and lower renewable energy availability during winter still put pressure on the grid. However, this line is blurred with increase participation of v2g causing higher discharge posing a challenge for line by increasing its value.

In the V2G+ scenario, as Figure 5.25 further shows, line loading stress also increases during winter. At 42% commuting, DMP rises from 30 %h in summer to 35 %h in winter, a 16.7% rise. Similarly, at 100% commuting, DMP rises from 40 %h in summer to 45 %h in winter, reflecting a 12.5% increase. Despite V2G+ offering more dynamic charging and discharging capabilities, winter continues to impose more significant challenges for line loading, primarily due to higher energy demand and reduced solar input. The trend sets to reverse when we consider increased v2g paricipation due to increase in discharging power as discussed eariler.

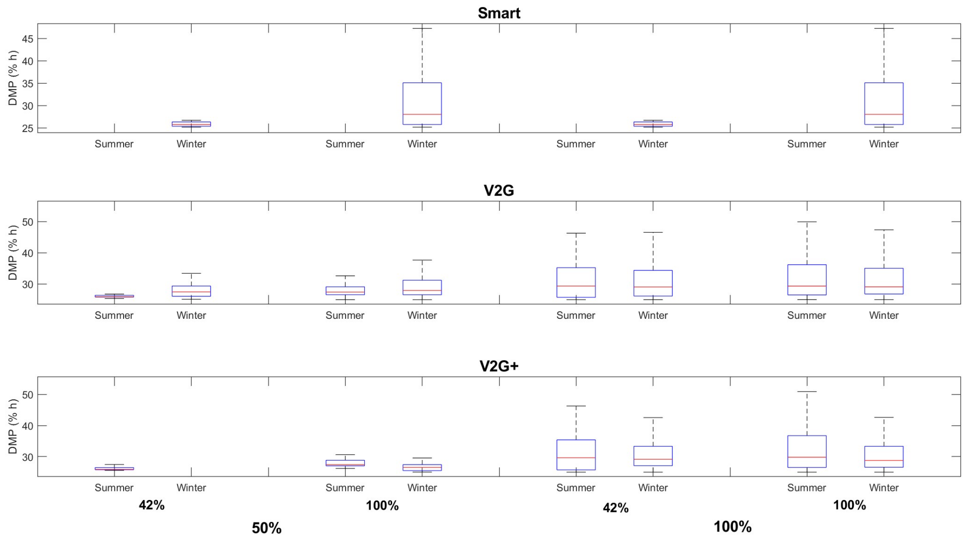

Figure 5.25: Line DMP values in the heavy suburban grid for different season.

As illustrated in Figure 5.26, the light suburban grid experiences an even more significant rise in line loading during winter, particularly in the Smart Charging scenario. At 42% commuting, DMP increases sharply from 35 %h in summer to 50 %h in winter, a 42.9% rise. At 100% commuting, DMP rises from 45 %h in summer to 60 %h in winter, reflecting a 33.3% increase in winter line stress. These findings indicate that Smart Charging struggles more in winter in the light grid, likely due to higher heating demands and reduced solar generation, placing additional strain on the grid infrastructure.

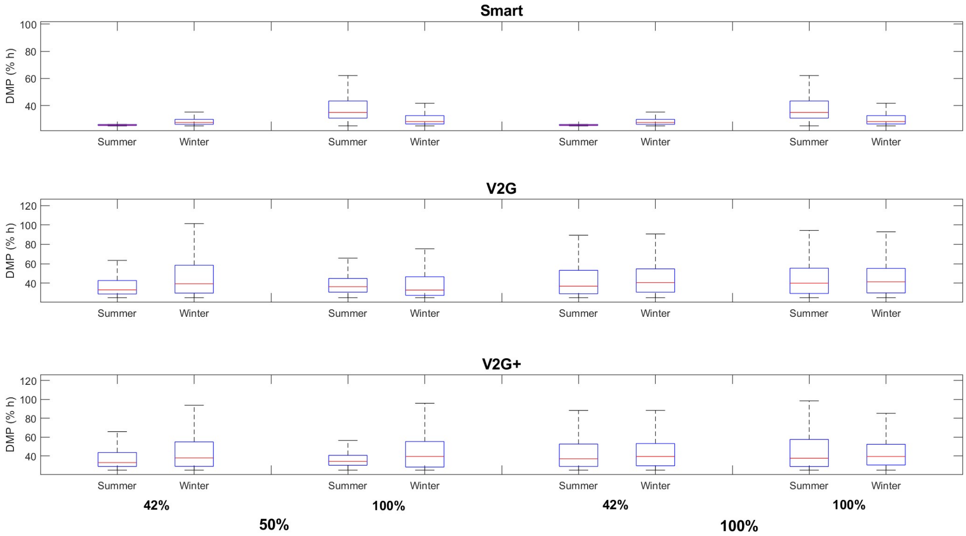

Figure 5.26: Line DMP values in the light suburban grid for different season.

For V2G, Figure 5.26 shows that line loading stress is most pronounced in winter. At 42% commuting, DMP increases from 40 %h in summer to 60 %h in winter, a 50% rise. At 100% commuting, DMP rises from 60 %h in summer to 80 %h in winter, reflecting a 33.3% increase. Despite V2G's capability to discharge energy and reduce grid stress, the light suburban grid experiences severe winter pressure, likely because the higher energy demand during this season overwhelms the system's capacity. However, similar to heavy suburban grid rend reverses as we increase the discharge capabilities.

For V2G+, Figure 5.26 shows a slightly more balanced pattern, but winter still leads to higher line loading. At 42% commuting, DMP increases from 45 %h in summer to 55 %h in winter, a 22.2% rise. At 100% commuting, DMP increases from 65 %h in summer to 75 %h in winter, reflecting a 15.4% increase. Although V2G+ performs better overall, winter remains challenging, especially in high commuting scenarios where the demand for energy intensifies, and solar generation remains limited.

This indicates that the increasing demand causes corresponding to winter season. However, the discharge does effect the line loading on significant level. Hence, high v2g participation poses problem in the grid causing the line loading to be almost similar in both the seasons.

Node

Figure 5.27 presents the nodal voltages for the grid under different seasonal conditions. It is evident that winter consistently proves to be the worst season compared to summer across all scenarios. While overvoltages are absent, winter experiences significantly higher undervoltages. Notably, undervoltage issues are exacerbated in the summer during 100% commuting.

When incorporating V2G (Vehicle-to-Grid), where EVs discharge power back to the grid, we observe that with 50% of EVs participating, no overvoltages occur. However, when all vehicles participate in discharging, there is a noticeable increase in overvoltages. This issue becomes more pronounced in summer, which is exacerbated by the increased PV (Photovoltaic) generation. Despite this, undervoltage levels remain constant across scenarios. A similar trend is noted in the mobile V2G scenario, where the undervoltages remain largely unchanged, but the increase in PV generation and EV discharging heightens the problem of overvoltages in the grid.

Figure 5.28 illustrates the nodal voltages for various seasons across different charging technologies. The undervoltage pattern remains consistent, with increasing magnitude and winter being the worst

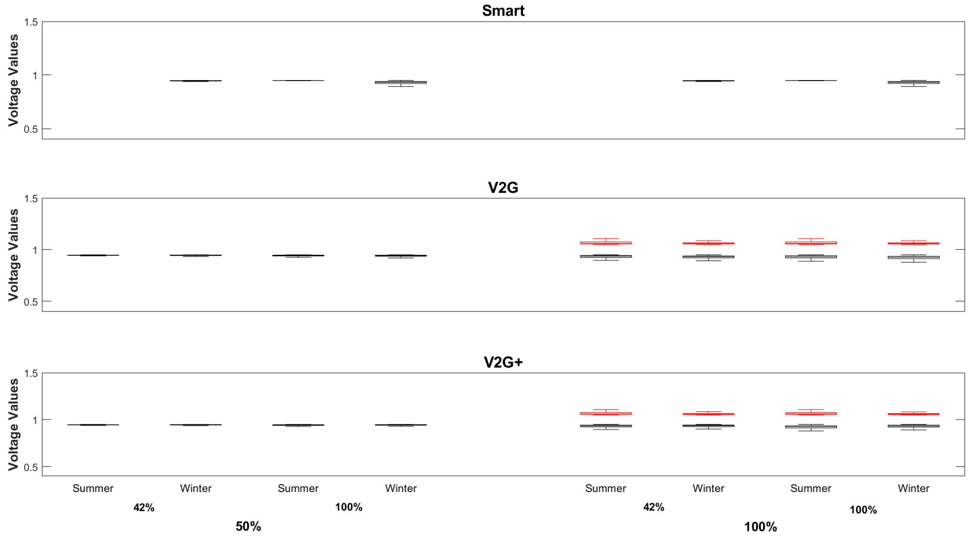

Figure 5.27: Nodal voltages under different seasonal conditions in Heavy suburban grid.

season. In the case of V2G, however, the discharge causes additional overloading in both winter and summer scenarios. The summer season emerges as particularly problematic due to the combination of PV generation and vehicle discharge, and the magnitude of overvoltage increases with higher discharge capacities. The mobile V2G scenario shows a similar trend, where undervoltages stay roughly constant, but increased PV generation and EV participation significantly aggravate overvoltage issues in the grid.

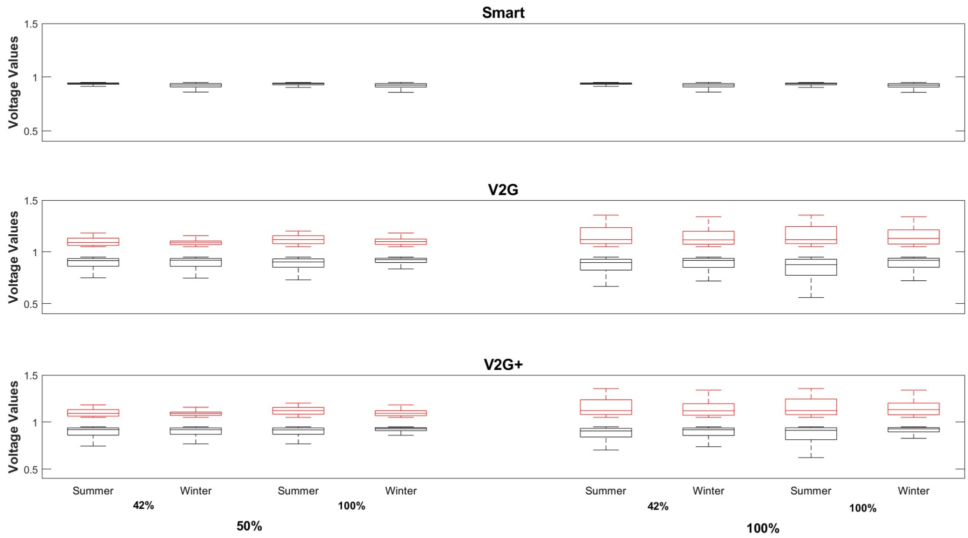

Figure 5.28: Nodal voltages across different seasons in light suburban grid.

6
Conclusion and Recommendation

6.1. Reflection on Result

Uncoordinated charging by individual users significantly impacts the stability of the Dutch low-voltage grid, especially in scenarios of high EV penetration. The absence of centralized control over charging and discharging behaviors, particularly during peak hours, exacerbates issues related to grid stability, load management, and voltage regulation. Moreover, increased EV penetration blurs the demand margins requested by a significant percentage, making it challenging for grid operators to predict and manage loads effectively.

One of the main challenges is increased transformer loading and overall grid stress. Uncoordinated charging, especially when users return home and plug in their EVs simultaneously, causes transformers to operate beyond their capacity. This leads to higher Duration Magnitude Product (DMP) values and frequent transformer overloads. In V2G scenarios, the situation worsens, as uncoordinated discharging leads to frequent power spikes, further stressing the transformers and increasing the likelihood of failures. The lack of mitigation strategies to solve problems caused by Time-of-Use (TOU) pricing, and the day-ahead market's failure to reflect changing demand, contribute to this lack of coordination.

Another major concern is the congestion and overloading of distribution lines. As more vehicles charge simultaneously, particularly those farther from transformers, the current requirements rise due to lower nodal voltages, contributing to increased line loading. This congestion can lead to overheating, equipment failure, and even outages. Although V2G capabilities offer some relief by enabling discharging during peak hours, the overall load on the grid remains high, particularly in high-commuting scenarios, thus failing to fully mitigate the stress on lines and transformers.

Voltage deviations also present a serious problem due to uncoordinated charging. The simultaneous charging of multiple vehicles during peak hours causes significant voltage drops, resulting in undervoltage conditions across the network. Conversely, in V2G scenarios, high discharging participation without coordination can lead to overvoltages when excess energy is injected back into the grid at times of low demand. Both undervoltage and overvoltage conditions pose risks to grid reliability, potentially causing equipment damage and power disruptions.

The combined effects of overloading and voltage deviations reduce the overall reliability of the grid. Transformers and lines experience accelerated wear and tear, increasing the likelihood of equipment failures. This, in turn, leads to potential outages and poses challenges for grid operators in managing unpredictable power fluctuations. Without centralized coordination and with assumptions of perfect knowledge of the system, managing the grid efficiently becomes increasingly difficult, leading to operational inefficiencies and higher maintenance costs.

Individual user behaviors, such as commuting patterns and seasonal charging habits, further complicate grid management. Higher commuting percentages, particularly in the Netherlands, significantly increase energy demand during peak hours, resulting in higher transformer and line loading. In winter, colder temperatures and increased energy demands for heating exacerbate these issues, causing voltage deviations and putting additional strain on the grid. In summer, the situation changes, with increased solar generation reducing net demand. However, the combination of high solar generation and uncoordinated V2G discharging can lead to overvoltages, particularly when demand is low.

V2G participation also plays a crucial role in influencing grid dynamics. While V2G technology has the potential to alleviate grid stress by distributing charging loads more evenly, uncoordinated discharging can worsen grid conditions, causing transformer overloading and voltage fluctuations. Higher V2G participation rates, without proper coordination, can exacerbate these challenges, especially during periods of high demand or high solar generation.

6.2. Recommendation for Future Works

Future research could focus on incorporating location-specific aspects into the analysis to provide grid-specific solutions. By changing the optimization approach to Particle Swarm Optimization (PSO), it would be possible to account for spatial variations in grid infrastructure and demand patterns. PSO optimization can enhance the efficiency of managing charging and discharging activities by finding optimal solutions that are tailored to specific regions within the grid.

Additionally, implementing quasi-dynamic load flow analysis using unbalanced load flow methods could further enhance the robustness of the model. Unbalanced load flow takes into account the asymmetrical distribution of loads across different phases of the power system, providing a more accurate representation of real-world conditions. This approach would improve the reliability of simulation results and help in designing strategies that are more effective in mitigating grid stress.

Strategies like dynamic pricing or the introduction of aggregators could also be explored to mitigate the issue of simultaneous charging. Dynamic pricing incentivizes users to shift their charging activities to off-peak hours by varying the cost of electricity based on demand. Aggregators can coordinate charging and discharging schedules among multiple EV users, optimizing the overall load on the grid. These strategies have the potential to reduce peak demand, alleviate transformer and line loading, and enhance grid stability.

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A

Appendix

A.1. Transformer Plots

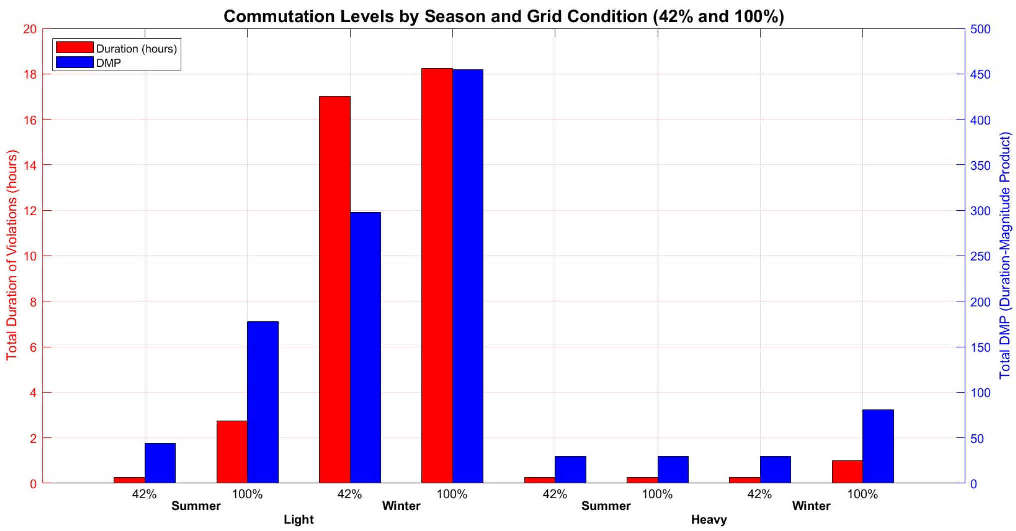

Figure A.1: DMP Smart Charging

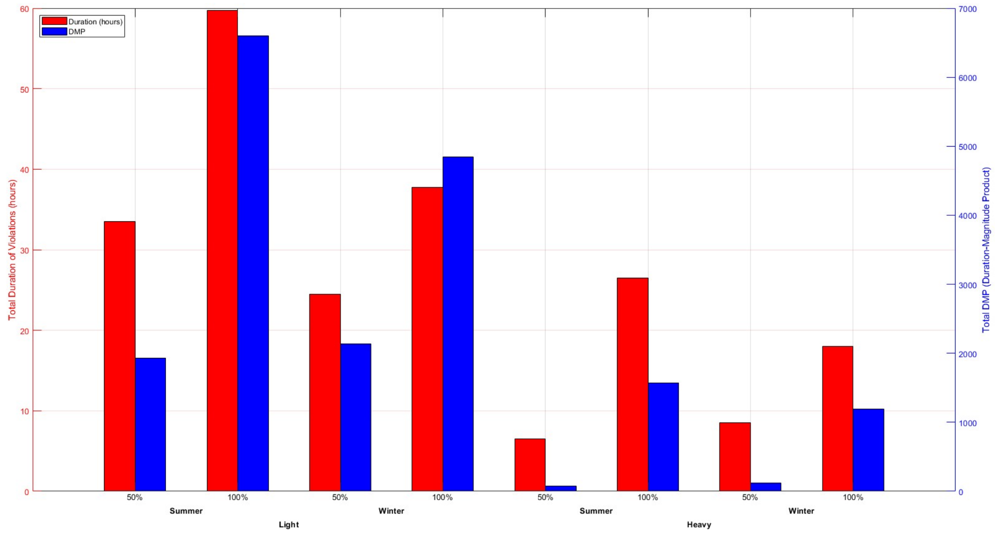

Figure A.2: DMP V2G 42% Commutation

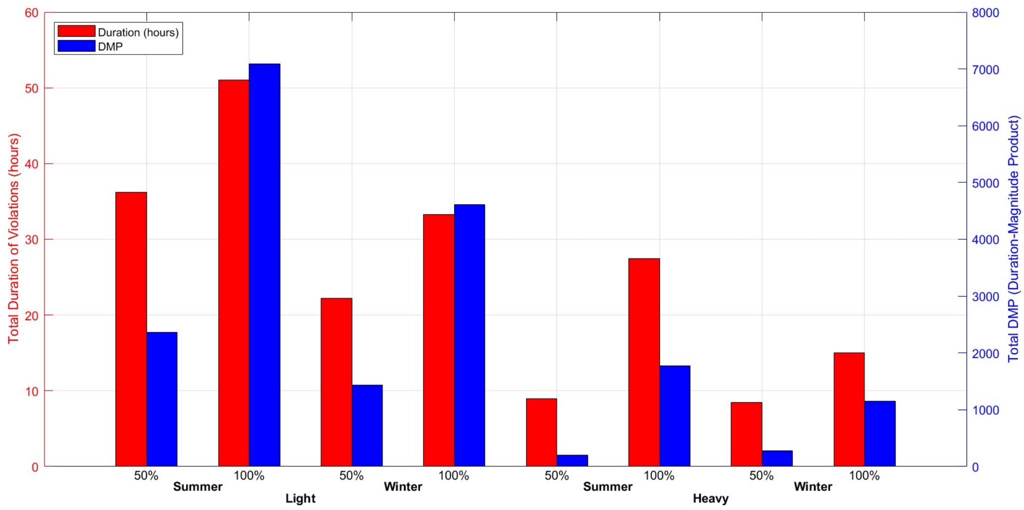

Figure A.3: DMP V2G 100% Commutation

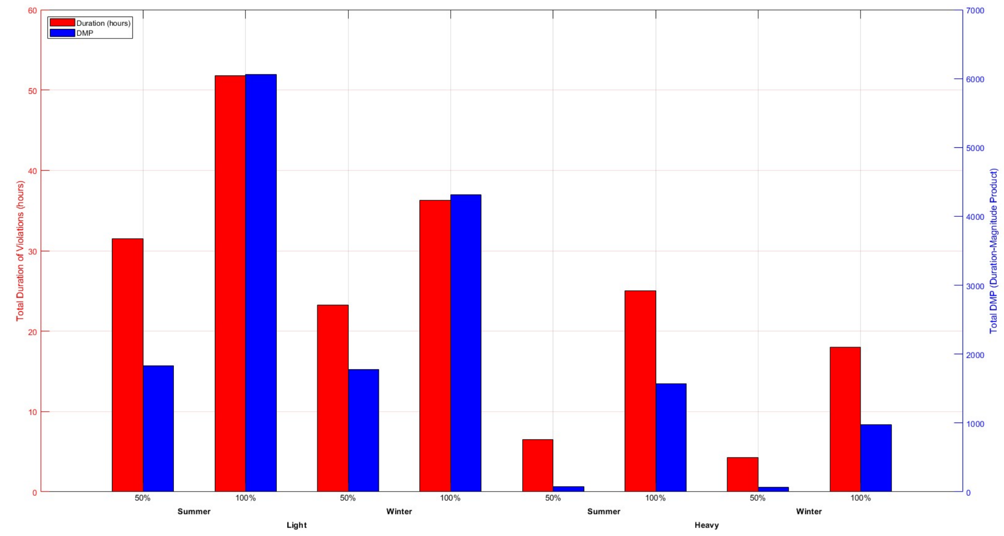

Figure A.4: DMP V2G+ 42% Commutation

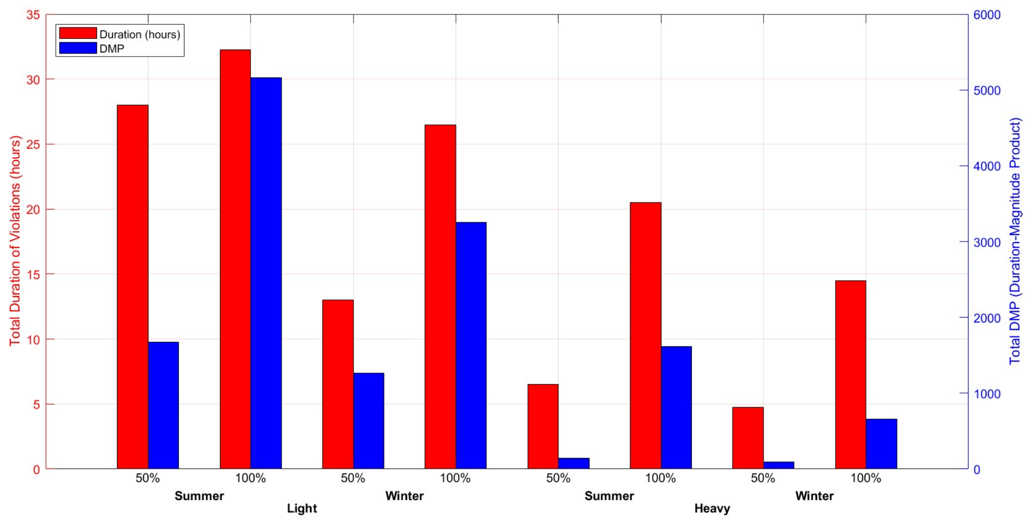

Figure A.5: DMP V2G+ 100% Commutation

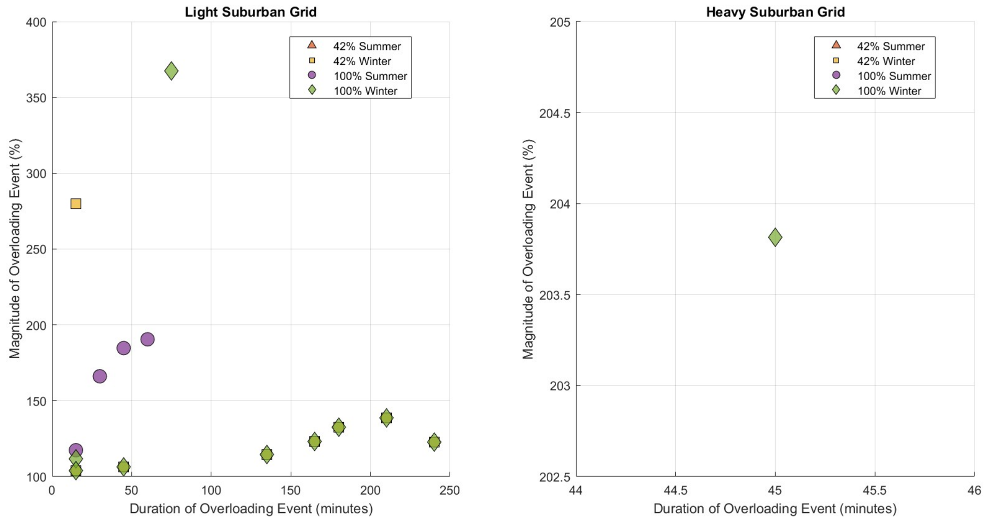

Figure A.6: Scatter Plot Smart Charging

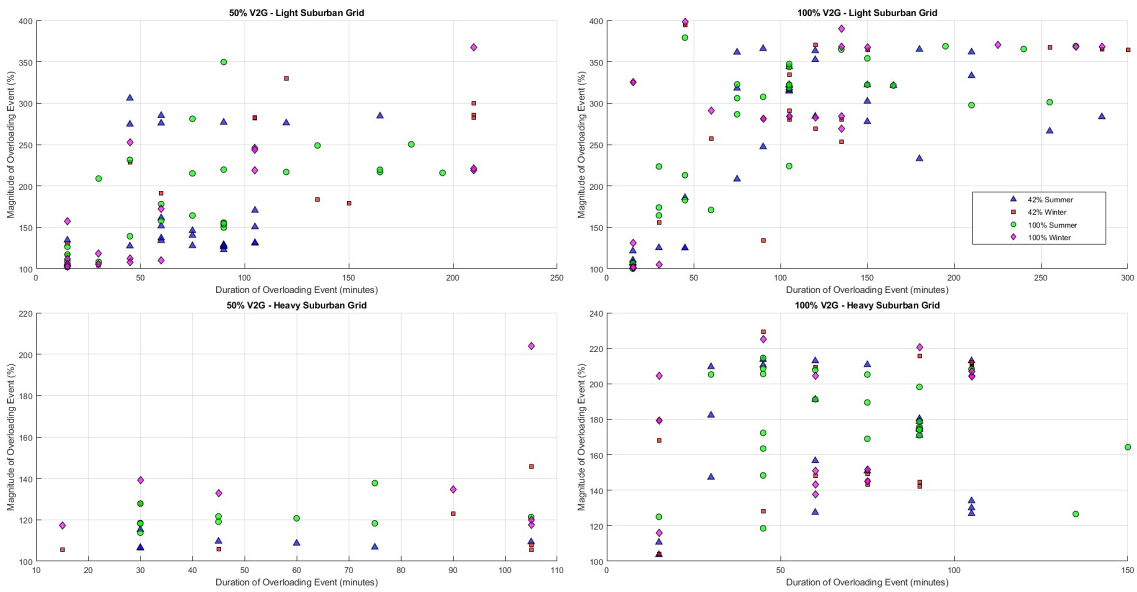

Figure A.7: Scatter Plot V2G

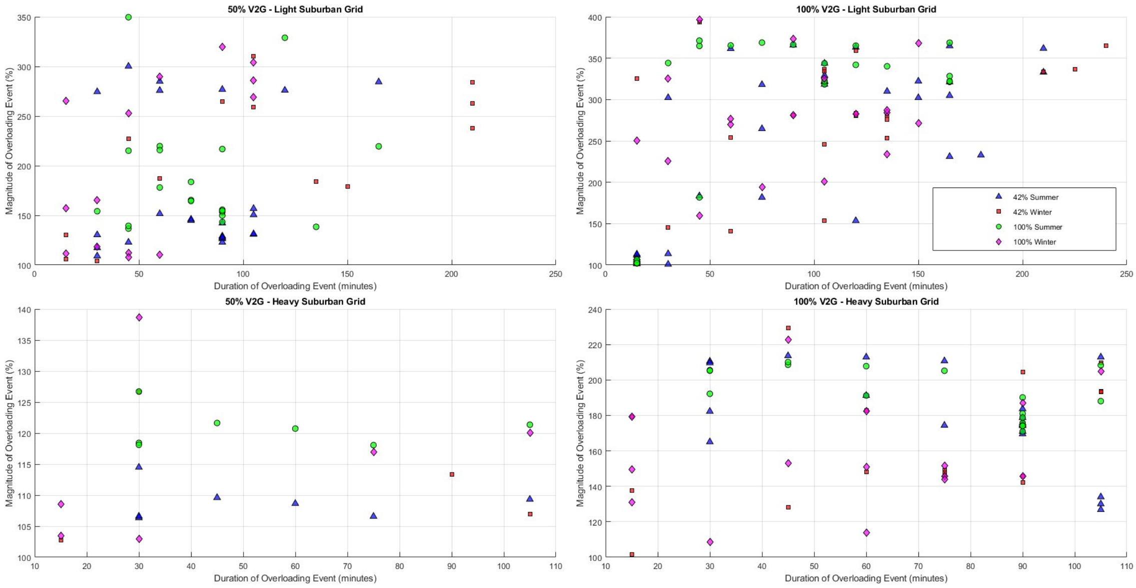

Figure A.8: Scatter Plot V2G+

A.2. Line Plots

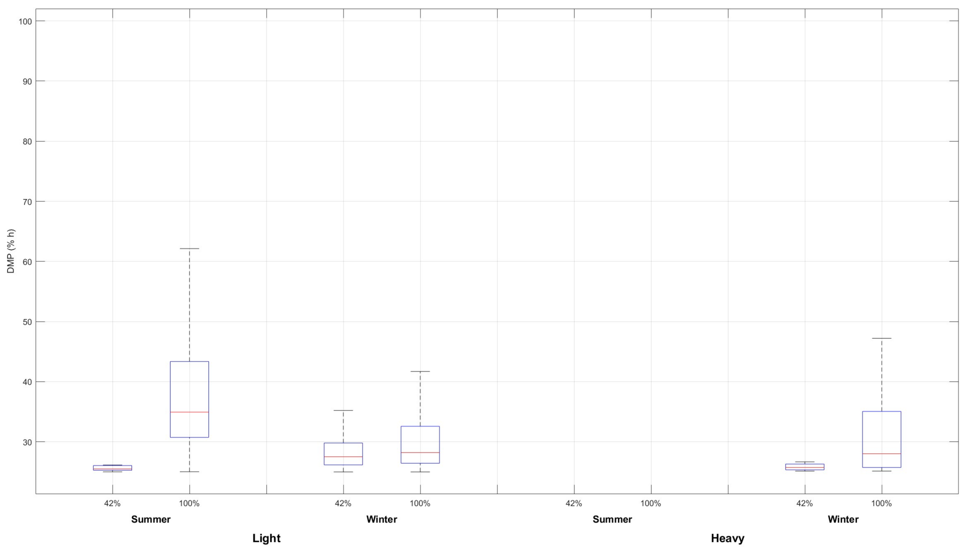

Figure A.9: Line Smart Charging DMP

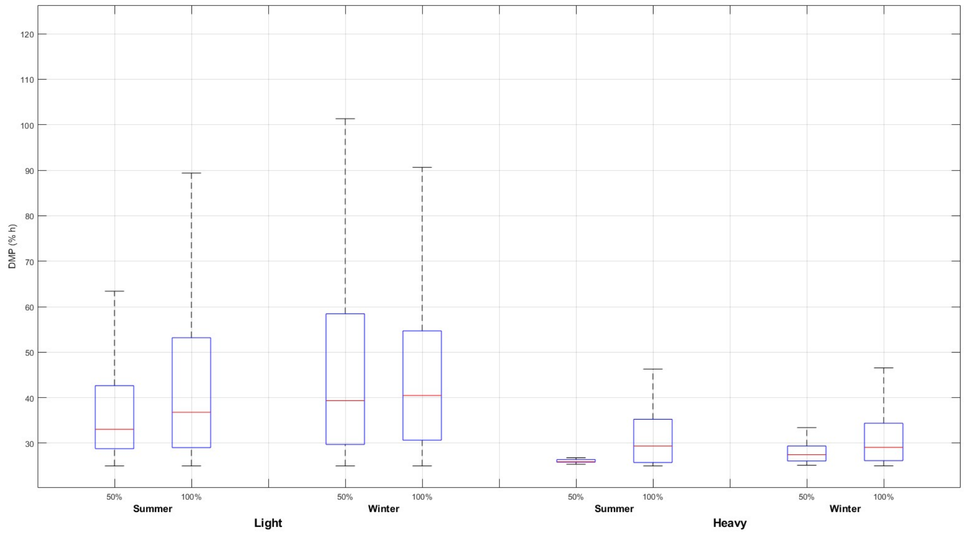

Figure A.10: Line V2G 42% Commutation DMP

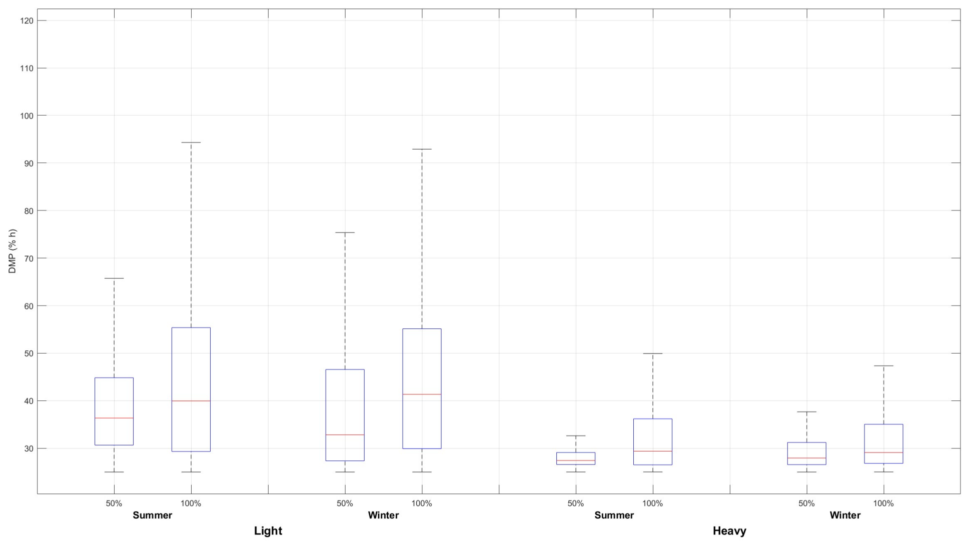

Figure A.11: Line V2G 100% Commutation DMP

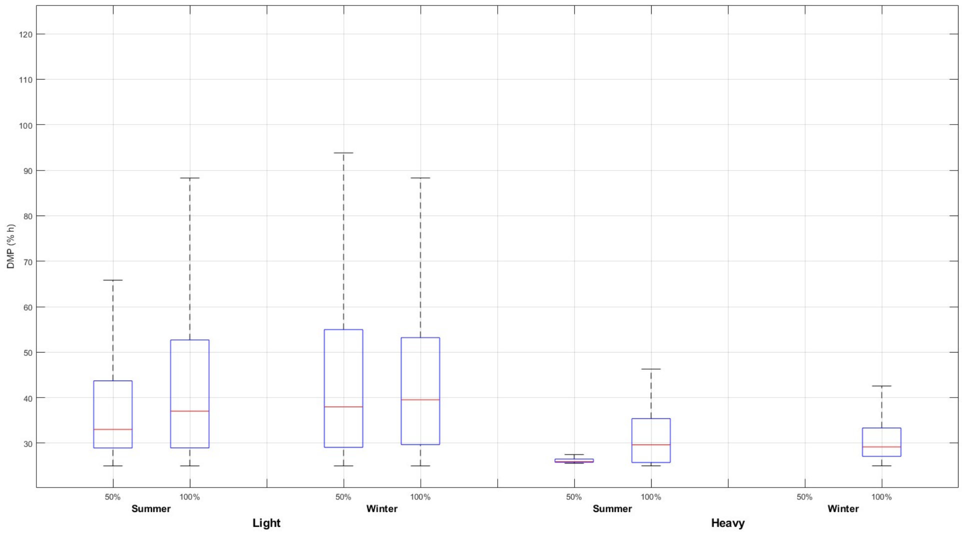

Figure A.12: Line V2G+ 42% Commutation DMP

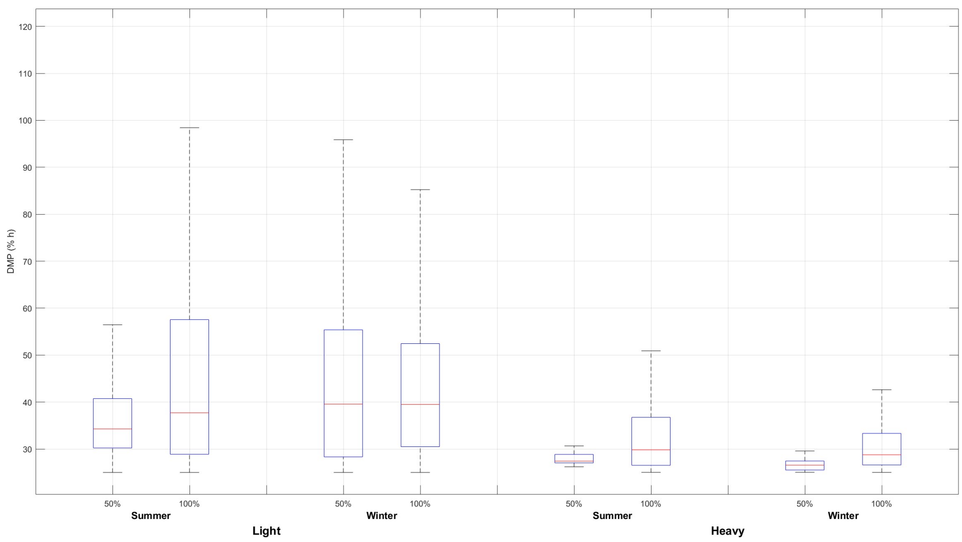

Figure A.13: Line V2G+ 100% Commutation DMP

A.3. Node Plots

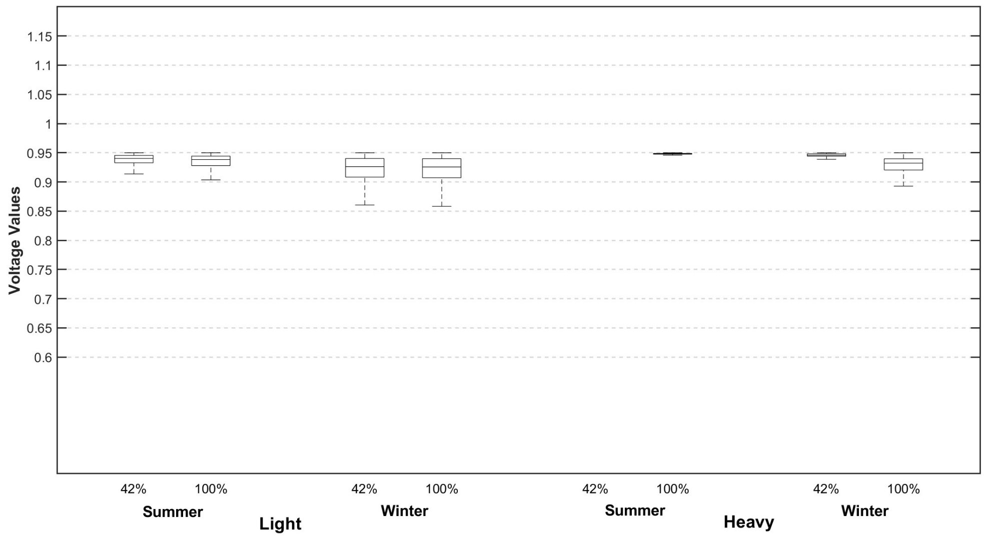

Figure A.14: Voltage Smart Charging

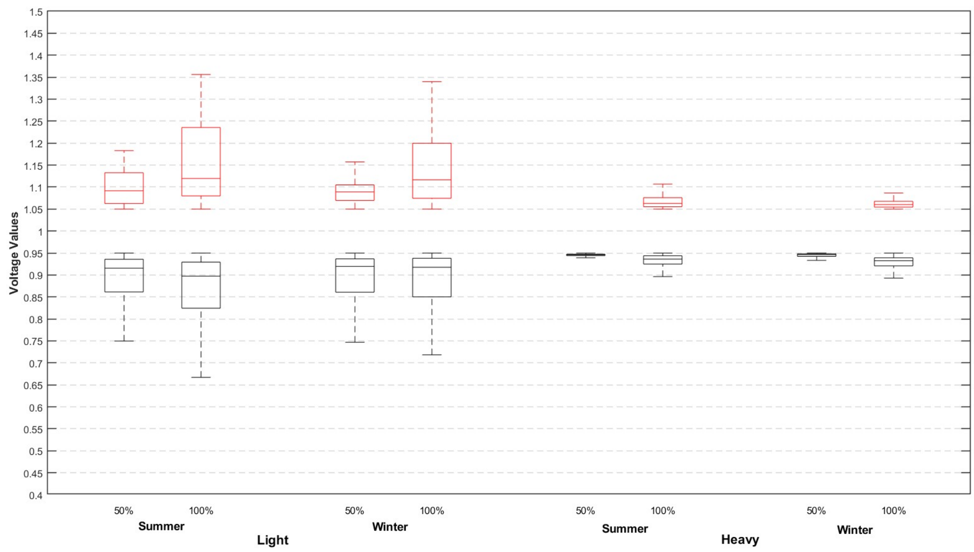

Figure A.15: Voltage V2G 42% Commuting

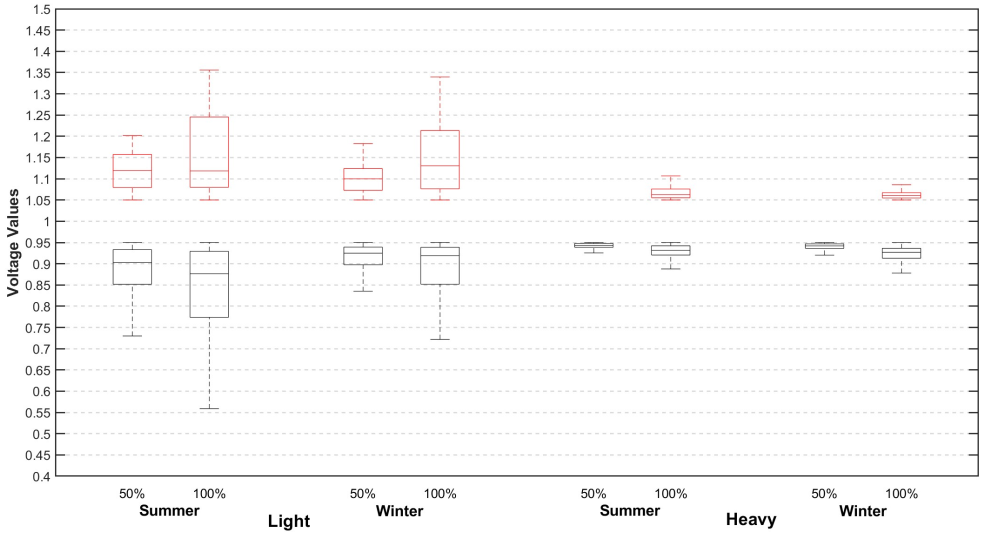

Figure A.16: Voltage V2G 100% Commuting

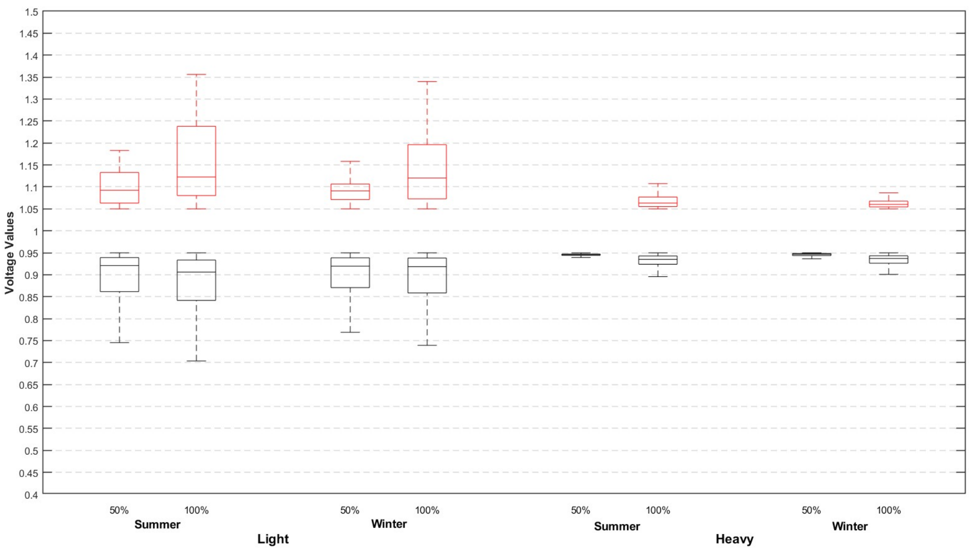

Figure A.17: Voltage V2G+ 42% Commuting

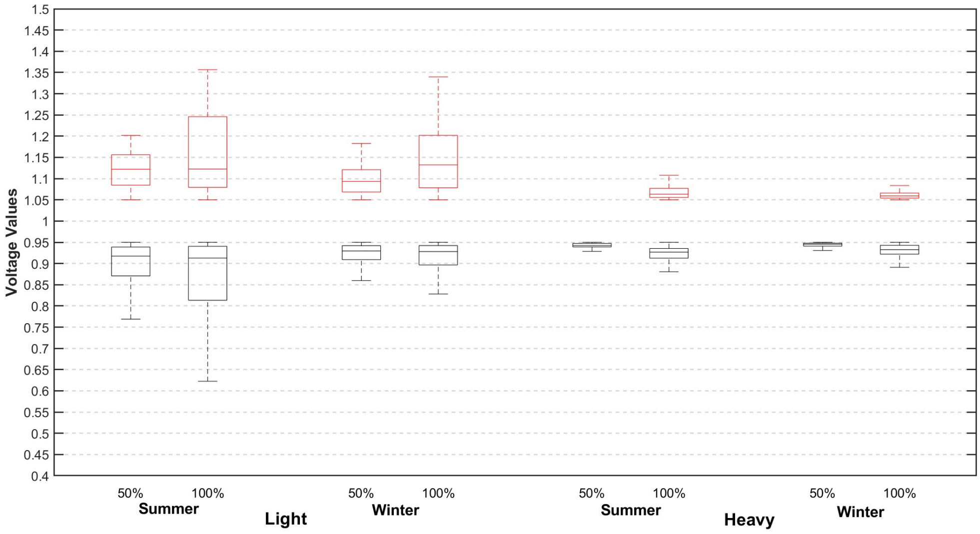

Figure A.18: Voltage V2G+ 100% Commuting